The Complex Nonlinear Causal Coupling Patterns between PM2.5 and Meteorological Factors in Tibetan Plateau: A Case Study in Xining

Zhixiao Zou
Key Laboratory of Environmental Change and Natural Disaster, Beijing Normal University, Beijing
Changxiu Cheng (chengcx@bnu.edu.cn)
Key Laboratory of Environmental Change and Natural Disaster, Beijing Normal University, Beijing
Shi Shen
Key Laboratory of Environmental Change and Natural Disaster, Beijing Normal University, Beijing

---

Research Article

Keywords: nonlinear state space, coupling, PM2.5, meteorological factors, plateau cities

Posted Date: June 25th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-634756/v1

Version of Record: A version of this preprint was published at IEEE Access on January 1st, 2021. See the published version at https://doi.org/10.1109/ACCESS.2021.3123455.

The complex nonlinear causal coupling patterns between PM2.5 and meteorological factors in Tibetan Plateau: a case study in Xining

Author: **Zhixiao Zou[1,2,3], Changxiu Cheng[1,2,3,4,*], Shi Shen[1,2,3]**

[1] Key Laboratory of Environmental Change and Natural Disaster, Beijing Normal University, Beijing, China;

[2] State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, China;

[3] Faculty of Geographical Science, Center for Geodata and Analysis, Beijing Normal University, Beijing, China;

[4] National Tibetan Plateau Data Center, Beijing, China

* Correspondence: chengcx@bnu.edu.cn

Abstract

PM2.5 pollution influences the population health and people's daily life. Because meteorological factors are main factor affecting the formation of PM2.5, the interaction between PM2.5 and meteorological factors needs to be better understood, both for air quality management and for PM2.5 projection. Here, we use a nonlinear state space method called the convergent cross mapping method to identify the complex coupling patterns between PM2.5 and meteorological factors in a plateau city: Xining. The results prove that PM2.5-meteorological coupling patterns change with seasons and PM2.5-meteorological coupling patterns are fixed in spring, autumn and winter. In spring, there is a negative unidirectional effect from precipitation to PM2.5 and a negative bidirectional effect between relative humidity and PM2.5. In autumn, there are some negative bidirectional effects between PM2.5 and relative humidity, precipitation, and air pressure, while solar radiation has a positive bidirectional effect on PM2.5. In winter, there are negative bidirectional couplings between PM2.5 and wind speed and temperature and a positive bidirectional coupling between relative humidity and PM2.5. Furthermore, relative humidity is a consistent driving factor affecting PM2.5. Air quality managers may alleviate PM2.5 by increasing relative

humidity. Thus, the results provide a meteorological means for improving air quality in plateau cities.

Keywords: nonlinear state space; coupling; PM2.5; meteorological factors; plateau cities

1. Introduction

PM2.5 pollution pose a serious threat to the health of the population. Long-term or short-term exposure to PM2.5 concentrations can increase the mortality rate caused by cardiovascular diseases (especially ischemic heart disease and stroke), the number of respiratory diseases, and the risk of disability in daily activities among the elderly[1-3]. In addition, PM2.5 pollution also influence people's life, because PM2.5 concentrations cause serious visibility problems[4]. The poor visibility may lead to more traffic accidents. Therefore, to solve the PM2.5 pollution is essential for the prevention of medical accidents due to air pollution.

Because atmospheric conditions are one of the main factors affecting the formation of PM2.5 concentrations, Air quality managers may attempt to alleviate PM2.5 through meteorological means. Meanwhile, some scholars have noted that physical-chemical models such as chemical transport models were effective for predicting PM2.5 concentrations by PM2.5-meteorological interactions. However, it is difficult to adjust their parameters for different regions or select proper parameters for different meteorological factors from first principles[5-6]. In this way, they need more information to guide parameter adjustment. Therefore, clarifying the complex nonlinear coupling between multiple meteorological factors and PM2.5 concentrations is of great theoretical significance and practical value for the PM2.5 prediction and for the decision-making of government for the environmental management[7-8].

Most studies have emphasized the direct effect of meteorological factors (e.g., temperature, humidity, wind, precipitation and water vapor pressure) on PM2.5 concentrations. For example, Tran and Mölder[9] noted that wind, temperature and moisture (water vapor pressure and relative humidity) could influence PM2.5. Kleine Deters[10] thought that the prediction of PM2.5 concentrations was from wind (speed and direction) and precipitation. Wang[11] believed that wind direction and relative humidity were the two main meteorological factors affecting PM2.5 concentrations. DeGaetano[12] and Yin[13] reported that temperature, relative humidity and wind speed were correlated with PM2.5 concentrations. Actually, there are interactions among meteorological factors, so that some meteorological factors have indirect influence on PM2.5. However, the complex nonlinear causal coupling between meteorological factors and PM2.5 concentrations is unclear.

Meanwhile, some scholars[14-16] found that the PM2.5 concentrations had feedbacks to meteorological factors. Zhong[17] pointed that Elevated PM2.5 concentrations could reduce surface temperature by back scattering short wave solar radiation. Yang[18] explained how PM2.5 negatively influenced the formation of winds. Zhao[19] revealed PM in the high-humidity environment tended to physicochemical reactions, which further affected PM. Therefore, exploring the complex nonlinear causal coupling patterns is more advantageous to understand the relationship between PM2.5 concentrations and meteorological factors.

Previous studies have examined the correlation analysis and attribution analysis between PM2.5 and meteorological factors[20-22]. However, what we need to explore is a nonlinear coupling causality. Correlation, regression methods, and GAMs were used to study PM2.5-meteorology interactions. Among these methods, correlation cannot determine whether there is a causal relationship between two variables and cannot identify the direction of causation transitivity. Regression methods, which assume that the data are stationary or in linear space, are often used to analyze the relationship between PM2.5 and meteorological factors in nature. However, nature is a typical nonstationary and nonlinear space. Thus, we need a nonlinear state space method to quantify the coupling between PM2.5 concentrations and meteorological factors. Some studies have noted that GAMs could solve this problem, but they could not quantify the individual influence of meteorological factors on PM2.5[23-24].

For causality analysis, Granger causality (GC) is a classic test to identify the causality[25]. Li[26] found that economic growth, industrialization and urbanization increased PM2.5 concentrations in the long run using GC. Sfetsos and Vlachogiannis[27] applied GC to quantify the causality between meteorological factors and PM. Actually, the key requirement of GC is separability, which means that GC is suitable for the stochastic and linear systems. GC test may fail to detect weak coupling between meteorological factors and PM2.5 concentrations. Therefore, we could use the convergent cross-mapping method. Sugihara[28] provided a new method called convergent cross-mapping (CCM) to reveal the nonlinear coupling causality between multiple meteorological factors. Compared with the abovementioned methods, this method can quantify the individual influence of meteorological factors on PM2.5 concentrations and describe the coupling between multiple meteorological factors and PM2.5 concentrations.

