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Influence of meteorological conditions on $PM_{2.5}$ concentrations across China: A review of methodology and mechanism

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ABSTRACT

Air pollution over China has attracted wide interest from public and academic community. $PM_{2.5}$ is the primary air pollutant across China. Quantifying interactions between meteorological conditions and $PM_{2.5}$ concentrations are essential to understand the variability of $PM_{2.5}$ and seek methods to control $PM_{2.5}$. Since 2013, the measurement of $PM_{2.5}$ has been widely made at 1436 stations across the country and more than 300 papers focusing on $PM_{2.5}$-meteorology interactions have been published. This article is a comprehensive review on the meteorological impact on $PM_{2.5}$ concentrations. We start with an introduction of general meteorological conditions and $PM_{2.5}$ concentrations across China, and then seasonal and spatial variations of meteorological influences on $PM_{2.5}$ concentrations. Next, major methods used to quantify meteorological influences on $PM_{2.5}$ concentrations are checked and compared. We find that causality analysis methods are more suitable for extracting the influence of individual meteorological factors whilst statistical models are good at quantifying the overall effect of multiple meteorological factors on $PM_{2.5}$ concentrations. Chemical Transport Models (CTMs) have the potential to provide dynamic estimation of $PM_{2.5}$ concentrations by considering anthropogenic emissions and the transport and evolution of pollutants. We then comprehensively examine the mechanisms how major meteorological factors may impact the $PM_{2.5}$ concentrations, including the dispersion, growth, chemical production, photolysis, and deposition of $PM_{2.5}$. The feedback effects of $PM_{2.5}$ concentrations on meteorological factors are also carefully examined. Based on this review, suggestions on future research and major meteorological approaches for mitigating $PM_{2.5}$ pollution are made finally.

1. Introduction

$PM_{2.5}$(atmospheric particles with aerodynamic diameters less than or equal to 2.5 μm) has become one major airborne pollutant across China and attracted widespread public interest, when a severe and persistent pollution episode occurred in Beijing in December 2012. Since then, $PM_{2.5}$ dominated haze episodes have been frequently reported across China (Huang et al., 2014; He et al., 2017; etc.). Due to its negative influence on human health (Lanzinger et al., 2016; Li et al., 2015b; etc.), studies concerning the characteristics (Zhang et al., 2013; Wang et al., 2016; etc.) and sources (Gu et al., 2014; Liu et al., 2014; etc.) of $PM_{2.5}$ have been massively conducted in recent years.

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One key step for comprehensively estimating and managing $PM_{2.5}$ pollution is to quantify its major influencing factors. Anthropogenic emissions have been widely accepted as the dominant driver for $PM_{2.5}$ concentrations, whilst meteorological conditions also exert a strong influence on long-term $PM_{2.5}$ variations (He et al., 2017). Yang et al. (2016) quantified that meteorological conditions alone contributed 1.8 out of 15 $\mu g\, m^{-3}$ $decade^{-1}$ $PM_{2.5}$ variation in eastern China from 1985 to 2005. Gui et al., (2019) calculated that meteorological conditions accounted for 48% of $PM_{2.5}$ variations in Eastern China from 1998 to 2016. Zhang et al. (2018) indicated that the relative contribution of meteorological conditions to heavy pollution episodes within Beijing-Tianjin-Hebei region was larger than 50% from 2013 to 2017. Chen et al., (2019) indicated that meteorological variations contributed about 20% of $PM_{2.5}$ reduction in Beijing from 2013 to 2017.

To further examine the strong, yet inconsistent meteorological influences on $PM_{2.5}$ concentrations, many studies have been conducted and suggest that multiple meteorological factors, including temperature (Li et al., 2015a; You et al., 2017; etc.), wind(Yin et al., 2017; etc.), humidity (Liao et al., 2017; Cheng et al., 2017; etc.), precipitation (Li et al., 2015; Guo et al., 2016; etc.), radiation (Chen et al., 2017), atmospheric pressure (Zhang et al., 2015; You et al., 2017; etc.) and planetary boundary layer height (Du et al., 2013; Zheng et al., 2017; etc.), are closely related to $PM_{2.5}$ concentrations.

Inspired by previous studies, we searched papers published since 2013 from "Web of Science" that include both "$PM_{2.5}$" and one of the following words: "meteorology" (or "meteorological"), "temperature", "wind", "humidity", "precipitation", "radiation", "atmospheric pressure" and "planetary boundary layer height" within "title, abstract and keywords". By May 19th, 2019, a total of 2047 papers were found with this search. We carefully reviewed these papers and removed irrelevant papers. Eventually, the number of papers concerning $PM_{2.5}$-meteorology interactions in China and other countries was 369 (as shown in Fig. 1) and 127 respectively, indicating that frequent haze episodes have attracted major research emphasis in China.

According to Fig. 1, a large proportion of studies concerning $PM_{2.5}$-Meteorology relationship has been conducted in those heavily polluted regions (e.g. Beijing-Tianjin-Hebei Region), developed regions with many major cities (e.g. Yangtze River Delta and Pearl River Delta) and regions with unique meteorological and geographical conditions (e.g. Sichuan Basin). The special interest in $PM_{2.5}$-meteorology interactions in mega cities (e.g. Beijing, Guangzhou, and Shanghai) is mainly attributed to the fact that high-concentration $PM_{2.5}$ in developed cities and air pollution exerts a major threat to public health in these cities with a large population density.

Here we conduct a critical review on the meteorological influences on $PM_{2.5}$ concentrations across China from the perspective of methodology and mechanism. To help readers understand the issue in question, we start with a brief introduction of general meteorological conditions and $PM_{2.5}$ concentrations, and follow with seasonal and spatial patterns of meteorological influences on $PM_{2.5}$ concentrations across China. A comprehensive comparison of different methods for quantifying meteorological influences on $PM_{2.5}$ concentrations and a comprehensive explanation of $PM_{2.5}$-meteorology interactions are the key parts of this study. We conclude with major challenges remained and suggestions on further study, and some mainstream meteorological means for mitigating $PM_{2.5}$ pollution.

2. General meteorological conditions and $PM_{2.5}$ concentrations across China

Due to its vast extent, as well as its continental and coastal surroundings, continental and oceanic effects on the climate across China vary gradually from strong oceanic influences in most coastal areas to strong continental influences in most inland areas. Therefore,

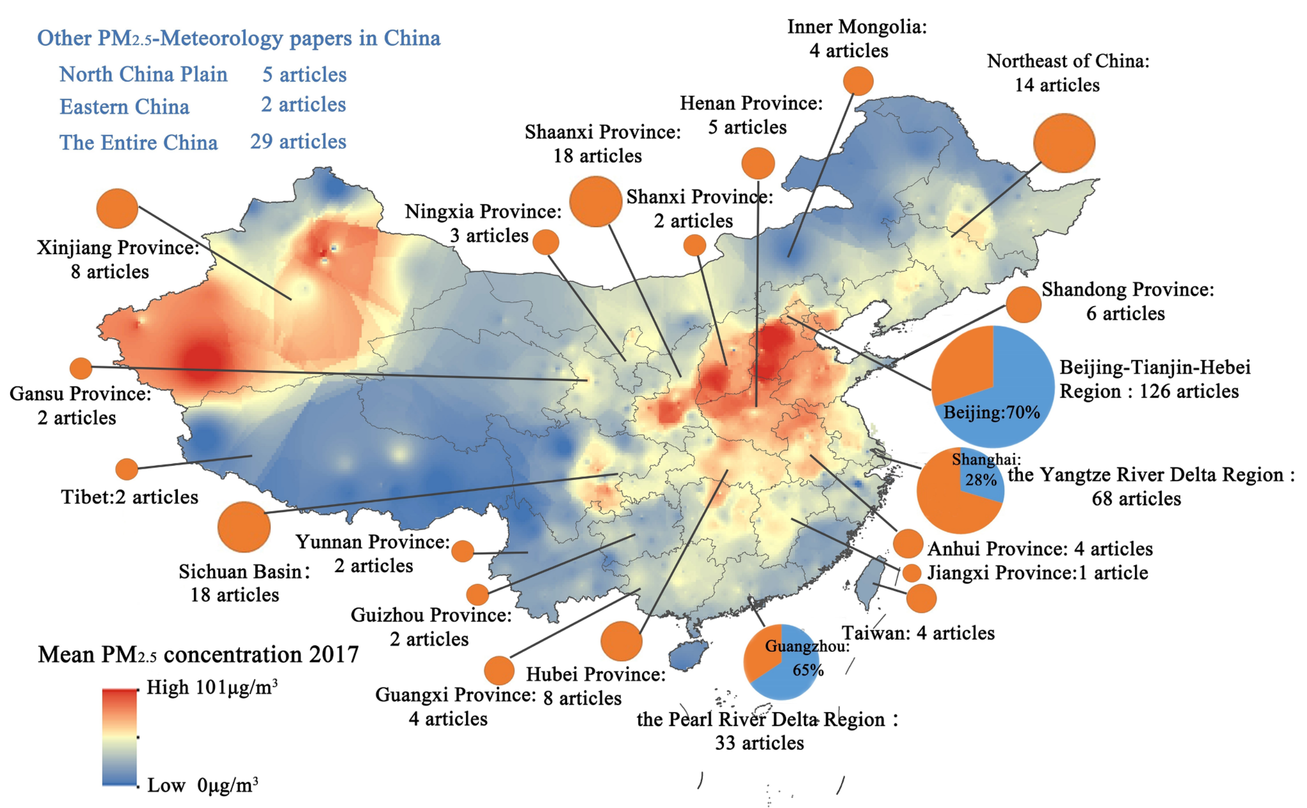

Fig. 1. The spatial distribution of $PM_{2.5}$-Meteorology Research across China since 2013. Papers are obtained from "Web of Science" that include both "$PM_{2.5}$" and one of the following words: "meteorology" (or "meteorological"), "temperature", "wind", "humidity", "precipitation", "radiation", "atmospheric pressure" and "planetary boundary layer height" within "title, abstract and keywords" on May 19th, 2019.

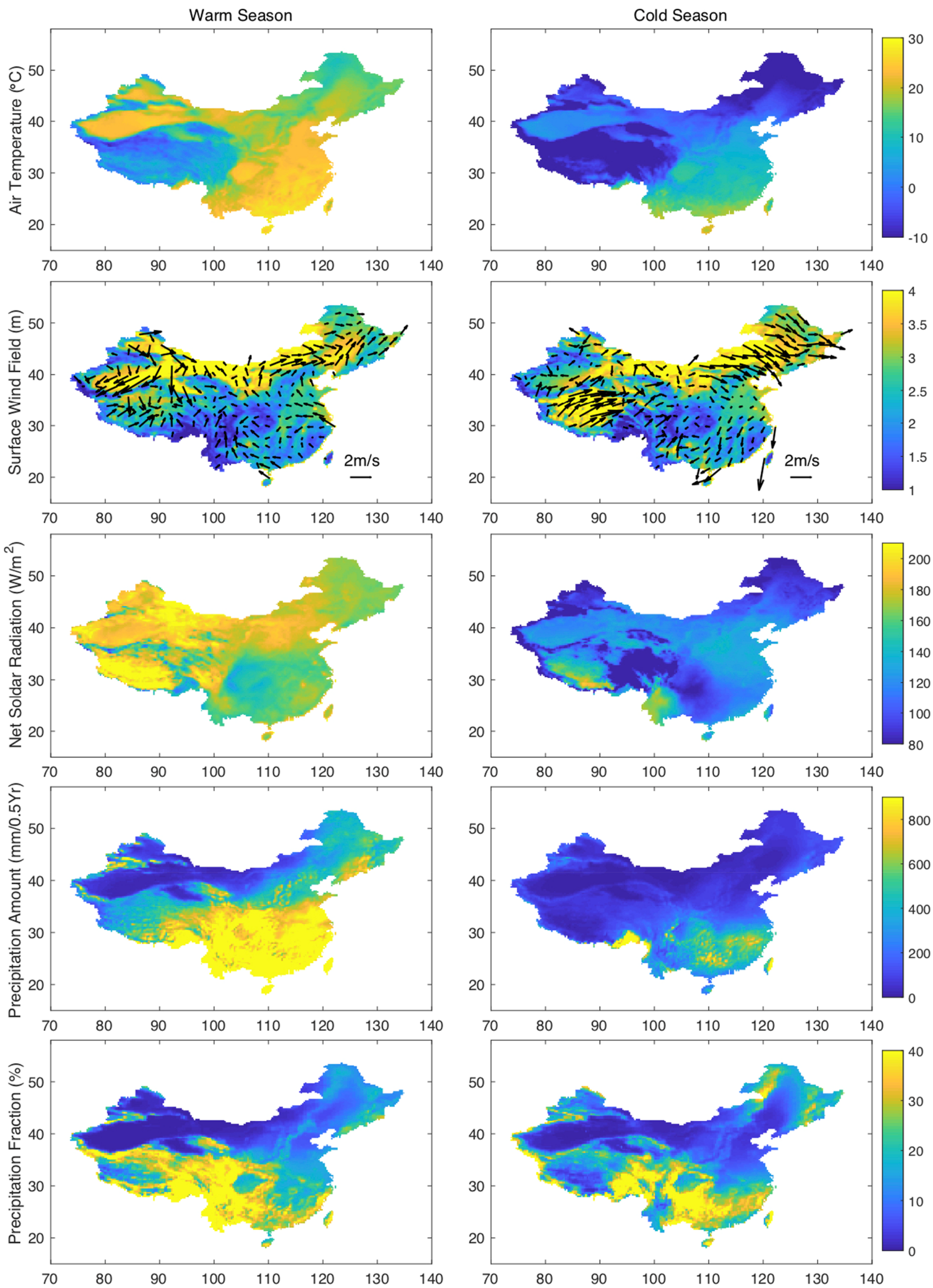

Fig. 2. General meteorological conditions across China from 1980 to 2010. The air temperature and wind field data are acquired from the 1°*1° ERA interim monthly mean dataset (European Centre for Medium-Range Weather Forecasts, ECMWF). Precipitation and solar radiation dataset are acquired at 2479 automatic meteorological station.

meteorological conditions across China demonstrate notable spatial variations.

2.1. General meteorological conditions across China

The air temperature decreases from southeast to northwest China expect for the Qinghai-Tibet Plateau in both the warm (May to October) and cold season (November to next April). The highest temperature (larger than 30 °C) appears over Southern China in the warm season, and the lowest temperature (lower than −10 °C) appears over the western Heilongjiang province and eastern Inner Mongolia in the cold season.

Asian Monsoon with topographical effects results in a large spatial and seasonal variation in terms of precipitation, and wind field over China (Fig. 2c–f). Southwest China experiences the largest precipitation amount and frequency in the warm season due to the effects of South Asian Summer Monsoon and local terrains. In the warm season, except for southwest China, the precipitation amount and frequency decrease

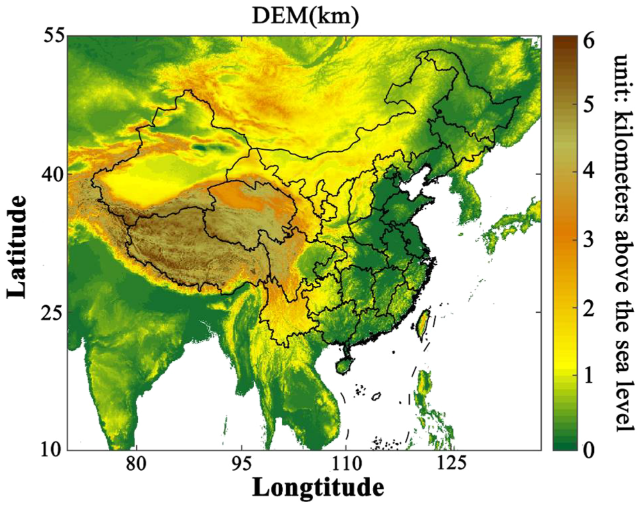

Fig. 3. General terrain conditions across China.

gradually from southeast to northwest China. In the cold season, affected by East Asian Winter Monsoon, prevailing northerly winds with dry air mass result in less and weaker precipitation over China and the most frequent precipitation appears in Yangtze River Delta.

The surface wind speed and direction are influenced by both the terrain and monsoon system. According to Fig. 2(g–h) and Fig. 3, relatively strong winds appear over high altitude and flat terrain regions. Due to the effects of terrain blocking, surface winds over Sichuan Basin and Beijing-Tianjin-Hebei region are notably lower than their surrounding areas. Controlled by Asian Monsoon, the wind direction switches from the prevailing northerly to the southerly wind from the cold season to warm season.

Fig. 2(i–j) demonstrates the distribution of solar radiation across China. Generally, the solar radiation is stronger in warm season than that in cold season. The average solar radiation is notably higher in Tibetan Plateau and the northwest arid and semi-arid region than that in eastern China. The weakest solar radiation appears in Sichuan Basin with about 150 W/m^2 in warm season and 100 W/m^2 in cold season whilst the strongest solar radiation appears over 230 W/m^2 in warm season and 200 W/m^2 in in cold season in Tibetan Plateau.

2.2. Spatial and temporal patterns of $PM_{2.5}$ concentrations across China

$PM_{2.5}$ concentrations are controlled by anthropogenic emissions and dispersion conditions controlled by topographical and meteorological factors. Consequently, the large variation of meteorological conditions contributes to notable spatio-temporal patterns of $PM_{2.5}$ concentrations across China (Huang et al., 2014; Xie et al., 2015; He et al., 2017).

2.2.1. Inter-annual variations of $PM_{2.5}$ concentrations across China

Long time-series satellite data have been increasingly employed to understand inter-annual variations of $PM_{2.5}$ concentrations. Peng et al. (2016) suggested that $PM_{2.5}$ concentrations increased rapidly in Central and Eastern China from 1999 to 2011. Specifically, a rapid $PM_{2.5}$ increase was observed within the heavily polluted Hebei, Henan and Shandong province from 1999 to 2007, followed by a notable $PM_{2.5}$ reduction in 2008. This remarkable decline was mainly attributed to a series of emission-reduction policies implemented during “2008 Beijing Olympic Games”, indicating that restricting anthropogenic emissions can play a key role in $PM_{2.5}$ reduction. From 2008 to 2012, $PM_{2.5}$ concentrations in this region remained stable, even slightly decreased, followed by a notable increase in 2013 (Ma et al., 2016b),

For better presenting inter-annual $PM_{2.5}$ variations across China, here we employed the 0.01° × 0.01° high-spatial-resolution dataset of annually average $PM_{2.5}$ concentrations, which was produced by integrating satellite-, simulation- and monitor-based data (Van Donkelaar et al., 2019) (Fig. 4). According to Fig. 4, significantly exacerbated $PM_{2.5}$ pollution in 2013, especially for heavily polluted North China plain, should be understood as a long-term, rather than short-term variation of $PM_{2.5}$ concentrations, characterized as a gradual increase from 2001 to 2007, a stable trend from 2008 to 2012, and a successive soar in 2013. Since 2014, with long-term intensive emission-reduction measures, $PM_{2.5}$ concentrations across China, especially in those major regions, have been reduced notably (Ma et al., 2016b).

2.2.2. Seasonal variations of $PM_{2.5}$ concentrations across China

As demonstrated in Fig. 5, $PM_{2.5}$ concentrations are generally the lowest in summer and the highest in winter at the national scale (Zhang and Cao, 2015; Li et al., 2017a). Zhang et al., (2014) concluded that seasonal $PM_{2.5}$ concentrations were generally ordered as follows: summer < spring < autumn < winter. The sudden increase of wintertime $PM_{2.5}$ concentrations across China, especially in northern parts of China, is mainly attributed to enhanced anthropogenic emissions for large-scale heating in regions to the North of Yellow River and unfavorable meteorological conditions (Wang et al., 2016, 2017). Without additional fuel combustion for central heating, the increase of wintertime $PM_{2.5}$ concentrations in southern parts of China is limited and mainly associated with unfavorable meteorology, such as low mixed boundary layer height. Similarly, low summertime $PM_{2.5}$ concentrations across China are mainly attributed to reduced anthropogenic emissions and favorable dispersion conditions for airborne pollutants. In addition to national similarities, seasonal characteristics of $PM_{2.5}$ concentrations across China also demonstrate some regional variations. For instance, $PM_{2.5}$ concentrations for Northwest and West, Central China are highest in spring rather than winter, which is mainly attributed to enhanced open biomass and burning dust particles (Zhang and Cao, 2015).

2.2.3. Spatial variations of $PM_{2.5}$ concentrations across China

$PM_{2.5}$ concentrations vary substantially across China (Yang et al., 2011; Li et al., 2017; Ye et al., 2018; etc.). Due to intense coal combustion for central heating, as well as large-scale biomass burning and excessive industrial combustion (Chai et al., 2014), $PM_{2.5}$ concentrations are notably higher in northern cities (He et al., 2017a). Meanwhile, $PM_{2.5}$ concentrations are generally lower in coastal cities with favorable dispersion conditions than those in inland cities (Zhang and Cao, 2015). The highest $PM_{2.5}$ concentrations appear in Beijing-Tianjin-Hebei region, which is mainly attributed to intensive coal consumption from heavy industries within Hebei province, regional transport and secondary production of $PM_{2.5}$ (Huang et al., 2014; Guo et al., 2014). Due to the transmission from high-concentration Dust (mainly PM_{10}) to $PM_{2.5}$, Xinjiang Taklimakan Desert is another region with extremely high annual mean $PM_{2.5}$ concentrations (> 95 μg/m^3), whilst the lowest $PM_{2.5}$ concentrations (< 10 μg/m^3) appear in northern Xinjiang, northern Inner Mongolia, northwest of Heilongjiang, northeastern Yunnan, western Sichuan, Tibet and Hainan, which are mainly less economically developed regions (Wang et al., 2013; Duan et al., 2015).

3. Spatial and temporal patterns of meteorological influences on $PM_{2.5}$ concentrations across China

Whilst anthropogenic emissions decide the total amount of airborne pollutants emitted to the atmospheric environment, meteorological conditions affect the accumulation and diffusion of $PM_{2.5}$ through multiple mechanisms. Complicated $PM_{2.5}$-meteorology interactions are controlled by both meteorological conditions and $PM_{2.5}$ levels (Chen et al., 2018). Consequently, large variations of meteorological conditions and $PM_{2.5}$ concentrations across China lead to notable characteristics of meteorological influences on $PM_{2.5}$ concentrations.

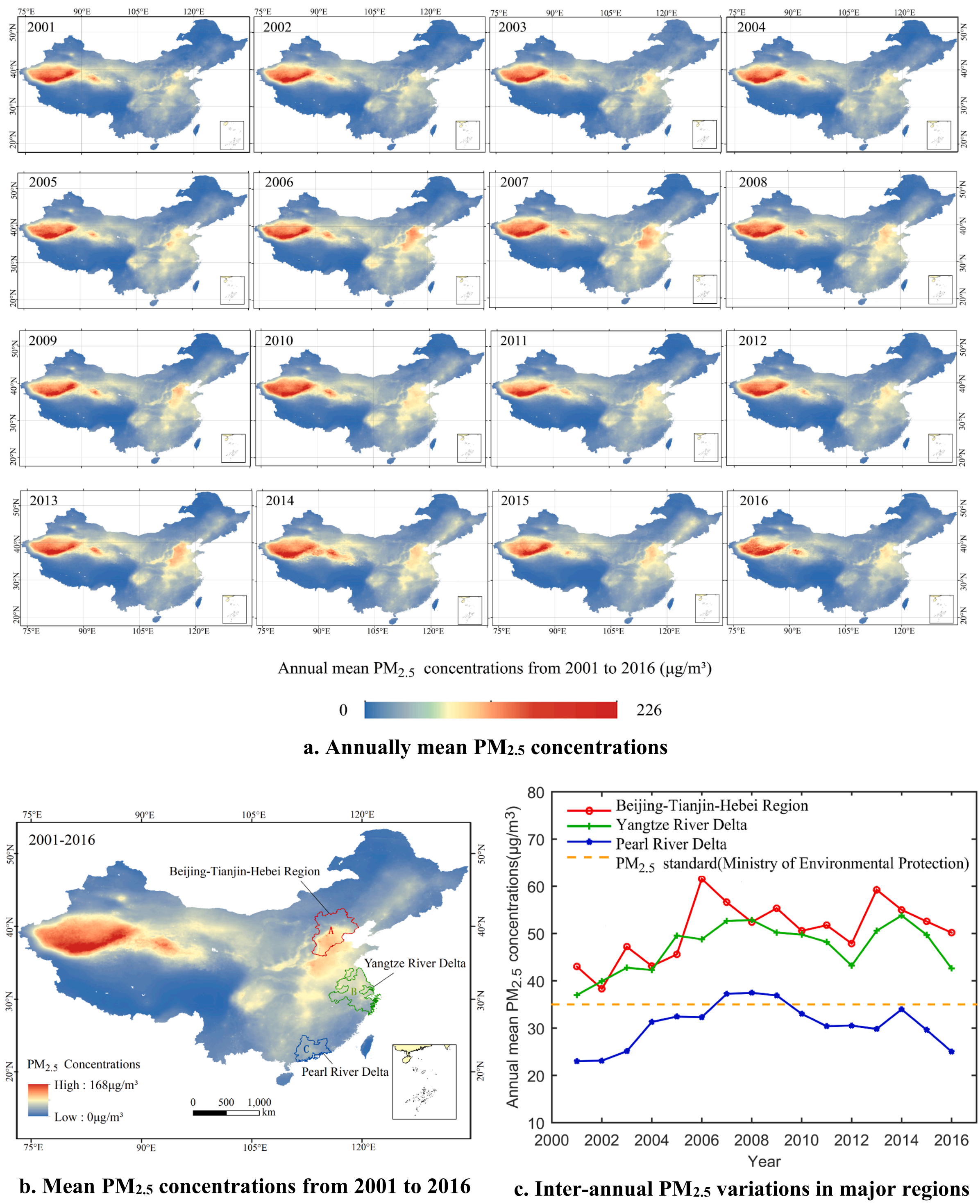

Fig. 4. Annual variations of $PM_{2.5}$ concentrations across China (2001–2016). Figure reproduced using $PM_{2.5}$ concentrations retrieved from satellite-, simulation- and monitor-based sources through Geographically Weighted Regression (Van Donkelaar et al., 2019).

3.1. Seasonal variations of meteorological influences on $PM_{2.5}$ concentrations

For a specific city, meteorological influences on $PM_{2.5}$ concentrations can vary across seasons. Zhang et al. (2015) found the dominant meteorological factor for $PM_{2.5}$ concentrations varied notably in different seasons for three mega cities, Beijing, Shanghai and Guangzhou, located in distant regions across China. At the national scale, Yang et al. (2017) revealed that relative humidity exerted a stronger influence on $PM_{2.5}$ concentrations in spring and winter. Meanwhile, temperature positively influenced $PM_{2.5}$ concentrations in winter and negatively influenced $PM_{2.5}$ concentrations in autumn. Zhang et al. (2018) and Chen et al. (2018) suggested that meteorological conditions exerted a strongest influence on $PM_{2.5}$-meteorology interactions in heavily polluted winter.