Convergent cross-mapping (CCM) has been successfully applied in PM2.5-meteorological interactions. Some studies[29-30] filtered the original dataset and extracted the predictors through CCM for forecasting the PM2.5 concentrations. Furthermore, Chen used CCM to examine the causal relationship between PM2.5 and meteorological factors in the Jing-Jin-Ji region[31] and some megacities across China[32]. They mainly compared the individual influence of meteorological factors on PM2.5 in different scales and find the main meteorological factors in different regions and seasons. As mentioned above, the quantitative coupling patterns between meteorological factors and PM2.5 concentrations is unclear. In this study, based on CCM, we mainly identify the complex nonlinear coupling networks in different seasons.

Additionally, most studies on the PM2.5 have focused on the non-plateau areas and not on the Tibetan Plateau (TP) [33-34]. Recently, the Tibetan Plateau has also been impacted by aerosol pollution[35-36]. The main resources are biomass burning and the transport of pollution from the nearby regions of Southeast Asia and the northern part of the Indian Peninsula. As the largest-scale and most populated city on TP, Xining also have experienced PM2.5 pollution and faced with critical public health challenge due to the relative high PM2.5 concentrations, population exposure, vulnerability, slight awareness and high altitude conditions.

In this paper, we used a nonlinear state space method called CCM. Based on this method, we obtained the coupling patterns between meteorological factors and PM2.5 in Xining. The main results we acquired were (a) the temporal and spatial characteristics of PM2.5 concentration in Xining in 2019, (b) the individual influence of meteorological factors on PM2.5 in Xining in 2019, and (c) the coupling pattern between PM2.5 and meteorological factors in different seasons in Xining in 2019.

Specifically, section 2 introduces the study area, defines the data sources and explains the research methods. Section 3 presents our results. Section 4 discusses some uncertainties. Finally, chapter 5 presents the conclusions and prospects.

2. Materials and Methods

2.1 Study area

Xining, the capital city of Qinghai Province, is located in the northeastern part of the Tibetan Plateau, with an average altitude of 2,261.2 m. It belongs to the plateau continental climate, with low air pressure, a large day-night temperature difference, less rainfall, long sunshine, and strong solar radiation. It is the largest city in the region and hosts the main economic and social activities on the Tibetan Plateau. With a permanent resident population of 2,387,000, it is the only central city on the Tibetan Plateau with a population greater than one million. The urban area of Xining is located at the confluence of the Huangshui River, Nanchuan River, and Beichuan River. It is surrounded by mountains and forms a cross valley. In general, the terrain is high in the northwest and low in the southeast.

As Fig. 1 demonstrates, the four meteorological stations in this study are all located in southeastern Xining, among which three stations (Municipal Environmental Monitoring Station (SHJJCZ), Chengbei District Government (CBQZF) and Silu Hospital (SLYY)) are located in the urban area of Xining, and one station (Fifth Water Plant, DWSC) is located in the suburbs.

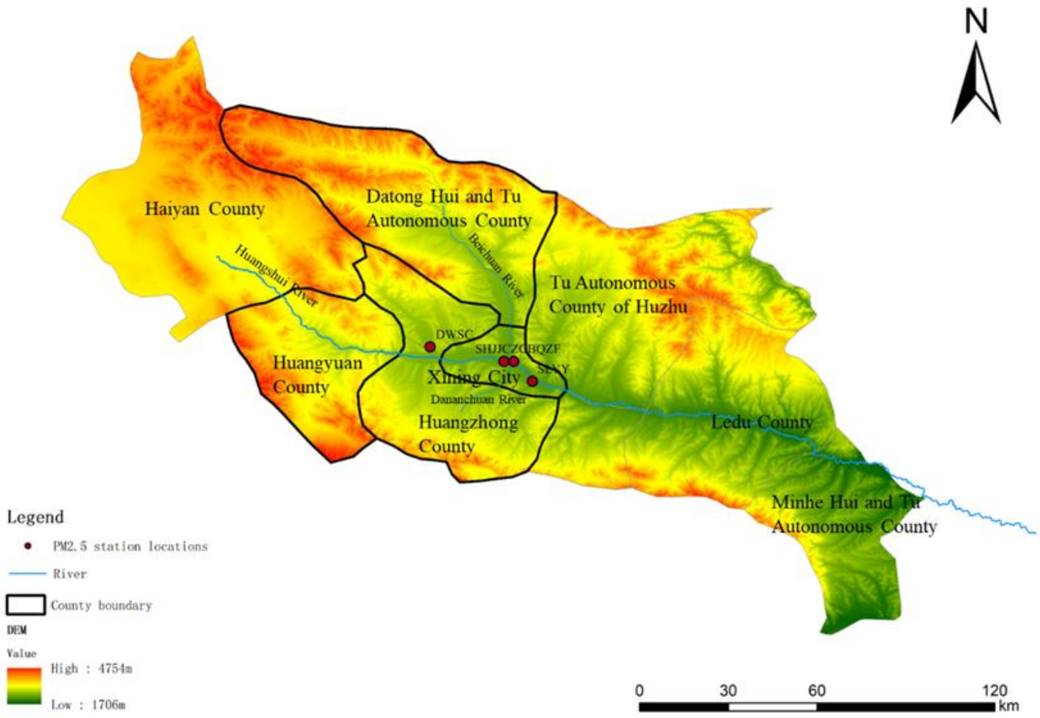

Figure 1. Geographical locations of PM2.5 stations and DEM in Xining

2.2 Data collection

As Table 1 shows, meteorological data were acquired from the China Meteorological Data Sharing Service System (http://data.cma.cn/). We studied eight kinds of meteorological factors: precipitation (PRE), wind speed (WS), wind direction (WD), pressure (PRS), temperature (TEM), water vapor pressure (e), sunshine duration (SSD), and relative humidity (RH). These factors were further categorized into subfactors. Precipitation is the total precipitation from 20 pm–20 pm. Wind speed includes the extreme wind speed (WSex), maximum wind speed (WSmax), wind speed and an average maximum wind speed of 2 minutes (WSmean2mins). The wind direction includes the maximum wind speed of the wind direction (WDex) and the maximum wind speed direction (WDmax). Pressure includes the daily mean pressure (PRSmean), daily maximum pressure (PRSmax), and daily minimum pressure (PRSmin). Temperature includes the daily mean temperature (TEMmean), daily maximum temperature (TEMmax) and daily minimum temperature (TEMmin). Water vapor pressure is the mean water vapor pressure. Solar radiation is represented by the daily sunshine duration (SSD). Relative humidity includes the daily mean relative humidity (RHmean) and daily minimum relative humidity (RHmin).