3.2. Spatial variations of meteorological influences on $PM_{2.5}$ concentrations.

As introduced above, $PM_{2.5}$ concentrations can be affected by

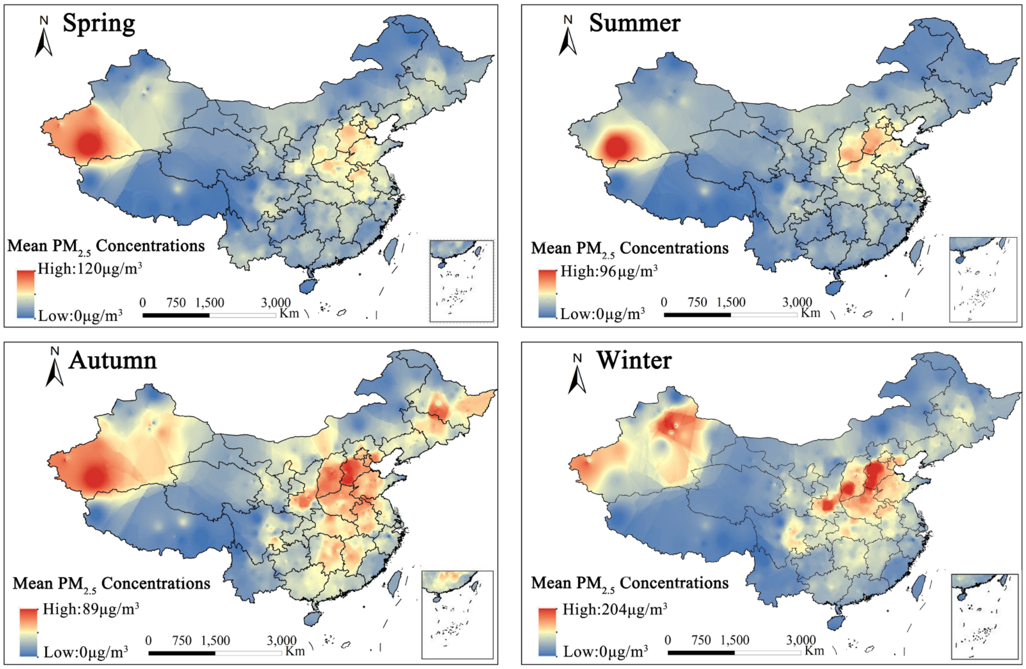

Fig. 5. Seasonal variations of mean $PM_{2.5}$ concentrations across China in 2017. Figure produced based on the interpolation of ground observed $PM_{2.5}$ data.

multiple meteorological factors. Here we conclude those studies that revealed dominant meteorological factors for $PM_{2.5}$ concentrations in specific regions (Table 1). In addition to studies conducted in isolated cities, some scholars (Yang et al., 2016; Chen et al., 2018) compared meteorological influences on $PM_{2.5}$ concentrations in major cities (regions) across China. Based on Goddard Earth Observing System (GEOS) chemical transport model (GEOS-Chem), Yang et al. (2016) revealed that wind, humidity and planetary boundary layer height exerted a major influence on $PM_{2.5}$ concentrations in Eastern China, Southern China and Northern China (Fig. 6).

Based on a quantitative causality analysis model, Convergent Cross Mapping (CCM), Chen et al., (2018) extracted the dominant meteorological factor for $PM_{2.5}$ concentrations in 188 monitoring cities (Fig. 7). According to Table 1 and Fig. 7, for heavily polluted Northeast China, North China Plain, and Sichuan Basin, wind speed and humidity exert a strong influence on $PM_{2.5}$ concentrations. For developed Yangtze River Delta and Pearl River Delta, in addition to wind speed and humidity, precipitation is another dominant meteorological factor. Temperature exerts a dominant influence on $PM_{2.5}$ concentrations in some inland cities whilst atmospheric pressure exerts a dominant influence mainly in some coastal cities. The dominant meteorological factors for $PM_{2.5}$ concentrations are closely related to geographical conditions (e.g. precipitation strongly influences $PM_{2.5}$ concentrations in coastal areas) and $PM_{2.5}$-meteorology interactions are notably stronger in heavily polluted regions than those in regions with slight pollution (Chen et al., 2018).

4. Methods for quantifying meteorological influences on $PM_{2.5}$ concentrations

Given complicated inner interactions in atmospheric environment, more advanced methods, instead of commonly employed correlation analysis, are required for better understanding $PM_{2.5}$-meteorology interactions (Pearce et al., 2011). Here we briefly review the principle, advantages and limitations of some promising methods for examining meteorological influences on $PM_{2.5}$ concentrations.

4.1. Causality models

Growing scholars attempt to employ robust causality models to remove interactions between individual meteorological factors. Here, we introduce two major causality analysis models, Granger Causality (GC) and Convergent Cross Mapping (CCM) as follows.

4.1.1. Granger causality (GC)

Granger causality (GC) (Granger et al., 1969) is a classic test to extract the potential causality between two variables. By verifying a hypothesis whether one variable casually affects another based on statistical analysis of two time series, the GC between two variables is detected. Recently, GC analysis has been increasingly employed for extracting the causality between individual meteorological factors and airborne pollutants. Jiang and Bai (2018) employed GC test to investigate whether $PM_{2.5}$ concentrations in one city affected those in its adjacent cities (Fig. 8). Wang et al. (2016) and Xiao et al., (2017) revealed GC causality of acid rain and prevailing wind direction on PM concentrations respectively. Sfetsos and Vlachogiannis (2010, 2013) integrated GC analysis with Pearson correlation to extract the quantitative causality between meteorological conditions and PM concentrations.

Some major disadvantages of GC test are as follows. Firstly, the causality of meteorological factors on $PM_{2.5}$ concentrations cannot be quantified through GC test and thus some scholars (Sfetsos and Vlachogiannis, 2010) considered the use of correlation coefficient as a complementary indictor, which as introduced above, might lead to large uncertainties. Secondly, GC test may fail to detect weak coupling between insignificant meteorological factors and $PM_{2.5}$ concentrations (Sugihara et al., 2012). To address these issues, casualty models suitable for extracting quantitative causality are required.

4.1.2. Convergent Cross Mapping (CCM)

Sugihara et al., (2012) proposed convergent cross mapping (CCM), which could effectively remove the influence of other variables and thus reliably quantify causality between two variables. Different from GC test, CCM is capable of detecting weak to moderate coupling and presenting bidirectional causality through convergent mapping. A convergent curve indicates extract causality of one variable on the

Table 1
Dominant meteorological factors for $PM_{2.5}$ concentrations in different regions across China.

Regions	Dominant meteorological factors	Other meteorological influencing factors
Gansu	Humidity (Guan et al., 2017)	Wind (Guan et al., 2017) Temperature (Guan et al., 2017)
Hubei	Temperature (Kuo et al., 2017; Wang et al., 2016)	Wind (Kuo et al., 2017) Humidity (Kuo et al., 2017) PBLH (Wang et al., 2016)
Shanxi	Wind (Yan et al., 2017) Temperature (Yan et al., 2017)	Humidity (Yan et al., 2017)
Shaanxi	Temperature (Wang et al., 2016) Humidity (Wang et al., 2016)	Atmospheric pressure (Wang et al., 2016)
Tibet	Atmospheric pressure (Bu et al., 2018, 2015) Temperature (Bu et al., 2018, 2015) Humidity (Bu et al., 2018, 2015)	Wind (Bu et al., 2018)
Taiwan	Temperature (Chi et al., 2017; Lai, 2018)	Wind (Chi et al., 2017; Lelieveld and Heintzenberg, 1992) PBLH (Lai, 2018)
Jiangxi	Temperature (Liu et al., 2016; Yang et al., 2018) Humidity (Liu et al., 2016; Yang et al., 2018)	Atmospheric pressure (Liu et al., 2016) Wind (Yang et al., 2018)
Shandong	Wind (Yan et al., 2017) Temperature (Liu et al., 2016)	Humidity (Liu et al., 2016)
Henan	Wind (Wang et al., 2017; Yu et al., 2018) Humidity (Wang et al., 2017; Yu et al., 2018)	Atmospheric pressure (Wang et al., 2017) Temperature (Wang et al., 2017; Yu et al., 2018)
Sichuan Basin	Wind (Liao et al., 2017; Wang et al., 2016) Humidity (Liao et al., 2017; Wang et al., 2016)	Precipitation (Liao et al., 2017)
Pearl River Delta	Wind (Cheng et al., 2015; Liu et al., 2015; Luo et al., 2018; Zhang et al., 2015) Humidity (Li et al., 2018; Liu et al., 2015; Zhang et al., 2015, 2017), Temperature (Zhang et al., 2015), Precipitation (Guo et al., 2012; Luo et al., 2018)	Radiation (Liu et al., 2015) Atmospheric pressure (Liu et al., 2015; Zhang et al., 2015) PBLH (Li et al., 2018)
Regions	Dominant meteorological factors	Other meteorological influencing factors
Northeast China	Wind (Chen et al., 2017; Fang et al., 2017) Humidity (Li et al., 2017) Temperature (Fang et al., 2017; Li et al., 2017)	Humidity (Fang et al., 2017) Atmospheric pressure (Fang et al., 2017; Li et al., 2017)
Yangtze River Delta	Wind (Chang et al., 2017; Jiang and Bai, 2018; Quan et al., 2013; Wang et al., 2015) Humidity (Jian et al., 2012; Li et al., 2014; Peng et al., 2015; Qu et al., 2017; Sun et al., 2016; Wang et al., 2016, 2017; Wu et al., 2015; Zhang et al., 2016) Temperature (Jian et al., 2012; Peng et al., 2015) Precipitation (Wang et al., 2016, 2015; Xu et al., 2016; Zhang et al., 2016)	PBLH (Qu et al., 2017; Sun et al., 2016; Wang et al., 2015) Wind (Sun et al., 2016; Xu et al., 2016) Radiation (Li et al., 2014)
Beijing-Tianjin-Hebei Region	Wind (Chen et al., 2017, 2016; Gao et al., 2017; Guo et al., 2017; He et al., 2015, 2017; Li et al., 2015; Ni et al., 2018; Qiu et al., 2015; Ren et al., 2016, 2018; Sun et al., 2013; Wang et al., 2018; Xu et al., 2017; Yang et al., 2018, 2017; Yin et al., 2016; Zhang et al., 2015; Zhou et al., 2015)Humidity (Chen et al., 2017; Cheng et al., 2015; Gao et al., 2017; Guo et al., 2017; Han et al., 2013; Hao et al., 2017; He et al., 2017; Hu et al., 2015; Li et al., 2017; Lou et al., 2019; Lyu et al., 2018; Ma et al., 2017; Qian et al., 2016; Qiu et al., 2015; Steiner and Chameides, 2005; Wang et al., 2016, 2013, 2018; Wu et al., 2016, 2019; Xu et al., 2017; Yang et al., 2017; Yin et al., 2017; You et al., 2017; Zhang et al., 2018, 2017)	Temperature (Gao et al., 2017; Han et al., 2013; He et al., 2017; Ni et al., 2018; Wang et al., 2016; Yang et al., 2017; Zhang et al., 2018) PBLH (Gao et al., 2017; He et al., 2015; He et al., 2017; Wu et al., 2016; Yang et al., 2017)Atmospheric pressure (Yin et al., 2017; You et al., 2017; Zhang et al., 2017)
Across China	Temperature (Chen et al., 2018; Li et al., 2017, 2019; Lin et al., 2015) Wind (Chen et al., 2018; He et al., 2017; Hu et al., 2015; Jia et al., 2015; Li et al., 2017; Zhang et al., 2018) Humidity (Chen et al., 2018; He et al., 2017; Jia et al., 2015; Li et al., 2017; Zhang et al., 2018) Precipitation (He et al., 2017; Li et al., 2015, 2017; Lin et al., 2015)	Radiation (Chen et al., 2018) Atmospheric pressure (Chen et al., 2018; Li et al., 2017; Li et al., 2019)

other; non-convergence curve indicates no causality between two variables. Compared with GC test, CCM is advantageous in extracting the predictive skill (ρ, ranging from 0 to 1), which explains the quantitative causality between two variables. Similar to the correlation coefficient, the ρ value provides quantitative reference for understanding the magnitude of the influence of multiple meteorological factors on $PM_{2.5}$ concentrations. The principle of CCM is illustrated in Fig. 9.

Due to its robustness, easy implementation and wide suitability, CCM has been used to examine the influence of major meteorological factors on $PM_{2.5}$ concentrations at the local (Chen et al., 2016), regional (Chen et al., 2017; Yao et al., 2017) and national scale (Chen et al., 2018). Based on a comparative study, Chen et al. (2017) indicated that CCM outperformed correlation analysis by better detecting mirage correlations, extracting weak coupling, and quantifying the asymmetrical bidirectional $PM_{2.5}$-meteorology interactions.

One major disadvantage is that CCM indicates no direction (positive/negative) of causal influences. Therefore, correlation analysis or GC test can be employed additionally to decide the direction of the causality whilst the ρ value decides the magnitude of the causality.

4.2. Statistical models

In addition to correlation and causality analysis, advanced statistical models have been employed to understand meteorological influences on $PM_{2.5}$ concentrations. Here we briefly introduce some frequently employed statistical models for investigating $PM_{2.5}$-meteorology relationship.