Table 1 Introduction to data

Data	Data type	Data source	Factors
Meteorological data	Station data	China Meteorological Data Sharing Service System (http://data.cma.cn/)	Precipitation (PRE), wind speed (WS), wind direction (WD), pressure (PRS), temperature (TEM), water vapor pressure (e), sunshine duration (SSD), relative humidity (RH)
Daily PM2.5 concentration data	Station data	Qingyue Open Environmental Data Center (https://data.epmap.org)	PM2.5 concentrations

Daily PM2.5 concentration data were obtained from Qingyue Open Environmental Data Center (https://data.epmap.org) from March 15, 2019, to March 15, 2020 (Table 1). This website provided PM2.5 data for each city by station in China. This study extracted PM2.5 data from four country-controlled stations in Xining (Chengbei District Government, PM2.5_CBQZF; Silu Hospital, PM2.5_SLYY; Municipal Environmental Monitoring Station, PM2.5_SHJJCZ; and Fifth Water Plant, PM2.5_DWSC).

2.3 Methods

This paper focuses on the key scientific problem of coupling patterns between PM2.5 concentrations and meteorological factors in different seasons in Xining. First, we obtained the PM2.5 station data and meteorological data in Xining and illustrated the spatiotemporal characteristics of PM2.5 concentrations in Xining in 2019. Second, based on the Pearson correlation coefficient, we screened the significant meteorological subfactors and acquired positive or negative correlations. Third, we used the causality CCM method to distinguish the spatiotemporal individual influence of meteorological factors on PM2.5 in Xining in 2019 and identified the coupling patterns between PM2.5 concentrations and meteorological factors in different seasons, which is beneficial for providing a scientific basis and theoretical suggestions for improving the air quality of Xining (Fig. 2).

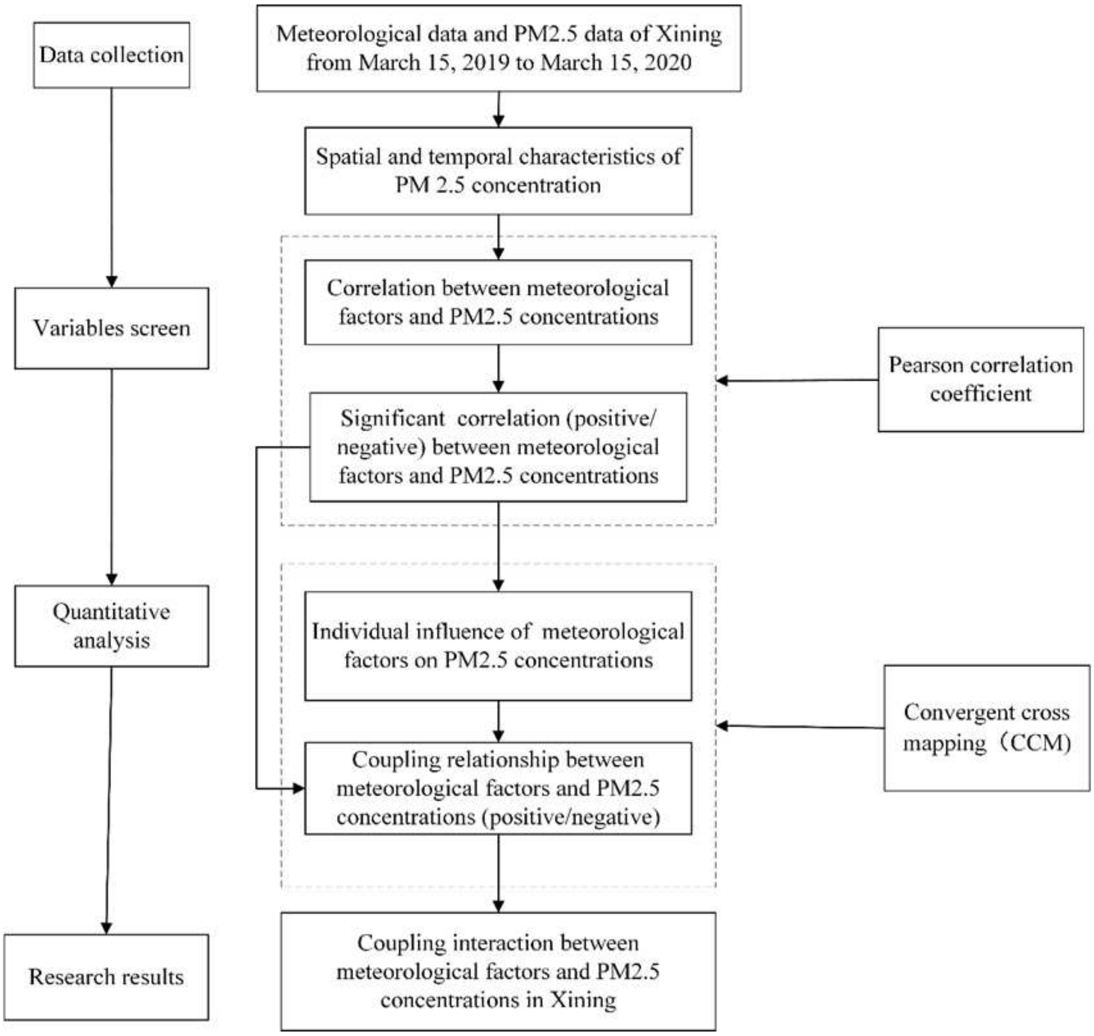

Figure 2 Framework of the study

2.3.1 Correlation analysis

The Pearson correlation coefficient was used to measure the correlation between meteorological factors and PM2.5 concentrations[37]. There were two problems to solve: the first was whether there was a correlation between each meteorological factor and the PM2.5 concentrations, and the second was what kind of correlation it was, that is, a positive or a negative correlation.

2.3.2 Convergent cross-mapping (CCM)

After finding the correlations, we needed a nonlinear state space method to identify the coupling between PM2.5 and meteorological factors. Fortunately, Sugihara (Sugihara et al., 2012) proposed the convergent cross-mapping (CCM) method. This is a method that can identify the coupling relationships (network) among individual variables in a complex system. The main algorithm of CCM is as follows. Consider two time series of length L, $\{X\} = \{X(1), X(2), \ldots, X(L)\}$, $\{Y\} = \{Y(1), Y(2), \ldots, Y(L)\}$. In this study, there were temporal variations in the meteorological factors and PM2.5 concentrations. The goal was to determine the causality between {X} and {Y} and identify what direction the coupling was (unidirectional causality/bidirectional causality). Take cross-mapping from X to Y as an example. First, we formed the lagged-coordinate vectors $\underline{x}(t) = \langle X(t), X(t-\tau), X(t-2\tau), \ldots, X(t-(E-1)\tau) \rangle$ for t=1+(E-1) to t=L. This set of vectors was defined as the "reconstructed manifold" or "shadow manifold" M_X. Next, we needed to generate a cross-mapped estimate of Y(t), denoted by $\hat{Y}(t)|M_X$, by locating the contemporaneous lagged-coordinate vector on M_X and finding its E+1 nearest neighbors. E+1 is the minimum number of points needed for a bounding simplex in an E-dimensional space. We used the distance w_i, generated by the E+1 nearest neighbors on M_X, to weight $Y(t_i)$ and obtain the estimate $\hat{Y}(t)|M_X$. Finally, the skill of the cross-map estimate (indicated by the correlation coefficient ρ value between observed and predicted), which ranged from 0 to 1, revealed the quantitative causality of X on Y. After obtaining the ρ value among multiple factors, we drew the coupling network among them. In this way, we acquired the coupling pattern between PM2.5 and meteorological factors.

$$\hat{Y}(t)|M_X = \sum w_i Y(t_i);\ \ i = 1 \ldots E+1$$

where $w_i = u_i / \sum u_j$ j=1…E+1, $u_i = \exp\{-d[\underline{x}(t), \underline{x}(t_i)] / d[\underline{x}(t), \underline{x}(t_1)]\}$. $d[\underline{x}(t), \underline{x}(t_i)]$ represents the Euclidean distance between two vectors.

The convergent cross-mapping algorithm is a backward-looking pattern. It examines the relationship between the current states and predicts the current Y rather than predicting the future value of Y based on the current X. To summarize, if variable Y from variable X by using the historical data is more reliable, the quantitative causality of variable X on the variable Y will be the stronger result.

3. Results

3.1 Spatial and temporal characteristics of PM 2.5

We used daily PM2.5 concentration data for the study period from March 15, 2019, to March 15, 2020, from the four state-controlled stations in Xining for analysis. Previous studies proved that PM2.5 in China has spatial and seasonal variations[38-40]. According to the high temperature, the period from June 1 to August 15 was defined as summer. Spring was defined from March 15 to May 31. Autumn was defined from August 16 to October 14. Winter was defined from October 15 to March 14. Therefore, we calculated the average daily PM2.5 concentrations of each season at the 4 stations and visualized them in Fig. 3.

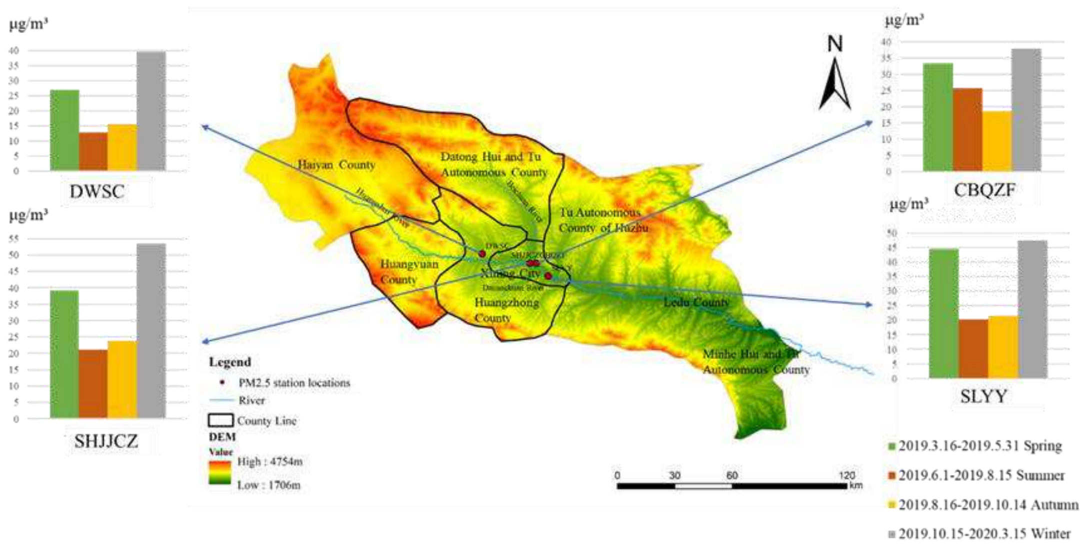

Figure 3 Spatial and seasonal characteristics of PM 2.5 concentration in Xining

Fig. 3 shows that at the four stations, the average PM2.5 concentrations in winter were the highest (over 35μg/m^3), followed by those in spring, because central heating occurs from October 15 to April 15 of the following year and burns coal, releasing more air pollutants. Compared with different stations, the mean PM2.5 concentrations at the suburban site Fifth Water Plant (DWSC) were the lowest in spring, summer, and autumn.

3.2 Correlation between meteorological factors and PM2.5

Some studies have noted that precipitation, relative humidity, and temperature were related to air quality in Xining[41]. In addition, previous studies[31, 42-44] have shown some influences of radiation, air pressure, wind speed, wind direction and water vapor pressure on PM2.5. To more comprehensively analyze the impact of meteorological factors on PM2.5, we examined precipitation, relative humidity, temperature, radiation, air pressure, wind speed, wind direction and water vapor pressure. In the last chapter, these factors were further categorized into subfactors: precipitation, wind speed (extreme wind speed, maximum wind speed wind speed, an average of 2 minutes maximum wind speed), wind direction (maximum wind speed of the wind direction, the maximum wind speed direction), pressure (average pressure, low pressure, high pressure), temperature (mean temperature, maximum temperature and minimum temperature), water vapor pressure, solar radiation (daily sunshine duration) and relative humidity (average relative humidity, minimum relative humidity).