4.2.1. Geographically Weighted Regression (GWR)

To comprehensively consider the influence of geographical locations on the spatial distribution and variations of individual variables, Fotheringham et al., (1998) proposed Geographically Weighted Regression (GWR), which presents variations of the influence of independent variables on dependent variables according to locations' changes (Lin et al., 2015). Specifically, GWR considers spatiotemporal variations by adjusting the coefficient of auxiliary variables according to specific characteristics of regions and seasons, instead of using unified parameters under all circumstances (Yang et al., 2017). Lin et al., (2015) employed multiple linear regression (MLR) to examine correlations between $PM_{2.5}$ concentrations and temperature and precipitation respectively, and successively GWR for presenting the spatial variations of the influence of temperature and precipitation on $PM_{2.5}$ concentrations. Similarly, Luo et al. (2017) adopted ordinary least squares and multivariate correlation analysis to identify decisive driving forces for $PM_{2.5}$ concentrations, and then GWR for exploring spatial heterogeneity of $tPM_{2.5}$-meteorology interactions.

Based on scattered observation data, GWR is suitable for estimating

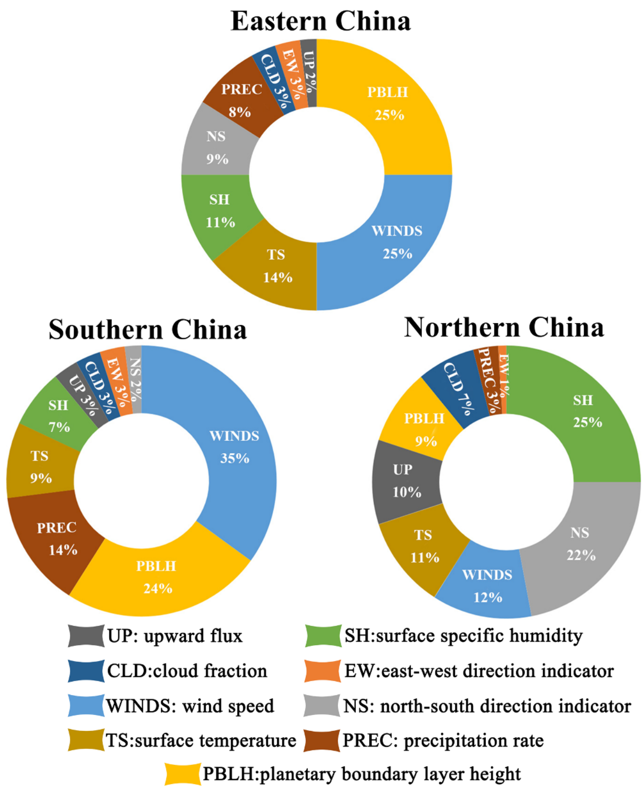

Fig. 6. The relative contribution of major meteorological factors to comprehensive meteorological influences on $PM_{2.5}$ variations in three major regions quantified using GEOS-Chem and LMG method (Figure).
reproduced from Yang et al., 2016

continuous meteorological influences on $PM_{2.5}$ concentrations over large areas. Nevertheless, before the implementation of GWR, most studies employed correlation analysis to explain $PM_{2.5}$-meteorology interactions, which may cause a diversity of uncertainties and significantly weaken the reliability of successive GWR. To address this issue, future studies can integrate GWR with causality analysis methods (e.g. CCM) to better estimate meteorological influences on $PM_{2.5}$ concentrations over continuous areas.

4.2.2. Generalized Additive Models (GAMs)

Generalized Additive Models (GAMs) employ smoothing splines for computing covariates (Hastie and Tibshirani, 1990) and are highly effective in air pollution research with complex non-linearity and complicated interactions (Schlink et al., 2006; Carslaw et al., 2007). Specifically, the integration of GAMs with marginal effects, partial residual plots is an efficient approach for characterizing the relationship between meteorological variables and airborne pollutants (Pearce et al., 2011). Huang et al., (2015) employed GAMs to consider the overall influence of multiple meteorological factors, based on which continuous $PM_{2.5}$ concentrations in Beijing were estimated with satisfactory R^2 and goodness-of-fit. However, this correlation- and covariate-based statistical model cannot quantify reliable causal influence of individual meteorological factors on $PM_{2.5}$ concentrations.

4.2.3. Composite meteorological index (CMI)

Given complicated interactions between multiple meteorological factors, properly designed composite meteorological index (CMI) that consider multiple major meteorological factors have been proposed to understand combined effects of overall meteorological conditions on $PM_{2.5}$ concentrations. Zhang et al. (2009) and Yang et al. (2009) proposed a Parameter linking Air-quality to Meteorological conditions index (PLAM) to give a composite evaluation of comprehensive meteorological conditions on air pollution. PLAM includes surface meteorological observation data, atmospheric temperature, difference of temperature and dew point, clouds, weather phenomena, atmospheric pressure, wind speed and direction, and stability. PLAM shows good performance in forecasting the occurrence of air pollution events (Zhang et al., 2009; Li et al., 2011), and diagnosing severe haze episodes in North China (Yang et al., 2016). Similarly, since air stagnation is commonly employed to explain the diffusion capability of atmospheric environments, Wang et al. (2018) improved the air stagnation definition of NOAA (Wang and Angell, 1999; Horton et al., 2014) and proposed a widely applicable threshold of air stagnation according to wind, precipitation and boundary layer height. This stagnation index can be used to attribute the occurrence of pollution episodes in China (Ning et al., 2018).

CMI are suitable for detecting overall stagnant conditions and limited in examining the influence of individual meteorological factors. Since composite meteorological index are designed with a pre-proposed combination of major meteorological factors, CMI are more easily applicable and less flexible than GAMs.

4.2.4. Kolmogorov-Zurbenko (KZ) filtering

The influence of long-term meteorological variations can be filtered to understand the adjusted time series of airborne pollutants mainly controlled by emission factors (Eskridge et al., 1997). To build an adjusted time series without disturbances from other major influencing factors, Rao et al. (1994) designed Kolmogorov-Zurbenko (KZ) filter, which employed iterative moving average to remove high-frequency variations. By comparing the original and adjusted trend, the relative contribution of meteorological conditions to temporal variations of airborne pollutants can be quantified. Based on a comprehensive comparison of mainstream trend-detection models, Eskridge et al (1997) indicated that the confidence of KZ filtering was the highest when handing long-time time series. KZ filtering has been increasingly employed to quantify meteorological influences on airborne pollutants. Based on KZ filtering, Ma et al. (2016a) quantified that the relative contribution of meteorological conditions to ozone variations in a rural station, Beijing from 2003 to 2015 was 5% whilst Chen et al., (2019) quantified that meteorological variations from 2013 to 2017 accounted for 20% of simultaneous $PM_{2.5}$ variations in Beijing.

When mainly focusing on the overall influence of meteorological conditions, KZ filter is not suitable for examining how individual meteorological factors influence $PM_{2.5}$ time series.

4.2.5. Land use regression (LUR)

Based on limited sites and variables that explain anthropogenic emissions (e.g., land use and population density) surrounding these sites (Olvera Alvarez et al., 2018), Land use regression (LUR) fits a regression model to observed $PM_{2.5}$ concentrations and $PM_{2.5}$ concentrations at unmeasured locations can be estimated using this model. LUR models have become a popular approach to explain spatial and temporal variations of airborne pollutants, as they are more accurate than interpolation methods and less complicated than dispersion modeling (Hoek et al., 2008). Recently, growing studies (Su et al., 2008; Stafoggia et al., 2017; Olvera Alvarez et al., 2018; Xu et al., 2019) have been conducted to add descriptions of meteorological conditions to LUR models for better predicting $PM_{2.5}$ concentrations, yet achieved mixed results for following reasons. Firstly, the influence of the same meteorological factor on $PM_{2.5}$ concentrations may vary from negative to positive across seasons (Olvera Alvarez et al., 2018). Furthermore, most LUR models simply consider wind for simulating the transport of $PM_{2.5}$, yet poorly explain how other meteorological factors quantitatively affect $PM_{2.5}$ concentrations. In this case, the use of additional meteorological factors may not enhance the accuracy of LUR models (Su et al., 2008; Johnson et al., 2013), and more emphasis should be placed on how to properly integrate those meteorological factors, which are strongly correlated with the accumulation and dispersion of $PM_{2.5,}$ into

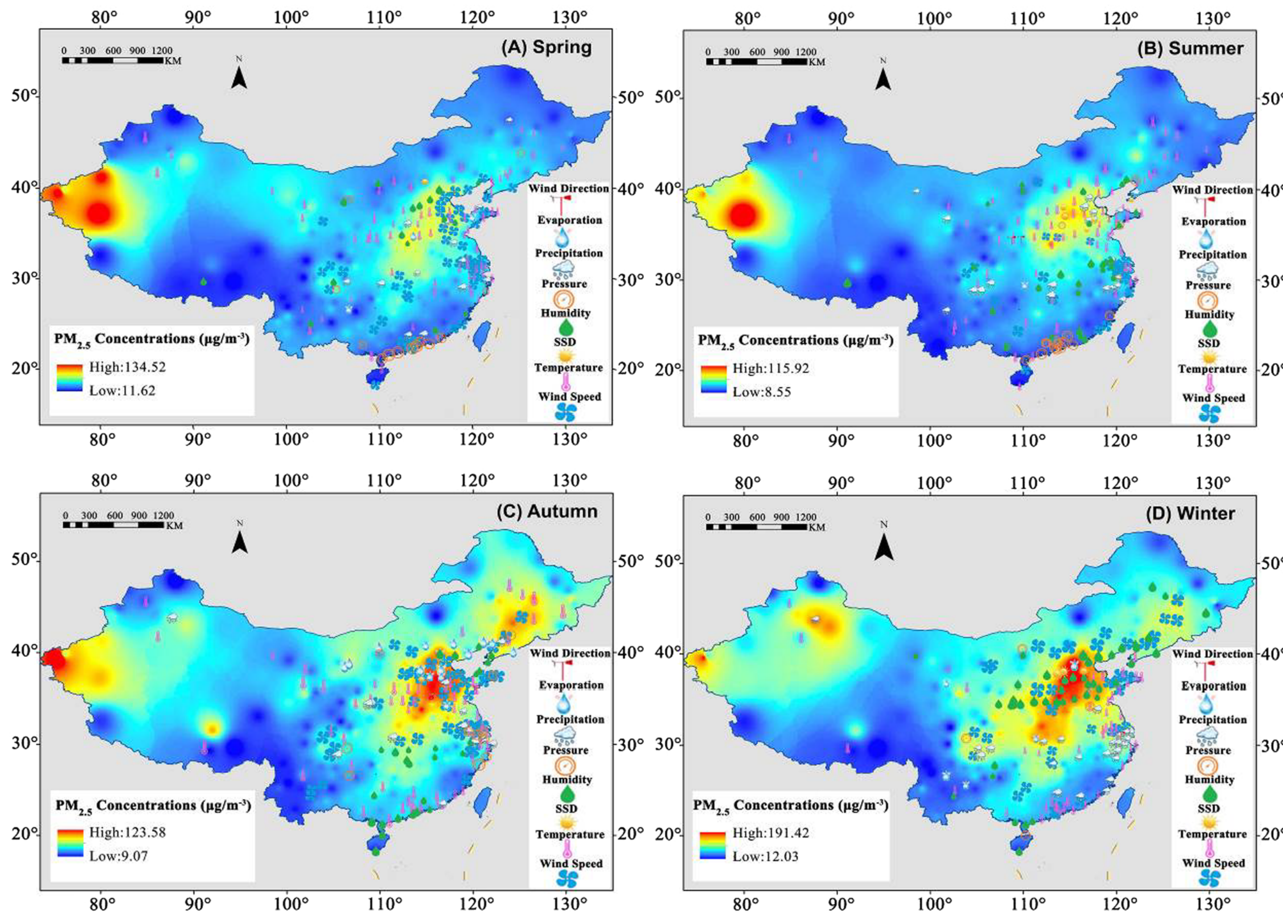

Fig. 7. Dominant meteorological factors for $PM_{2.5}$ concentrations across China extracted using CCM (Figure).
reproduced from Chen et al., 2018

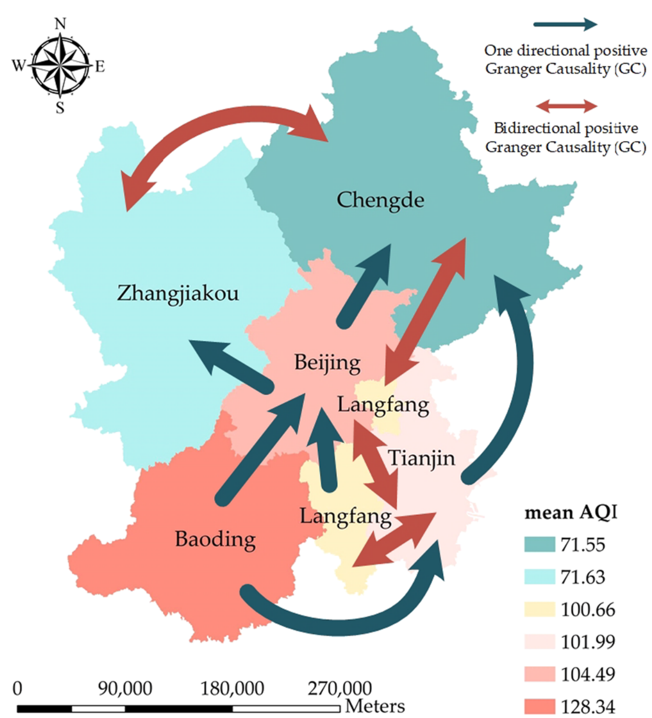

Fig. 8. Granger Causality (GC) between air quality in major cities within Beijing-Tianjin-Hebei region (Figure).
reproduced from Jiang and Bai, 2018

LUR models.

In addition to GWR, GAM, KZ, LUR and CMI, such statistical methods as boosted regression tree (BRT) (Li et al., 2017a) and principal component analysis (PCA) (Wang et al., 2016) are also useful tools for quantifying comprehensive meteorological influences on $PM_{2.5}$ concentrations.