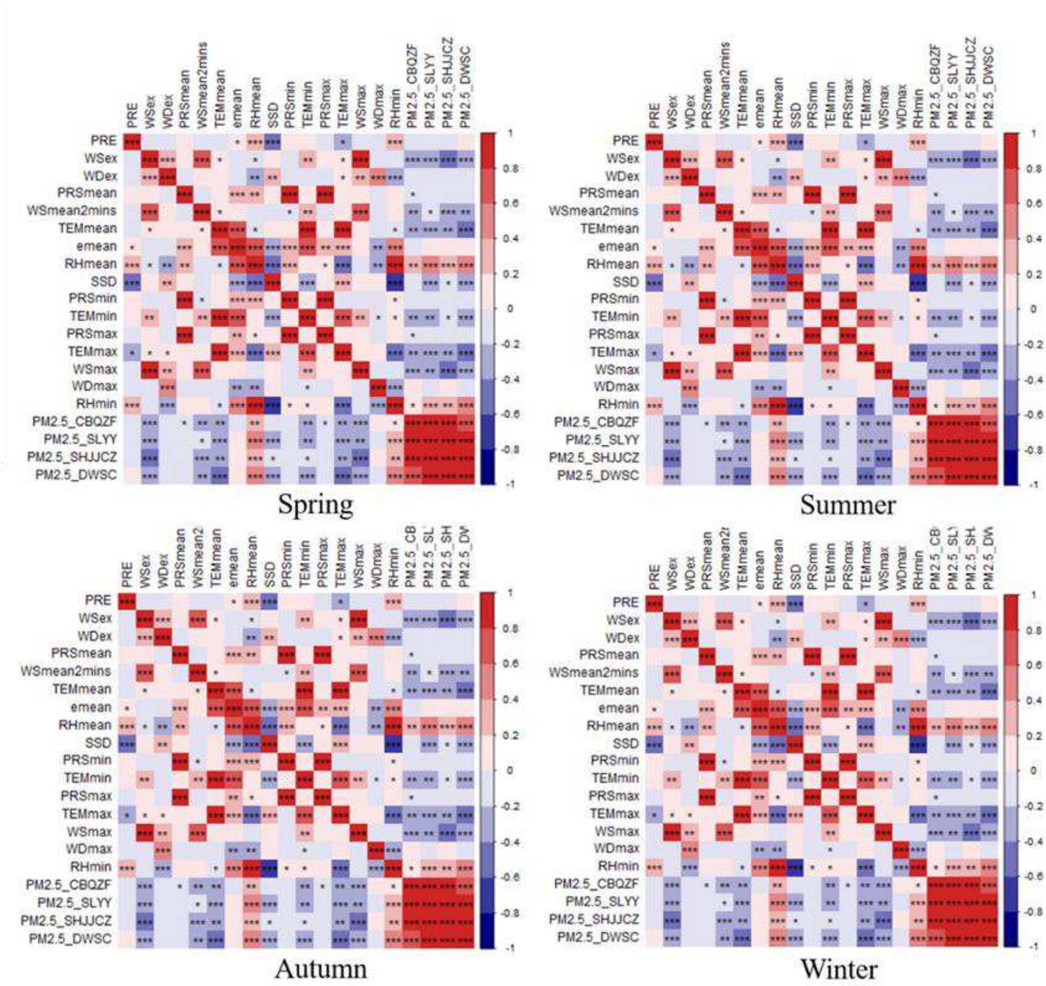

Figure 4 Seasonal correlations between individual meteorological factors and PM2.5 concentrations for different stations. **Correlation is significant at the 0.01 level (2 tailed); *Correlation is significant at the 0.05 level (2 tailed). Red squares show positive correlations, and blue squares show negative correlations.

According to the division of seasons, we obtained the correlation analysis results in Fig. 4. The meteorological factors strongly correlated with PM2.5 concentrations were extracted from each station. The correlation between meteorological factors and PM2.5 daily concentrations changed with season and station. The correlation between PM2.5 concentration and meteorological factors was strong in autumn and winter but weak in spring and summer. In addition, there was a correlation between meteorological factors, which varied by season. The correlation significance between PM2.5 concentrations at different stations was vital in all seasons except spring. Finally, the significant meteorological factors were screened, providing the foundation for causal analysis.

3.3 Causality between meteorological factors and PM 2.5

For the significant variables in Fig. 4, we adopted the CCM method to obtain the individual influence of meteorological factors on PM2.5 concentrations. According to different seasons, we could calculate the seasonal causality for each station. Despite multiple subfactors affecting PM2.5, the most significant p-value of subfactors represented the meteorological factors for each station. The ρ values between meteorological factors and PM2.5 are shown in Table 2. The value of prediction skill (p-value) ranged from 0 to 1, indicating the influence of one variable on another variable.

Table 2 Seasonal causality between individual meteorological factors and PM2.5 concentrations for different stations.

	Spring	ρ value	Summer	ρ value	Autumn	ρ value	Winter	ρ value
CBQZF	PRE	0.237	PRSmax	0.156	PRE	0.056	WSex	0.158
	RHmin	0.368	WSex	0.015	RHmean	0.268	PRSmax	0.16
			WDex	0.088	SSD	0.356	RHmean	0.17
					TEMmax	0	TEMmax	0.2
					PRSmax	0.136		
SLYY			RHmean	0.217	PRE	0.117	WSex	0.118
			PRSmax	0.209	PRSmean	0.042	RHmean	0.338
					RHmean	0.177	SSD	0.097
					SSD	0.267	TEMmax	0.315
					TEMmax	0		
SHJJCZ	PRE	0.348	WSex	0.182	PRE	0.075	WSex	0.294
	e	0.487	PRE	0.118	PRSmean	0.102	RHmean	0.301
	RHmean	0.535	PRSmean	0.053	RHmean	0.25	TEMmax	0.208
			RHmean	0.354	SSD	0.202	SSD	0.067
					TEMmax	0		

DWSC	PRE	0.271	TEMmin	0.17	PRE	0.067	WSex	0.189
	RHmean	0.327	PRSmax	0.183	RHmean	0.171	RHmean	0.439
			e	0.173	SSD	0.054	SSD	0.135
					PRSmax	0.214	TEMmax	0.406
					TEMmax	0		

3.3.1. Individual influence of different meteorological factors on the PM2.5

To better explain the individual influence (ρ value) of different meteorological factors on the PM2.5 concentrations, a rose wind map was drawn by R programming, as shown in Fig. 5. Each wind rose petal demonstrates a kind of meteorological factor, and the size represents the maximum value of all subfactors.

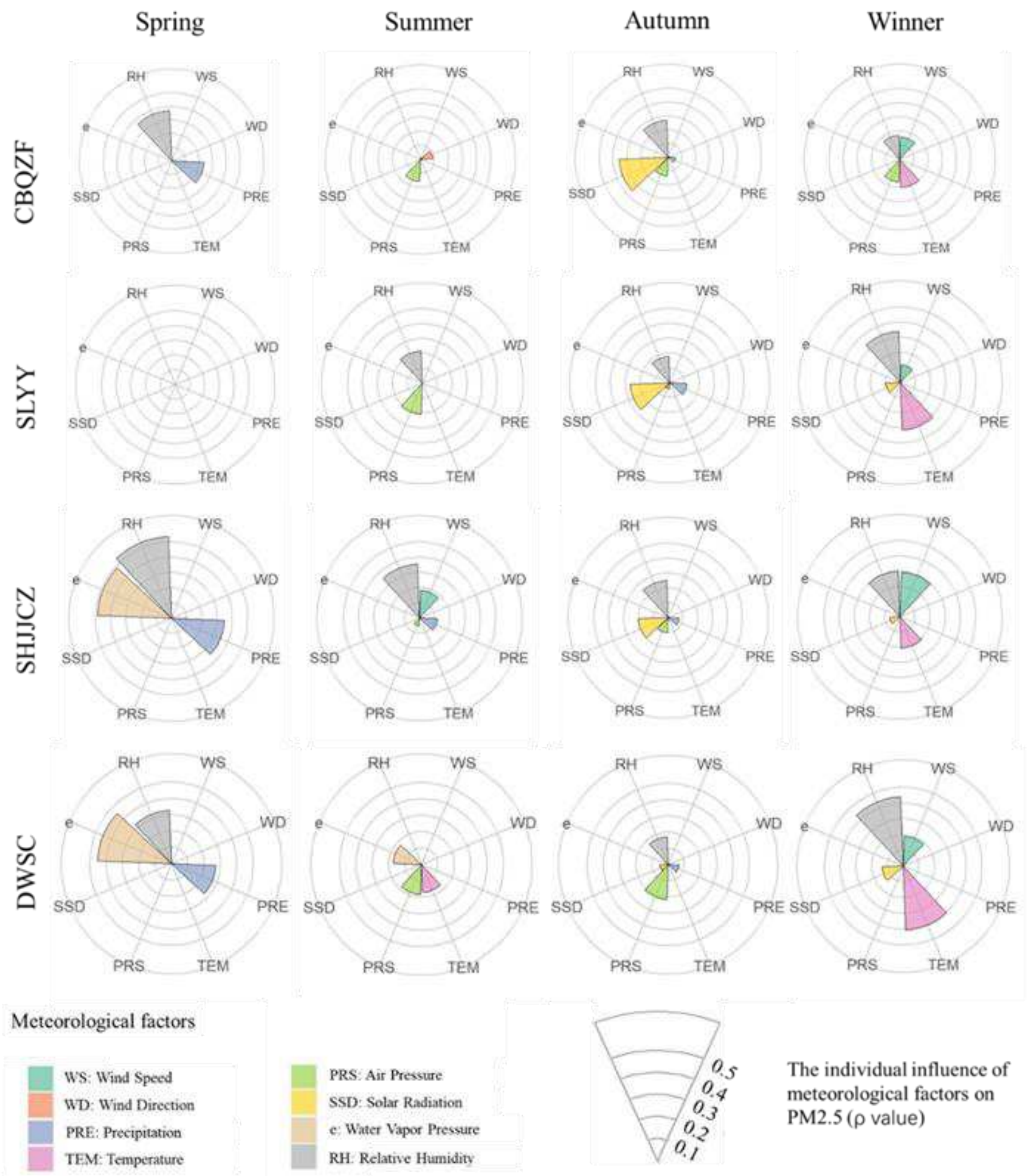

Figure 5 Seasonal and spatial causality between individual meteorological factors and PM2.5 concentrations for different stations.

The individual influences of meteorological factors in the four seasons were different. However, the meteorological factors of different stations in spring, autumn, and winter were similar. In spring, PM2.5 was mainly affected by precipitation and relative humidity. In summer, different stations had different main meteorological factors. The factors differed at different stations. In autumn, relative humidity, precipitation, air pressure, and sunshine duration largely influenced PM2.5. In winter, relative humidity, wind speed, and temperature were the dominant meteorological factors affecting PM2.5. Based on the main meteorological factors in spring, autumn and winter, we used them to analyze the coupling patterns of PM2.5 and meteorological factors.

3.3.2 Coupling pattern of PM2.5 and meteorological factors

According to the wind rose map, the network diagram of meteorological factors and PM2.5 was drawn and is shown in Fig. 6. These four stations in spring, autumn, and winter had different PM2.5-meteorological coupling patterns, but there was a similar PM2.5-meteorological coupling pattern for the three seasons. There was no fixed coupling pattern in summer. The PM2.5-meteorological coupling pattern in spring and summer was simple, while the PM2.5-meteorological coupling pattern in autumn and winter was complicated. Meanwhile, the feedback effects of PM2.5 concentrations on individual meteorological factors were explained[43] (Li et al., 2015a). Next, we