4.3. Chemical Transport Models (CTMs)

Physical-Chemical models such as Chemical Transport Models (CTMs) are effective for simulating $PM_{2.5}$-meteorology interactions (Yang et al., 2017). Amongst those classic CTMs, WRF-CAMx has been widely employed for estimating the formation and transport of $PM_{2.5}$ pollutions. WRF-CAMx includes Weather Research and Forecasting model (WRF, http://www2.mmm.ucar.edu/wrf/users/), Sparse Matrix Operator Kernel Emission model (SMOKE, https://www.cmascenter.org/cmaq/) and a Comprehensive Air Quality Model with Extensions (CAMx, http://www.camx.com/) (Bove et al., 2014). WRF-CAMx comprehensively examines the influence of anthropogenic emissions and simulates the transformation and transport of airborne pollutants using a unified and detailed description of meteorological fields (Grell et al., 2005), including zonal wind, meridional wind, humidity, temperature, atmospheric pressure, precipitation, boundary layer heights, geopotential height, and so forth. Consequently, how dynamic meteorological conditions influence $PM_{2.5}$ concentrations are better understood with WRF-CAMx. Compared with causality analysis and statistical methods, WRF-CAMx additionally considers another major influence for $PM_{2.5}$ concentrations, anthropogenic emissions. Due to its wide suitability and balanced consideration of multiple influencing

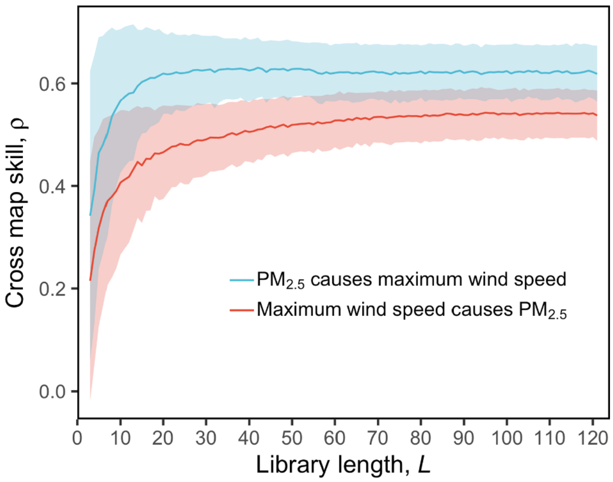

Fig. 9. An example of using CCM for quantifying bidirectional interactions between daily. $PM_{2.5}$ concentrations and maximum wind speed in Beijing during 2016/11/15–2017/03/15. ρ: predictive skill. L: time lag. X causes Y stands for the causality influence of variable X on Y. "Maximum wind speed causes $PM_{2.5}$" indicates the causal influence of maximum wind speed on $PM_{2.5}$ concentration. ρ suggests the predictive skill of retrieving $PM_{2.5}$ concentrations using based on maximum wind speed. Lines and shaded regions show mean ± SD of cross map skill ρ from 1000 random samples.

factors, WRF-CAMx has been implemented at both the regional scale (Bei et al., 2017) and local scale (Xu et al., 2016; Chen et al., 2017; etc.).

Major disadvantages of WRF-CAMx and other CTMs lie in following aspects. Firstly, a diversity of issues may lead to uncertainties in model outputs, including the deficiency of PBL schemes (Tie et al., 2015; Bei et al., 2017), heterogeneous/aqueous processes (Li et al., 2011), emission inventories (Xu et al., 2016) and spatio-temporal allocations (Tie et al., 2010). Secondly, complicated terrains lead to difficulties in selecting proper parameters for different meteorological factors (Chen et al., 2017; Chu et al., 2016), causing extra challenges in implementing this model and comparing model outputs at large scales. For better applying WRF-CAMx in China, more emphasis should be placed on parameter optimization to suit this model under different geographical and meteorological conditions. The suitability and advantages of different methods are briefly concluded as Table 2.

5. Underlying mechanisms of $PM_{2.5}$-meteorology interactions

With a long history of aerosol research, interactions between aerosols and meteorological influences have been in-depth investigated (Albrecht, 1989; Lelieveld and Heintzenberg, 1992; Jacobson et al., 2001; Rosenfeld et al., 2014; etc.). However, the composition of aerosols can be highly complicated and vary significantly both spatially and temporally (Pöschl et al., 2005; Calvo et al., 2013; Sun et al., 2017). Given notable variations in aerosol compositions and complicated mechanisms between meteorological factors and different airborne pollutants, previous studies concerning aerosol-meteorology interactions may not precisely explain $PM_{2.5}$-meteorology interactions.

It is generally acknowledged that $PM_{2.5}$ concentrations are affected by multiple meteorological factors (Fig. 10). However, few studies attempt to present a comprehensive review of underlying mechanisms how different meteorological factors may influence $PM_{2.5}$ concentrations and why this type of interactions varies notably across China, causing major challenges in interpreting and comparing varying findings from different case studies. To fill this gap, here we comprehensively review relevant references and conclude how major meteorological factors may influence $PM_{2.5}$ concentrations through different mechanisms. Meanwhile, underlying mechanisms how $PM_{2.5}$ concentrations exert feedback effects on individual meteorological factors are explained. It is worth mentioning that in addition to synoptic-scale factors, large-scale air motion is also an important driver for the variation of local and regional variations of $PM_{2.5}$ concentrations. However, this type of large-scale air motion mainly influences $PM_{2.5}$ concentration by adjusting such individual meteorological factors as wind speed (Chen and Wang, 2015; Guo et al., 2017), temperature (Chen and Wang, 2015), PBLH (Liu et al., 2018) humidity (Chen et al., 2019). Therefore, the mechanisms how large-scale air motion influence $PM_{2.5}$ concentrations can also be understood as the combined effects of individual meteorological factors.

5.1. *Interactions between $PM_{2.5}$ concentrations and temperature*

Temperature is one dominant meteorological influencing factor for $PM_{2.5}$ concentrations across China (He et al., 2017b; Chen et al., 2018). The mechanisms how temperature interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.1.1. *Influences of temperature on $PM_{2.5}$ concentrations*

The influence direction (positive/negative) of temperature on $PM_{2.5}$ concentrations varies across regions through different mechanisms.

Negative influences: A negative influence of temperature on $PM_{2.5}$ concentrations has been detected in such areas as Sichuan Basin (Li et al., 2015a), Nanchang city (Liu et al., 2016), Fuxin (He and Wang, 2017) and Beijing (Qiu et al., 2015). This type of negative influences is mainly attributed to temperature-related atmospheric convections and the evaporation loss of $PM_{2.5}$. Firstly, under high-temperature conditions, there are strong thermal activities such as turbulence, making an accelerated dispersion of $PM_{2.5}$ (Yang et al., 2016). Conversely, low temperature weakens atmospheric convection and enhances the accumulation of $PM_{2.5}$ (Li et al., 2015a; Li et al., 2014a). Secondly, high temperature leads to an increased evaporation loss of $PM_{2.5}$ (Liu et al., 2015), including the loss of vapor (Liu et al., 2015), ammonium nitrate (Megaritis et al., 2014; Chuang et al., 2017) and other volatile or semi-volatile components (Wang et al., 2006), and a decreased $PM_{2.5}$ concentration.

Table 2
A comparison of different methods for quantifying meteological influences on $PM_{2.5}$ concentrations.

Models	Advantages	Limitations
GC	Extracting causality direction (+/−) for individual factors	Not quantitative
CCM	Extracting quantitative causality for individual factors	No causality direction
GWR	Simulating continuous spatio-temporal variations of $PM_{2.5}$ concentrations based on multiple factors	Limited by the use of correlation coefficient
GAM	Estimating $PM_{2.5}$ concentrations based on multiple factors	Not for individual factors
CMI	Predicting stagnant conditions based on fixed factors	Lack of flexibility
KZ	Quantifying the relative contribution of meteorological conditions to $PM_{2.5}$ variations	Not for individual factors
LUR	Predicting $PM_{2.5}$ concentrations according to specific emission scenarios of different land use types	Difficult for integrating complicated meteorological conditions into LUR models
CTM	Dynamically simulating $PM_{2.5}$ concentrations based on detailed meteorological conditions and emissions scenarios	Limited by a diversity of uncertainties

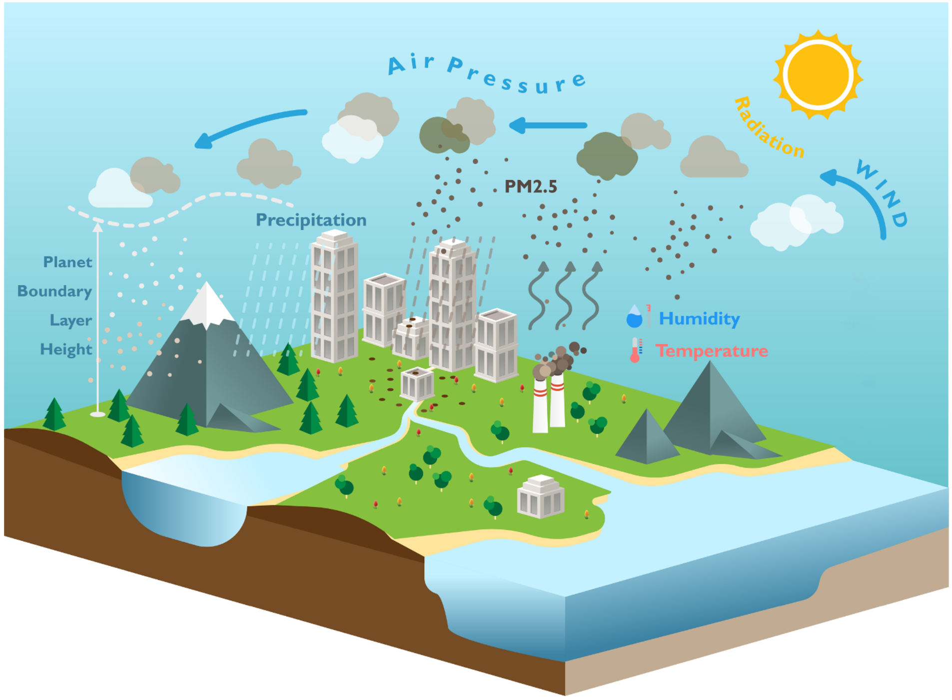

Fig. 10. Multiple meteorological factors that influence $PM_{2.5}$ concentrations.

Positive influences: A positive influence of temperature on $PM_{2.5}$ concentrations has been found in Beijing (Zhang et al., 2015; Han et al., 2016; You et al., 2017), Taiyuan (Zhang et al., 2016), Hangzhou (Jian et al., 2012; Peng et al., 2015) and Guangzhou (Zhang et al., 2016). This type of positive influences is mainly attributed to the influence of temperature inversion on the diffusion of $PM_{2.5}$ and the impact of temperature on the production rate of precursors and secondary pollutants. Firstly, in winter, due to the low surface temperature the increase in temperature may lead to the formation of temperature inversion layers, which are unfavorable conditions for the atmospheric movement and can cause the accumulation of $PM_{2.5}$ (Wang et al., 2013; Li et al., 2015; Xu et al., 2019). The existence of temperature inversion is a major meteorological driver for the formation of haze episodes. Severe haze episodes caused by persistent temperature inversion were observed in a diversity of regions across China, including Beijing (Zhong et al., 2017a; Zhu et al., 2018; Liu et al., 2019; Zhao et al., 2019), Shenyang (Li et al., 2019), Shanghai (Liu et al., 2019), Central-East China (Chun et al., 2020) and Xi'an (Wang et al., 2016). Secondly, high-temperature promotes photochemical reactions and produces more precursors of $PM_{2.5}$ and other secondary pollutants, causing the increase of $PM_{2.5}$ concentrations (Jian et al., 2012; Zhang et al., 2015).

For the same city (e.g. Beijing), temperature can either negatively (Qiu et al., 2015) or positively (You et al., 2017; Zhang et al., 2015; Han et al., 2016; etc.) influence $PM_{2.5}$ concentrations, indicating that the overall influence of temperature on $PM_{2.5}$ concentrations may vary notably through different mechanisms.

5.1.2. *Feedback effects of $PM_{2.5}$ concentrations on temperature*

By scattering and reflecting more solar radiation, high-concentration $PM_{2.5}$ reduce surface temperature (Yang et al., 2016; Zhong et al., 2017a, 2017b). The decreased near-ground temperature leads to a weak atmospheric movement of $PM_{2.5}$ and thus an enhanced $PM_{2.5}$ accumulation. Meanwhile, when $PM_{2.5}$ pollution episodes occur along with the appearance of temperature inversion layers, the notably decreased near-ground temperature and the stable atmospheric structure (Zhu et al., 2018) can further enhance the existing anomalous inversion. This type of strong bidirectional interactions between $PM_{2.5}$ concentrations and temperature inversion result in an increasingly stagnant environment during haze episodes, which is unfavorable for the dispersion of high-concentration $PM_{2.5}$ and causes further deterioration of $PM_{2.5}$ pollution (Zhu et al., 2018; Zhao et al., 2019).

5.2. *Interactions between $PM_{2.5}$ concentrations and wind speed*

Wind speed is one major influencing factor for $PM_{2.5}$ concentrations across China, especially in winter, when strong winds are crucial for disturbing stagnant environments caused by high-concentration $PM_{2.5}$ (He et al., 2017b). The mechanisms how wind speed interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.2.1. *Influences of wind speed on $PM_{2.5}$ concentrations*

Although a negative influence of wind speed on $PM_{2.5}$ concentrations is generally consistent across China (He et al., 2017b), wind speed may also positively influence $PM_{2.5}$ concentrations through different mechanisms.