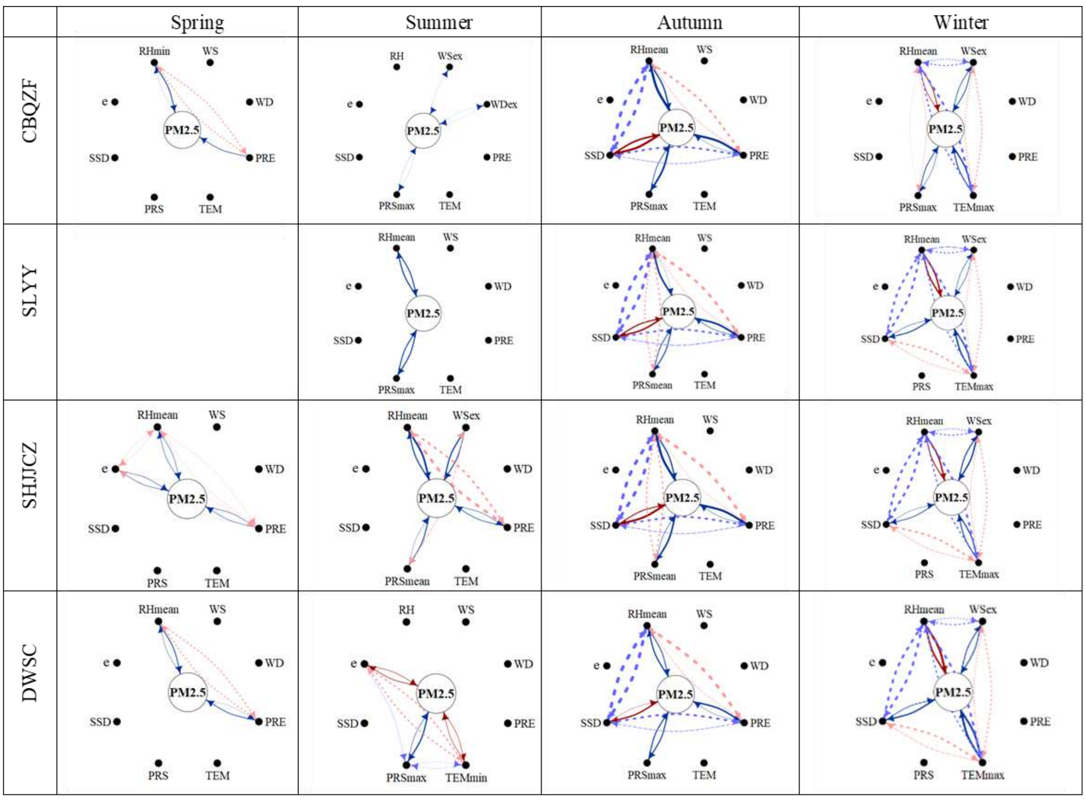

Figure 6 Seasonal and spatial coupling between individual meteorological factors and PM2.5 concentrations for different stations. Red represents a positive influence, and blue represents a negative influence. The solid line arrows show the causality between meteorological factors and PM2.5, while the dotted line arrows show the causality between meteorological factors. Two-way arrows show bidirectional causality, and one-way arrows show unidirectional causality. The thickness of the line arrows indicates the proportional size of the ρ value.

extracted the common meteorological factors from different stations in each season and analyzed the coupling patterns between these meteorological factors and PM2.5 to determine the coupling pattern of each season.

In spring, precipitation and humidity were the most influential meteorological factors affecting the PM2.5 concentrations. Both relative humidity and precipitation had a negative effect on PM2.5. Higher precipitation led to lower PM2.5 concentrations because of wet deposition. When precipitation increased, relative humidity increased. Similarly, when relative humidity increased, precipitation increased. In a wet environment, there was bidirectional coupling between PM2.5 and humidity. This result means that high humidity led to low PM2.5 concentrations and that feedback from low PM2.5 concentrations could increase the humidity. In this way, strong negative bidirectional PM2.5-humidity coupling would strengthen the effects of humidity on PM2.5 concentrations. At the same time, the increased precipitation caused increased relative humidity, which would also indirectly influence the PM2.5 concentrations (Fig. 7(a)).

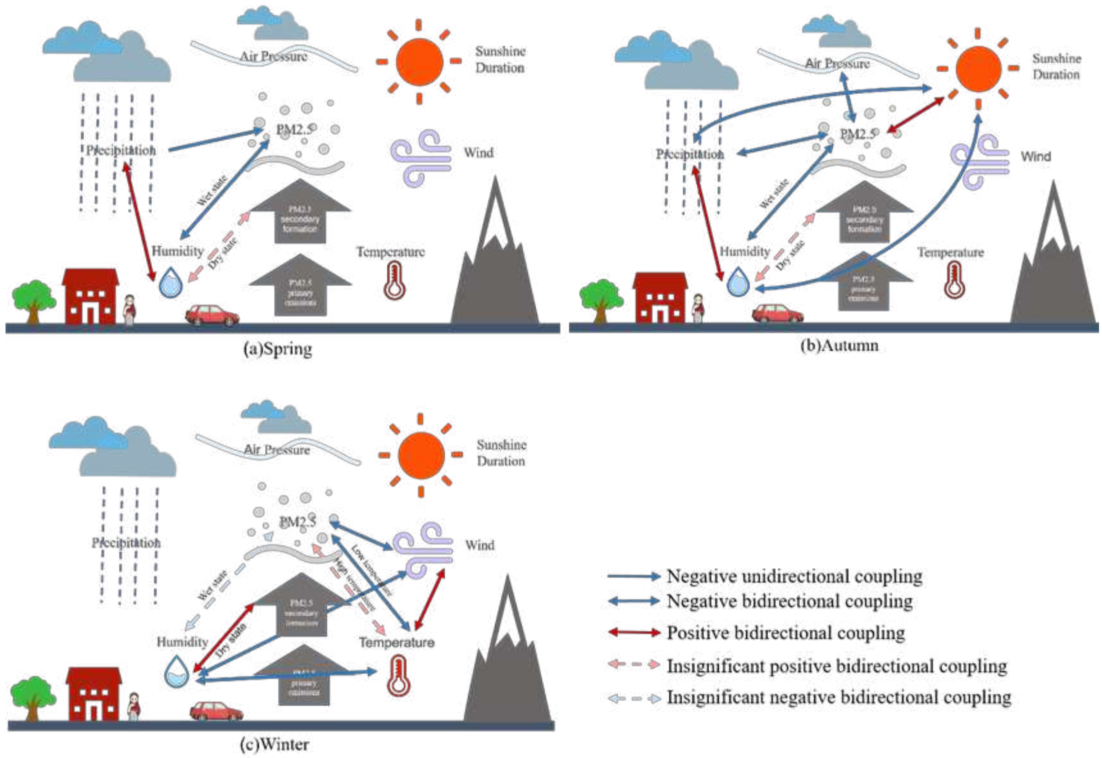

Figure 7 (a) Coupling pattern of meteorological factors and PM 2.5 concentration in spring (b) Coupling pattern of meteorological factors and PM 2.5 concentration in autumn (c) Coupling pattern of meteorological factors and PM 2.5 concentration in winter.

In autumn, relative humidity, precipitation and air pressure all had negative effects on PM2.5, while sunshine duration had a positive effect on PM2.5. The influence of air pressure on PM2.5 was relatively independent. That is, it did not affect the PM2.5 concentrations indirectly through the influence of meteorological factors. Precipitation had a strong positive influence on relative humidity, which increased the negative influence on PM2.5. Precipitation had a negative effect on sunshine hours, which also strengthened the negative effect on PM2.5 concentrations. There was a negative bidirectional coupling between relative humidity and sunshine hours (Fig. 7(b)).

In winter, in a dry state, there was a positive coupling between PM2.5 and relative humidity. Temperature had a negative effect on relative humidity. Wind speed and temperature had a negative bidirectional coupling on PM2.5. As the temperature increased, the saturated water vapor pressure increased, and the relative humidity decreased. This result means that temperature not only directly affected PM2.5 but also indirectly influenced PM2.5 by affecting relative humidity. Temperature positively impacted wind speed, so it strengthened the negative impact on PM2.5 (Fig. 7(c)).