Negative influences: A negative influence of wind speed on $PM_{2.5}$ concentrations has been detected in Beijing (Zhang et al., 2015; Huang et al., 2015; Ren et al., 2018), Northeast China (Chen et al., 2017; Fang et al., 2017; Li et al., 2017b), Sichuan Basin (Wang et al., 2016; Liao et al., 2017), Shanghai (Wu et al., 2015; Xu et al., 2015), Shandong (Yan et al., 2017) and Pearl River Delta (Zhang et al., 2015). Firstly, increasing wind speed, high wind speed in particular, usually leads to a favorable condition for the diffusion process of $PM_{2.5}$ (Zhang et al., 2017). Therefore, increasing wind speed results in a stronger blowing-off effect on $PM_{2.5}$ concentrations. Secondly, since wind speed is a crucial factor for the evaporation rate of $PM_{2.5}$ (Han et al., 2018), increasing wind speed can lead to an enhanced evaporation loss and indirectly reduced mass concentration of $PM_{2.5}$.

Positive influences: Wind speed may positively influence $PM_{2.5}$ concentrations under specific conditions as follows. Firstly, for weak winds, increasing wind speed may cause small turbulence intensity, weak atmospheric horizontal movement and dominant sinking movement in upper air, forming an unfavorable dispersion conditions for $PM_{2.5}$ and other pollutants (Ren et al., 2016; Xu, et al., 2016; Su et al., 2017; Yang et al., 2017). Weak winds are an important meteorological driver for the formation of haze episodes. Haze episodes caused by weak winds were observed in Beijing (He et al., 2015; Zhong et al., 2017a, 2017b; Liu et al., 2019), Handan (Yang et al., 2018), Shenyang (Li et al., 2019), Yangtze River Delta (Li et al., 2014b; Sun et al., 2016) and Sichuan (Liao et al., 2017). Secondly, under unique geographical conditions and wind directions, increasing wind speed may conversely cause the accumulation of $PM_{2.5}$. For instance, dominant northerly winds blow away $PM_{2.5}$ in downtown areas of Beijing (Guo et al., 2017) whilst $PM_{2.5}$ transported by increasing southerly winds are mainly stopped by mountains surrounding Beijing, causing enhanced $PM_{2.5}$ concentrations in Beijing (Yuan et al., 2015; Chen et al., 2017). Thirdly, extremely strong winds may bring in sandstorm episodes, leading to high PM_{10} concentrations and successive high $PM_{2.5}$ concentrations caused by the transmission between PM_{10} and $PM_{2.5}$ (Li and Li, 2013; Wang et al., 2015).

5.2.2. Feedback effects of $PM_{2.5}$ concentrations on wind speed.

Based on CCM and correlation analysis, Chen et al. (2017) revealed a strong negative feedback effect of $PM_{2.5}$ concentrations on wind speed in Beijing-Tianjin-Hebei region. Similarly, a further weakened wind speed was frequently observed during heavy pollution episodes in Beijing (Liu et al., 2013; Yang et al., 2015; Guo et al., 2017; Ren et al., 2018), Shenyang (Li et al., 2019) and Xi'an (Wang et al., 2016). Yang et al. (2015) explained the potential mechanisms how high-concentration $PM_{2.5}$ negatively affected the formation and evolution of winds. Firstly, high-concentrations $PM_{2.5}$ usually lead to stagnant environments and weak high-pressure systems, causing a slowed wind speed. Secondly, under stagnant environments and high-pressure systems induced by high-concentration $PM_{2.5}$, megacities (e.g. Beijing and Xi'an) further serve as obstacles that significantly slow down the speed of winds passing by this region.

Weakened winds due to high-concentration $PM_{2.5}$ can further favor the accumulation of $PM_{2.5}$ (Yang et al., 2016; Chen et al., 2017). Yang et al., (2016) suggested this type of $PM_{2.5}$-wind interactions further contributed to around 12% of $PM_{2.5}$ concentrations in Beijing. Strong bidirectional $PM_{2.5}$-wind interactions make wind speed a strong driver for the rapid formation and slow dispersion of haze episodes in the heavily polluted Beijing-Tianjin-Hebei region.

5.3. Interactions between $PM_{2.5}$ concentrations and wind direction

The influence of wind direction on $PM_{2.5}$ concentrations is generally weak and inconsistent at the national scale (Chen et al., 2018). The mechanisms how wind direction interacts with $PM_{2.5}$ concentrations are briefly introduced as follows.

5.3.1. Influences of wind direction on $PM_{2.5}$ concentrations

The influence of wind direction on $PM_{2.5}$ concentrations demonstrates no clear patterns to follow. With long-term observation data, Yang et al., (2016) found that weaker northerly winds were the main reason for enhanced $PM_{2.5}$ concentrations over North China Plain whilst weaker westerly winds led to enhanced $PM_{2.5}$ concentrations over Eastern China. How wind direction influences $PM_{2.5}$ concentrations in a specific city highly depends on local geographical conditions and the distribution of $PM_{2.5}$ concentrations. As mentioned above, for Beijing, northerly winds negatively influence local $PM_{2.5}$ concentrations by blowing away pollutants whilst southerly winds leads to the accumulation of $PM_{2.5}$ through the blocking effect of surrounding mountains (Zhao et al., 2009; Zhao et al., 2019). The existence of wind directional shears, which refer to the rapid change of wind direction, further adds the uncertainty to the influence of wind directions on $PM_{2.5}$ concentrations (Chen et al., 2017). Meanwhile, the rapid diurnal variations of wind directions can lead to summertime haze episodes (Sun et al., 2013). For Central China, Northerly winds transport $PM_{2.5}$ from heavily polluted Yangtze River Delta and significantly increase local $PM_{2.5}$ concentrations (Yang et al., 2016). For Yangtze River Delta, northerly winds that transport $PM_{2.5}$ from heavily polluted North China plain may lead to local or regional haze episodes (Ni et al., 2018; Liu et al., 2019). For Central-East China, the change of wind direction from south to north can lead to persistent haze episodes (Chun et al., 2020).

5.3.2. Feedback effects of $PM_{2.5}$ concentrations on wind direction

High-concentration $PM_{2.5}$ induced stagnant conditions and weak high-pressure systems prevent the formation of strong winds and disturb the direction of winds passing by (Yang et al., 2015). For mega cities (e.g. Beijing) with high $PM_{2.5}$ concentrations, this type of blocking effects for reducing wind speed and disturbing wind direction is further advanced. Increasing $PM_{2.5}$ concentrations lead to the decreased downwelling solar radiation and surface temperature, which reduces the downward transport of upper level momentum and disturbs wind direction (Yang et al., 2016).

5.4. Interactions between $PM_{2.5}$ concentrations and humidity

Humidity strongly influences $PM_{2.5}$ concentrations across China, especially in heavily polluted North China Plain and winter (He et al., 2017b; Chen et al., 2018). The mechanisms how humidity interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.4.1. Influences of humidity on $PM_{2.5}$ concentrations

The influence of humidity on $PM_{2.5}$ concentrations varies with the increase of humidity.

Positive influences: A positive influence of humidity on $PM_{2.5}$ concentrations has been found in a diversity of cities across China, including Beijing (Zhou et al., 2015; Cheng et al., 2015; Qiu et al., 2015), Suzhou (Liu et al., 2015), Nanjing (Kang et al., 2013; Chen et al., 2016), Guangzhou (Zhang et al., 2016), Sichuan Basin (Wang et al., 2016; Liao et al., 2017), and Beijing-Tianjin-Hebei region (Han et al., 2018; Cheng et al., 2017). Humidity exerts a positive influence on $PM_{2.5}$ concentrations through three major mechanisms. Firstly, higher humidity makes $PM_{2.5}$ attached with more vapor and notably increases $PM_{2.5}$ mass concentration, which is the hygroscopic increase and accumulation of $PM_{2.5}$ (Wang, J. and Ogawa, 2015; Cheng et al., 2017; Liao et al., 2017). Conversely, lower relative humidity leads to an increased evaporation loss of $PM_{2.5}$ (Liu et al., 2015), the opposite process of hygroscopic increase. In recent years, Tandem Differential Mobility Analyser has been increasingly used to quantify the influence of hygroscopic increase on $PM_{2.5}$ concentrations (Trueblood et al., 2018; Chen et al., 2019; etc). Secondly, with high solar radiation and temperature, high humidity may promote secondary formation of $PM_{2.5}$ (Zhou et al., 2015; Zhao et al., 2016; Han et al., 2016). Thirdly, gas-to-particle partitioning is promoted under high-humidity conditions, and thus increases the fraction of hygroscopic components, especially ammonium nitrate, which further increases water uptake and the mass concentration of $PM_{2.5}$. Since humidity positively influences $PM_{2.5}$ concentrations through multiple mechanisms, high humidity contributes significantly to the formation of haze episodes. Severe haze episodes caused by high humidity were observed in different regions across China, including Beijing (Zhong et al., 2017b), Shenyang (Li et al., 2019), Yangtze River Delta (Li et al., 2014b; Sun et al., 2016), Xiamen (Wu et al., 2019), Xi'an (Wang et al., 2016) and Sichuan (Liao et al., 2017).

Negative influences: A negative influence of humidity on $PM_{2.5}$ concentrations has been found in Changsha, Nanchang, Fuzhou, Nanning and some other cities (Lin et al., 2009). Some thresholds, such as 70% (Wang and Ogawa, 2015) or 80% (Zhang et al., 2015), exist to differentiate the influence direction of humidity on $PM_{2.5}$ concentrations. When relative humidity is higher than the threshold, increasing humidity makes suspended particles coalesce and these particles become heavy enough for dry deposition (particles drop) and wet deposition (precipitation) (Li et al., 2015a), leading to a significantly reduced $PM_{2.5}$ concentration.

5.4.2. Feedback effects of $PM_{2.5}$ concentrations on humidity

For winter, high-concentration $PM_{2.5}$ in the heavily polluted Beijing-Tianjin-Hebei region exert strong positive influences on humidity (Chen et al., 2017), which can be attributed to the following reasons. Firstly, high-concentration $PM_{2.5}$ lead to a stagnant atmospheric environment with a weakened wind speed, within which the vapor evaporation has been constrained significantly (Yang et al., 2015b). The limited vapor loss increases the environmental humidity, which further increases $PM_{2.5}$ concentrations. Secondly, aerosols with high-concentration $PM_{2.5}$ cool the low boundary temperature by reducing the downwelling solar radiation, leading to a decrease in evaporation loss of $PM_{2.5}$ (Yang et al., 2016b; Zhao et al., 2019). Similar to wind speed, strong bidirectional $PM_{2.5}$-humidity interactions lead to a stagnant atmospheric environment, rapid formation and slow dispersion of haze episodes in North China plain.

5.5. Interactions between $PM_{2.5}$ concentrations and precipitation

Precipitation exerts a dominant influence on $PM_{2.5}$ concentrations in regions with a large amount of precipitation and moderate $PM_{2.5}$ levels, including major cities within Yangtze River Delta and Pearl River Delta, and some coastal cities (Chen et al., 2018). The mechanisms how precipitation interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.5.1. Influences of precipitation on $PM_{2.5}$ concentrations

Despite a generally negative influence (He et al., 2017b), precipitation may positively influence $PM_{2.5}$ concentrations under specific conditions.

Negative influence: A negative influence of precipitation on $PM_{2.5}$ concentrations has been found in Beijing (Zhang et al., 2015; Qiu et al., 2015), Sichuan Basin (Li et al., 2015) and Hangzhou (Jian et al., 2012). Precipitation negatively influences $PM_{2.5}$ concentrations through the washing effect, one major mechanism for removing atmospheric pollutants. It occurs when raindrops interact with gaseous pollutants through absorption and collision, and with $PM_{2.5}$ through collision-coalescence, which successively leads to a wet decomposition and significantly reduced $PM_{2.5}$ concentrations (Jian et al., 2012; Li et al., 2015; Wang et al., 2018). Both the amount of precipitation and local $PM_{2.5}$ levels control the washing effect of precipitation. Based on a distributed lag non-linear model (DLNM), Guo et al., (2016) revealed that the washing effect of precipitation on $PM_{2.5}$ concentrations in Xi'an, an inland city with relatively high $PM_{2.5}$ concentrations, was much weaker than that in Guangzhou, a coastal city with low $PM_{2.5}$ concentrations.

Positive influence: A majority of studies has analyzed the negative washing effect of precipitation on $PM_{2.5}$ concentrations, yet how slight precipitation quantitatively influences $PM_{2.5}$ concentrations has rarely been investigated through field survey or statistical analysis. Yadav et al., (2014) suggested that precipitation had much stronger influences on PM_{10} than $PM_{2.5}$. Shen et al. (2016) and Wang et al. (2018) further pointed out that strong precipitation exerted notable scavenging effects on $PM_{2.5}$ concentrations whilst weak precipitation and rainy fog processes might increase $PM_{2.5}$ concentrations. $PM_{2.5}$ are much smaller than PM_{10} and thus weak precipitation scavenges $PM_{2.5}$ limitedly. Conversely, weak precipitation leads to an increased atmospheric humidity, and successive hygroscopic increase leads to enhanced $PM_{2.5}$ concentrations.

5.5.2. Feedback effects of $PM_{2.5}$ concentrations on precipitation

The feedback effects of $PM_{2.5}$ concentrations on precipitation are more complicated and less straightforward. Firstly, $PM_{2.5}$ concentrations influence the magnitude of precipitation. $PM_{2.5}$ can serve as condensation nuclei of clouds and act on the number and size of cloud droplets. Therefore, high-concentration $PM_{2.5}$ may exert different influences on precipitation, suppressing light precipitation and strengthening heavy precipitation (Albrecht, 1989; Rosenfeld et al., 2014). Secondly, $PM_{2.5}$, especially high-concentration $PM_{2.5}$ can modulate the magnitude of precipitation through the aerosol radiactive effects (Lelieveld and Heintzenberg, 1992; Jacobson, 2001). Thirdly, $PM_{2.5}$ concentrations can influence the occurrence time (Guo et al., 2014; Zhou et al., 2018) and locations (Fan et al., 2015) of precipitation by changing cloud properties.

5.6. Interactions between $PM_{2.5}$ concentrations and radiation

The influence of radiation on $PM_{2.5}$ concentrations varies across China and serves as a major influencing factor in some specific regions (Chen et al., 2018). The mechanisms how radiation interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.6.1. Influences of radiation on $PM_{2.5}$ concentrations

Variations of solar radiation, in terms of both aerosols and cloud properties, can be described by SSD (sunshine duration), which measures the duration of received sunshine in a given period (e.g. a day or a year) for a given location (Wang et al., 2012). For winter, SSD strongly influences $PM_{2.5}$ concentrations in heavily polluted Beijing-Tianjin-Hebei region (Huang et al., 2015; Qian et al., 2016; Chen et al., 2017, 2018). The negative influence of SSD on $PM_{2.5}$ concentrations is mainly attributed to two reasons. Firstly, an increase in SSD leads to more solar radiation received by the near-surface atmospheric environment and thus an increase in near-surface temperature, promoting the upward movement and diffusion of $PM_{2.5}$. Secondly, organic carbon is a major component of $PM_{2.5}$ (Guo et al., 2012; Cao et al., 2014) and the increase in SSD leads to more intensive atmospheric photolysis that occurs on organic carbon and successively reduces the mass concentration of $PM_{2.5}$.

5.6.2. Feedback effects of $PM_{2.5}$ concentrations on radiation

Generally, high-concentration $PM_{2.5}$ exert a negative feedback effect on SSD through two mechanisms. Firstly, during haze episodes, high-concentration $PM_{2.5}$ block the radiation received in the surface atmospheric environment and reduce the surface temperature, which further suppresses the upward air motion and low-level air convergence (Thompson and Eidhammer, 2014; Yang et al., 2016b; Zhou et al., 2018) and may form or aggravate temperature inversion (Zhong et al., 2017b), causing additional increase of $PM_{2.5}$ pollution. Secondly, SSD is proposed as a general indicator of cloudiness (WMO, 1996). Therefore, the more cloud, the less SSD. High-concentration $PM_{2.5}$ induced stagnant conditions and weak winds, which are unfavorable for the dispersion of thick aerosols (clouds), lead to decreased SSD (Yang et al., 2016a).

5.7. Interactions between $PM_{2.5}$ concentrations and atmospheric pressure

Different from other factors that mainly influence $PM_{2.5}$ concentrations in heavily polluted winter, atmospheric pressure can be a major meteorological factor for $PM_{2.5}$ concentrations in other seasons (Chen et al., 2018). The mechanisms how atmospheric pressure interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.7.1. Influences of atmospheric pressure on $PM_{2.5}$ concentrations

Generally, high-pressure systems lead to stagnant environments, which are unfavorable for $PM_{2.5}$ dispersion (Hsu and Cheng, 2016). On the other hand, atmospheric pressure may influence $PM_{2.5}$ concentrations indirectly by affecting other factors such as humidity and wind, whose influences on $PM_{2.5}$ concentrations are subject to geographical conditions and spatial distributions of $PM_{2.5}$ levels. Consequently, the influence of atmospheric pressure on $PM_{2.5}$ concentrations varies notably across regions and seasons.

Negative influences: A negative influence of atmospheric pressure on $PM_{2.5}$ concentrations has been found in Beijing (Zhang et al., 2015;

You et al., 2017), Hangzhou (Jian et al., 2012) and Weizhou (Gao et al., 2017). Atmospheric pressure negatively influences $PM_{2.5}$ concentrations through the formation of lower-level wind convergence, which affects the accumulation and diffusion of $PM_{2.5}$ (You et al., 2017). Meanwhile, atmospheric pressure can negatively influence $PM_{2.5}$ concentrations by affecting other factors (Zhang et al., 2015). For instance, an increased pressure gradient can lead to enhanced wind speed, which significantly reduces $PM_{2.5}$ concentrations. On the other hand, low-pressure systems usually occur with high humidity, the two of which together may cause joint effects on the nucleation, condensation and coagulation of $PM_{2.5}$, leading to increased $PM_{2.5}$ concentrations (Jian et al., 2012).

Positive influences: A positive influence of atmospheric pressure on $PM_{2.5}$ concentrations has been found in Beijing-Tianjin-Hebei region (Miao et al., 2017), Sichuan Basin (Li et al., 2015) and Xiamen (Wu et al., 2019). For a pollution episode in Beijing-Tianjin-Hebei region, high-pressure systems induced stagnant conditions influenced the regional transport of $PM_{2.5}$ and caused high-concentration $PM_{2.5}$ (Miao et al., 2017). For Sichuan Basin with unique terrain conditions, Li et al., (2015) suggested that updraft in the low-pressure center promoted the dispersion of $PM_{2.5}$. Conversely, downdraft in the high-pressure center restrained the upward movement of PM, resulting in the accumulation of $PM_{2.5}$. For Xiamen as a coastal city, the subtropical high induced high humidity led to a haze episode (Wang et al., 2016).

5.7.2. Feedback effects of $PM_{2.5}$ concentrations on atmospheric pressure

Due to a variety of influencing factors, how $PM_{2.5}$ concentrations influence atmospheric pressure is highly complicated. Here we simply explain the general concepts how $PM_{2.5}$ concentrations may influence atmospheric pressure under common geographical and meteorological conditions. For scattering aerosols, high-concentration $PM_{2.5}$ block the solar radiation received in the surface and make the surface temperature decrease (Steiner and Chameides, 2005; Yang et al., 2016a, b), leading to limited movements and increased density of air mass. The reduced vertical air convection or increased downward movement of cold condensed air mass results in an increase of atmospheric pressure. For absorbing aerosols, they not only reduce surface temperature, but also increase near-surface temperature (Ramanathan and Carmichael, 2008; Wang et al., 2013), which may result in the formation of an inversion layer near surface. This can result in reduced vertical and horizontal motion and further lower atmospheric pressure (Ramanathan and Carmichael, 2008). Furthermore, absorbing aerosols may burn out clouds by absorbing solar radiation at the cloud height level (Kaufman and Koren, 2006; Koren et al., 2008), leading to more solar radiation received by ground. This effect heats the ground, increases the vertical convection and lowers surface atmospheric pressure.

5.8. Interactions between $PM_{2.5}$ concentrations and planetary boundary layer height

Planetary boundary layer (PBL) is not a direct meteorological variable, but a variable related to both temperature and winds. $PM_{2.5}$-meteorology interactions are closely related to the variation of planetary boundary layer height (PBLH) (Emeis and Schäfer, 2006). The mechanisms how PBLH interacts with $PM_{2.5}$ concentrations are briefly explained as follows.

5.8.1. Influences of PBLH on $PM_{2.5}$ concentrations

Despite a generally negative influence, PBLH may positively influence $PM_{2.5}$ concentrations under specific conditions.

Negative influence: A consistent negative influence of PBLH on $PM_{2.5}$ concentrations has been found in Beijing (Tie et al., 2015; Luan et al., 2018), Xi'an (Du et al., 2013), Tianjin (Quan et al., 2013) and Central-eastern China (Wang et al., 2014). $PM_{2.5}$ concentrations are highly sensitive to PBLH, which decides the height to which $PM_{2.5}$ can disperse (Tie et al., 2015). With a given amount of emitted pollutants, $PM_{2.5}$ accumulates gradually inside PBL and leads to the accumulation of $PM_{2.5}$ if there is no upper reaches for further dispersion of $PM_{2.5}$ (Du et al., 2013; Zheng et al., 2017). The same amount of pollutants leads to a large $PM_{2.5}$ concentration if the container of pollutants, PBLH is small. Conversely, a small $PM_{2.5}$ concentration results from a large PBLH. Since the interactions between $PM_{2.5}$ concentrations and multiple meteorological factors occur in PBL, low PBLH is a major meteorological driver for severe haze episodes that were observed in Beijing (He et al., 2015; Zhu et al., 2018), Shenyang (Li et al., 2019) and Yangtze River Delta (Sun et al., 2016; Liu et al., 2019).

Positive influence: Boundary layers could be categorized as Convective Boundary Layer (CBL), Neutral Boundary layer (NBL), Stable Boundary layer (SBL) and the thermostatic stability conditions for each type of boundary layers were distinct(Zhang et al., 2018). Convective Boundary Layers, where the negative correlation between BLH and $PM_{2.5}$ concentrations was the strongest, perform to dissipate more aerosols in heavily polluted areas than the Neutral Boundary layer. Stable boundary layers happen under the highest cloud cover. Due to the unique formation mechanism and thermodynamical conditions, positive correlations can exist between stable boundary layer height and $PM_{2.5}$ concentrations (Lou et al., 2019).

5.8.2. Feedback effects of $PM_{2.5}$ concentrations on PBLH

$PM_{2.5}$ concentrations exert a negative influence on PBLH mainly by adjusting received solar radiation (Quan et al., 2013; Luan et al., 2018). High-concentration $PM_{2.5}$ notably reduce surface downwelling radiation. In a clear day, PBL develops fully through solar radiation-induced surface heating whilst high-concentration $PM_{2.5}$ absorb and scatter a large proportion of solar radiation, leading to a constrained development of PBL and a low PBLH (Luan et al., 2018). The low PBLH depresses the diffusion of $PM_{2.5}$ to upper reaches and further increases $PM_{2.5}$ concentrations (Quan et al., 2013). Strong bidirectional $PM_{2.5}$-PBLH interactions are one major reason for stagnant conditions and long duration of wintertime haze episodes. Low PBLH is an important cause for the formation of haze episodes. The induced high-concentration $PM_{2.5}$ further suppresses the development of PBLH and lead to a lower PBLH, which deteriorate the haze episodes (Zhu et al., 2018; Li et al., 2019).

A brief review of mechanisms how major meteorological factors influence $PM_{2.5}$ concentrations is demonstrated as Fig. 11.

6. Major challenges for better understanding meteorological influences on $PM_{2.5}$ concentrations

More and more methods have been employed to comprehensively understand meteorological influences on $PM_{2.5}$ concentrations from different perspectives. Causality models (e.g. CCM) and statistical models (e.g. GAM, CMI and KZ) are capable of quantifying the influence of individual and multiple meteorological factors on $PM_{2.5}$ concentrations respectively. CTMs consider dynamic variations of both emission and meteorological factors, and have been widely used for simulating $PM_{2.5}$ concentrations. Despite a growing availability of advanced models, major challenges remain for verifying model outputs, improving model accuracy, and linking relevant research to more practical implementations.

6.1. The lack of experimental methods for better verifying outputs from different models

Due to difficulties in monitoring invisible physical and chemical reactions, the influence of one specific meteorological factor on $PM_{2.5}$ concentrations can hardly be isolated and measured. Without reliable accuracy assessment based on field-experiment data, a quantitative comparison between different methods (e.g. correlation analysis, causality models, statistical models and CTMs), especially the types and

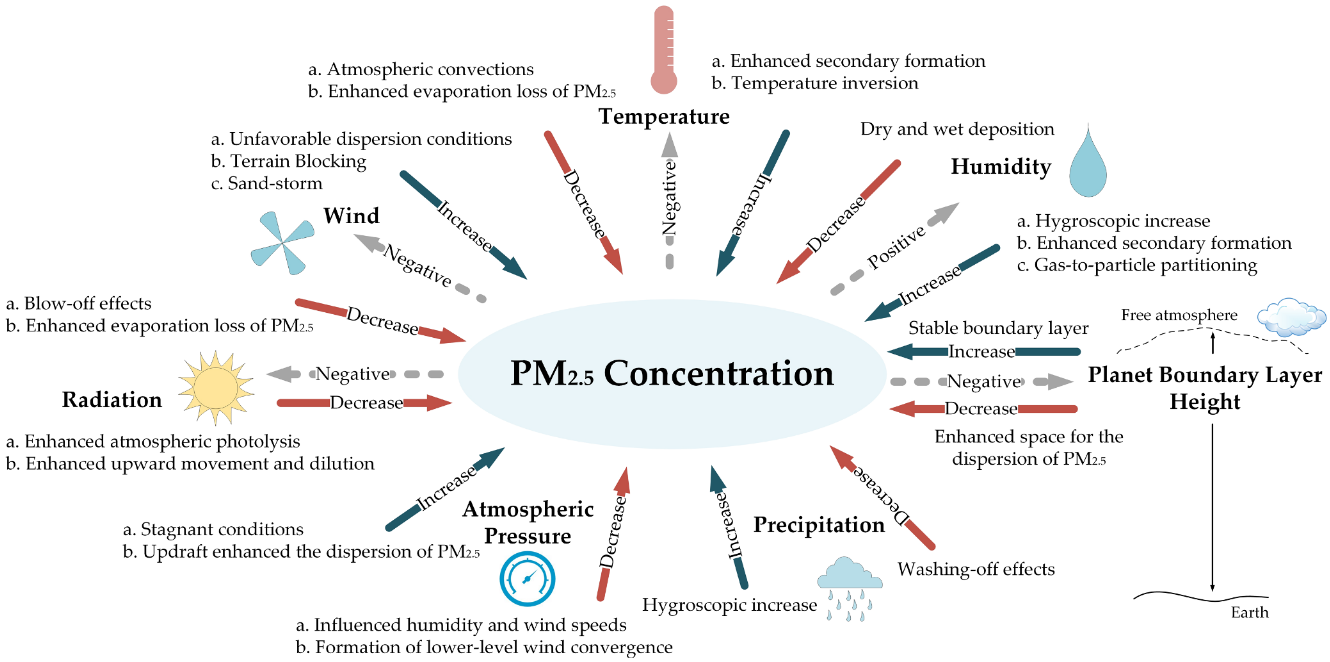

Fig. 11. How major meteorological factors influence $PM_{2.5}$ concentrations through different mechanisms.

magnitude of errors and uncertainty, cannot be conducted.

One potential solution for collecting reliable experimental data is the use of smog chambers, which aim to control the inner environment artificially, and thus simulate the real atmosphere (Lee et al., 2009) to analyze the simultaneous variations of airborne pollutants and a series of variables (McNeill et al., 2012; Stone et al., 2012; Ma et al., 2014; Riva et al., 2015, 2016). However, smog chambers have rarely been employed to observe how different meteorological factors quantitatively influence $PM_{2.5}$ concentrations. With the development of smog chambers, especially forthcoming huge smog chambers in Beijing (http://finance.ifeng.com/a/20140302/11781038_0.shtml), whose size will be over 300 m^3, it is possible to better simulate the real atmospheric environment and successively measure how $PM_{2.5}$ concentrations change with simultaneous variations of one specific meteorological factor by fixing other factors.

Another major challenge for better understanding $PM_{2.5}$-meteorology interactions lies in the lack of vertical structures of $PM_{2.5}$ and temperature (Guo et al., 2019). Recently, sounder (Zeng et al., 2019; Liu et al., 2019) and sounding (Guo et al., 2019) data have been increasingly used to comprehensively feature the vertical variations of meteorological factors and provide an unprecedented opportunity to better understand $PM_{2.5}$-meteorology interactions.

With reliable reference data, the performance of different methods in quantifying $PM_{2.5}$-meteorology relationship can be systematically evaluated, based on which scholars can better select methods and parameters according to different geographical and atmospheric conditions.

6.2. *Unsatisfactory accuracy and suitability of model simulation*

CTMs are advantageous in estimating $PM_{2.5}$ concentrations by comprehensively considering anthropogenic emissions and overall meteorological influences. However, the accuracy of CTMs is generally low and varies significantly across regions. The uncertainty mainly lies in inaccurate or coarse-scale emission inventories and incomplete understanding of reaction mechanism between precursors (Chen et al., 2017).

The reliability of these models can be improved from following perspectives. Firstly, the availability of more reliable emission inventories. For better predicting and managing $PM_{2.5}$ pollution, more accurate and detailed emission inventories have been produced. For instance, multi-resolution Emission Inventory for China, MEIC (http://www.meicmodel.org/) has been produced and regularly updated by Tsinghua University and many institutions, and widely employed for simulating regional and national $PM_{2.5}$ concentrations. Meanwhile, local governments and environmental institutions are making growing efforts on local emission inventories, such as Beijing emission inventory (http://www.cee.cn/), which provide fine-scale emission data for better simulating local $PM_{2.5}$ concentrations and conduct source apportionment. However, fine-scale emission inventories are currently limitedly available to specific institutions and the progressively increasing availability of these inventories is crucial for improved model simulation. Secondly, better descriptions of reaction mechanisms. Due to complicated reaction mechanisms between precursors, CTMs may significantly underestimate $PM_{2.5}$ concentrations, especially during pollution episodes (Li et al., 2011), which is a major challenge for simulating $PM_{2.5}$ concentrations. For instance, without consideration of heterogeneous/aqueous reactions between sulfate, nitrate, and ammonium (denoted as SNA) in high-humidity environment, WRF-CAMx failed to simulate maximum $PM_{2.5}$ concentrations during extreme haze episodes (Chen et al., 2016). To fill this gap, Chen et al., (2016) added equations that quantitatively explain heterogeneous/aqueous reactions to WRF-CAMx and notably enhanced the performance of WRF-CAMx in simulating peak $PM_{2.5}$ concentrations. Similarly, by providing CTMs with more reliable descriptions of reaction mechanisms under unique meteorological conditions and $PM_{2.5}$ levels, simulation outputs can be significantly improved.

6.3. *Limited attempts to extract quantitative results with more practical meaning*

The value of correlation coefficient or ρ value can hardly be directly interpreted with practical meaning or employed for predicting and managing $PM_{2.5}$ concentrations. For instance, ρ value of wind speed on $PM_{2.5}$ concentrations, calculated as 0.5, may simply suggest that wind speed is a more important influencing factor than SSD (ρ = 0.4). On the other hand, how $PM_{2.5}$ concentrations change quantitatively with a certain amount variation of wind speed cannot be understood according to the ρ value. Guo et al., (2016) established a non-linear model to predict precipitation caused $PM_{2.5}$ variations in Xi'an and Guangzhou, respectively. Guo et al., (2016) revealed that 20 mm rainfall led to a decrease of 46 mg/m^3 in $PM_{2.5}$ concentrations in Xi'an and a decrease of 8 mg/m^3 in Guangzhou. This research presented findings that could be easily understood and directly related to practical prediction and management of $PM_{2.5}$ pollution, providing useful references for future research. With long time-series data, advanced models and enhanced experimental conditions, meteorological influences on $PM_{2.5}$ concentrations should be further presented using more indicative metrics with straightforward and practical meaning.

6.4. The lack of studies that investigate the overall effects of $PM_{2.5}$-meteorology interactions

Strong bidirectional $PM_{2.5}$-meteorology interactions further exacerbate $PM_{2.5}$ pollution significantly, leading to notable underestimation of model-simulated $PM_{2.5}$ concentrations during heavy pollution episodes. Therefore, the overall effects of $PM_{2.5}$-meteorology interactions on the variation of $PM_{2.5}$ concentrations, which has rarely been investigated before, should be a key subject for understanding and managing $PM_{2.5}$ pollution. Given the difficulty in employing theoretical statistical models for simulating complicated and unstable physical and chemical reactions, properly designed CTM simulations and smog-chamber-based experiments can be potential solutions for quantifying the overall effects of bidirectional $PM_{2.5}$-meteorology interactions on $PM_{2.5}$ concentrations.

7. Major meteorological means for mitigating $PM_{2.5}$ pollution in China.

Meteorological influences have been recognized as a crucial driver for exacerbating or mitigating $PM_{2.5}$ pollution and growing emphasis from local governments has been placed on $PM_{2.5}$ reduction using meteorological means. Here we briefly introduce some environmental implementations that attempt to improve local $PM_{2.5}$ concentrations through different meteorological means (Fig. 12).

7.1. Reducing $PM_{2.5}$ concentrations through wind

As a heavily polluted mega city, Beijing is located in a basin-shape landscape surrounded by mountains. Major meteorological conditions, including wind, temperature, humidity and PBLH, are all altered here to be comparatively favorable for $PM_{2.5}$ accumulation (Bei et al., 2016; Zhang et al., 2019), and consequently wind is crucial for the transport and dispersion of $PM_{2.5}$ (Zhao et al., 2016).

Recently, Beijing wind-corridor project (Beijing Municipal Government, 2017) has become one of the most well-known environment projects. By creating five major wind corridors with 500 m-width, more strong wintertime northwesterly winds can be brought in. In addition to the blowing-off effect, larger wind speeds lead to larger SSD, larger evaporation and smaller humidity, which further reduces $PM_{2.5}$ concentrations in Beijing (Chen et al., 2017). Meanwhile, these wind-corridors have notable effects on the reduction of ambient temperature in summer, leading to the constrained ozone production rate in Beijing (Cheng et al., 2018). Therefore, the forthcoming wind-corridor project is promising to comprehensively mitigate air pollution in Beijing through multiple mechanisms. Given their potential effects on air quality improvement, mega cities all over China, such as Guangdong, Chengdu, Zhengzhou and Nanjing, have also proposed concrete plans for establishing local wind- corridors to reduce $PM_{2.5}$ concentrations.

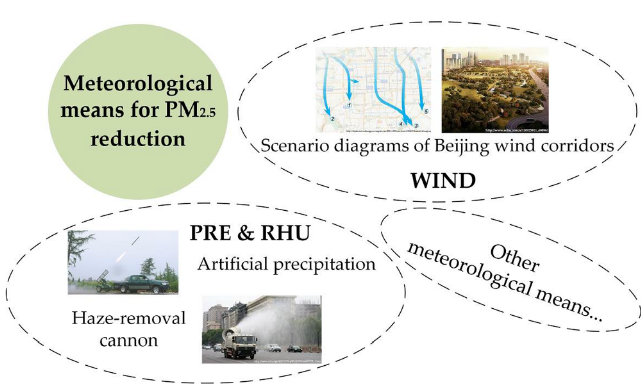

Fig. 12. Major meteorological means for reducing $PM_{2.5}$ concentrations.

As explained above, unfavorable wind direction may conversely increase $PM_{2.5}$ concentrations. For instance, strong southwesterly winds in Beijing lead to the accumulation of $PM_{2.5}$ caused by surrounding mountains. Therefore, the direction of wind-corridors should be properly designed according to local geographical and meteorological conditions.

7.2. Reducing $PM_{2.5}$ concentrations through precipitation (humidity)

Extremely high humidity leads to wet deposition of $PM_{2.5}$ (Li et al., 2015b). Hence, artificial precipitation enhancement is often employed for instantly reducing $PM_{2.5}$ concentrations in such megacities as Wuhan and Nanjing. Nevertheless, large-scale artificial precipitation enhancement is highly resource consuming and may not be frequently conducted. Therefore, some alternative approaches that simulate the process of precipitation have been proposed and implemented to reduce $PM_{2.5}$ concentrations. Yu (2014) proposed that high-building water spray could reduce $PM_{2.5}$ concentrations rapidly and this type of device has been implemented in Xi'an. Similarly, one type of so-called "haze-removal cannon" devices, which are carried on vehicles and spry a large amount of water vapors up to a height of 80 m and a distance of 100 m, has been applied in Shijiazhuang, Xi'an and Zhangjiakou. Compared with large wind-corridor projects, contingent artificial precipitation enhancement (or other similar approaches) requires much less resources and reduces local $PM_{2.5}$ concentrations instantly. However, artificial precipitation enhancement exerts limited influence on long-term $PM_{2.5}$-meteorology interactions. The implementation of artificial precipitation enhancement is not constrained by geographical conditions, though the washing-off effects on $PM_{2.5}$ concentrations are subject to local $PM_{2.5}$ levels.

8. Conclusions

This research comprehensively reviews recent studies concerning meteorological influences on $PM_{2.5}$ concentrations across China in terms of characteristics, methodology and mechanisms. Major conclusions are presented as follows:

(a) We compare major methods for examining meteorological influences on $PM_{2.5}$ concentrations. Causality analysis models (e.g. CCM) are suitable for quantifying the influence of individual meteorological factors whilst statistical models (e.g. GAM, KZ and CMI) are advantageous for understanding the comprehensive influence of multiple meteorological factors on $PM_{2.5}$ concentrations. By considering emission and meteorological factors, Chemical Transport Models (CTMs) provide reliable reference for dynamically estimating $PM_{2.5}$ concentrations.

(b) We review how temperature, wind speed, wind direction, humidity, precipitation, radiation, atmospheric pressure and planetary boundary layer height interact with $PM_{2.5}$ concentrations through different mechanisms, including the dispersion, growth, chemical production, photolysis, and deposition of $PM_{2.5}$. providing a comprehensive background for understanding the large variation of meteorological influences on $PM_{2.5}$ concentrations across China. We also explain the feedback effects of $PM_{2.5}$ concentrations on these meteorological factors and suggest that strong bidirectional $PM_{2.5}$-meteorology interactions are a major driver for exacerbated $PM_{2.5}$ pollution.

(c) We propose several aspects for better understanding $PM_{2.5}$-meteorology interactions. Firstly, more field-experiments (e.g. smog chambers, sounder and sounding) for verifying model outputs should be conducted. Secondly, simulation accuracy of CTM models should be improved based on the availability of fine-scale emission inventories and comprehensive descriptions of reaction mechanisms. Thirdly, quantitative results with more practical meaning should be extracted to provide straightforward reference for predicting and managing $PM_{2.5}$ pollution. Fourthly, the overall effects of bidirectional $PM_{2.5}$-meteorology interactions on $PM_{2.5}$ concentrations should be further investigated.

(d) We conclude the principle and suitability of major approaches that aim to mitigate $PM_{2.5}$ pollution through such meteorological means as wind corridors and artificial precipitation, and suggest these approaches implemented according to local geographical conditions, meteorological conditions and $PM_{2.5}$ levels.

CRediT authorship contribution statement

Ziyue Chen: Conceptualization, Methodology, Writing - original draft. **Danlu Chen:** Data curation, Formal analysis, Visualization. **Chuanfeng Zhao:** Methodology, Writing - review & editing. **Mei-po Kwan:** Writing - review & editing. **Jun Cai:** Data curation, Formal analysis, Visualization. **Yan Zhuang:** Data curation, Formal analysis, Visualization. **Bo Zhao:** Visualization. **Xiaoyan Wang:** Writing - review & editing, Visualization. **Bin Chen:** Data curation, Visualization. **Jing Yang:** Methodology, Writing - review & editing. **Ruiyuan Li:** Data curation, Formal analysis, Visualization. **Bin He:** Data curation, Formal analysis. **Bingbo Gao:** Data curation, Formal analysis. **Kaicun Wang:** Conceptualization, Methodology, Writing - review & editing. **Bing Xu:** Conceptualization, Writing - review & editing.

Declaration of Competing Interest

The authors declared that they have no conflicts of interest to this work.

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Appendix A. Supplementary material

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