4. Discussion

Previous studies put more emphasis on the relationship between individual meteorological factors and PM2.5 concentrations[33]. We obtained the coupling patterns between PM2.5 concentrations and meteorological factors. Based on these coupling patterns, we can design or adjust physical-chemical models for PM2.5 simulation or prediction.

According to the coupling patterns in different seasons, individual meteorological factors can influence local PM2.5 concentrations indirectly by interacting with other meteorological factors. Managers can take meteorological measures in different seasons to reduce the PM2.5 concentrations. In spring, they could reduce PM2.5 concentrations by increasing precipitation and relative humidity. In autumn, controlling precipitation, air pressure, relative humidity or solar radiation could mitigate the PM2.5 concentrations. In winter, they could adjust the temperature, relative humidity and wind speed to decrease the PM2.5 concentrations. In general, managing the relative humidity is the most effective method.

In terms of different seasons, as shown in Fig. 7, the negative influence of meteorological factors on PM2.5 was greater than the positive influence on seasonal coupling patterns. This may be make PM2.5 concentrations unstable. It means it will not continue to increase or decrease. The weather conditions are different every day. Higher precipitation leads to lower PM2.5 concentrations and lower precipitation in the same coupling pattern, leading to more PM2.5. In this way, the variation in weather causes fluctuations in PM2.5 concentrations. PM2.5 concentrations were dynamically stable over time. Compared with different seasons or coupling patterns, there is a critical value for the same meteorological factor. This result means that the influence of the same meteorological factor on PM2.5 in different states is different (e.g., relative humidity). In a wet state, the increased precipitation increased relative humidity. In a dry state, there was a positive coupling between PM2.5 and relative humidity.

It is worth noting that the PM 2.5 concentrations at the Fifth Water Plant station were lower than those at other stations. On the one hand, the land-use type of Chengbei District Government, Silu Hospital, Municipal Environmental Monitoring Station is urban land, but the Fifth Water Plant in the suburban area is irrigated land (a kind of dry land). Urban land creates more dust than irrigated land. Additionally, it may be because there is less traffic in the suburbs than that in the cities, and PM2.5 partly comes from the exhaust gas discharged into the atmosphere when vehicles use fuel on the roads.

This paper takes a plateau city as an example, but the method can be extended to other cities or regions. It can discover the PM2.5-meteorological patterns in different cities or regions. Meanwhile, it can also be extended to a larger time scale. It can find the PM2.5-meteorological patterns of different years or the seasonal PM2.5-meteorological patterns in different years.

5. Conclusions

In this paper, we analyzed the temporal and spatial characteristics of PM2.5 concentrations in Xining in 2019. More importantly, based on CCM, we revealed the temporal and spatial individual influences of meteorological factors on PM2.5 and identified coupling patterns between PM2.5 and meteorological factors in different seasons in 2019 in Xining. The key findings were as follows.

Based on a seasonal comparison, the PM2.5-meteorological coupling patterns were different in the four seasons in Xining. In spring, autumn and winter, there was a similar PM2.5-meteorological coupling pattern. There was no fixed coupling pattern in summer. The PM2.5-meteorological coupling pattern in spring and summer was simple, while the PM2.5-meteorological coupling pattern in autumn and winter was complicated.

The research suggests that individual meteorological factors can influence local PM2.5 concentrations indirectly by interacting with other meteorological factors. In spring, higher precipitation leads to lower PM2.5 concentrations, and higher relative humidity in the wet environment leads to lower PM2.5 concentrations. There is positive bidirectional coupling between precipitation and humidity. In autumn, relative humidity in the wet environment, precipitation and air pressure all negatively influence PM2.5, while sunshine duration positively influences PM2.5 In comparison, the influence of air pressure on PM2.5 is relatively independent. In winter, wind speed and low temperatures have a negative bidirectional coupling on PM2.5. There is a positive coupling between PM2.5 and relative humidity in a wet environment. Due to the coupling among relative humidity, wind speed and temperature, one of them can indirectly affect PM2.5.

The meteorological influence on PM2.5 concentrations was seasonally similar in Xining. In spring, PM2.5 was mainly affected by precipitation and relative humidity. In autumn, relative humidity, precipitation, air pressure, and sunshine duration mainly influenced PM2.5. In winter, relative humidity, wind speed and temperature were the dominant meteorological factors affecting PM2.5. Generally, relative humidity was the most important influencing factor affecting PM2.5 concentrations.

According to the coupling pattern in different seasons, managers could take different measures in different seasons to reduce the PM2.5 concentrations. It would be the most advantageous to reduce PM2.5 concentrations by decreasing relative humidity. In the future, we can extend this method to larger temporal and spatial scales; for example, we can analyze it for more years and expand it nationwide. Therefore, a PM2.5-meteorological coupling pattern at a larger scale could be acquired.

6. References

1. Brook, R. D., Newby, D. E. & Rajagopalan, S. Air Pollution and Cardiometabolic Disease: An Update and Call for Clinical Trials. *AM J HYPERTENS.* 31, 1-10 (2017).
2. Hayes, R. B. et al. PM2.5 Air Pollution and Cause-Specific Cardiovascular Disease Mortality. *INT J EPIDEMIOL.* 49, 25-35 (2020).
3. Lv, Y. et al. Long-Term Exposure to PM2.5 and Incidence of Disability in Activities of Daily Living Among Oldest Old. *ENVIRON POLLUT.* 259, 113910 (2020).
4. Pui, D. Y. H., Chen, S. & Zuo, Z. PM 2.5 in China: Measurements, Sources, Visibility and Health Effects, and Mitigation. *PARTICUOLOGY.* 13, 1-26 (2014).
5. Reichstein, M. et al. Deep Learning and Process Understanding for Data-Driven Earth System Science. *Nature (London).* 566, 195-204 (2019).
6. Sharma, A. et al. WRF-Chem Simulated Surface Ozone Over South Asia During the Pre-Monsoon: Effects of Emission Inventories and Chemical Mechanisms. *ATMOS CHEM PHYS.* 17, 14393-14413 (2017).
7. Chen, G. et al. A Machine Learning Method to Estimate PM2.5 Concentrations Across China with Remote Sensing, Meteorological and Land Use Information. *SCI TOTAL ENVIRON.* 636, 52-60 (2018).

8. Pérez P, T. A. R. J. Prediction of PM Concentrations Several Hours in Advance Using Neural Networks in Santiago, Chile. *ATMOS ENVIRON.* (2000).
9. Tran, H. N. Q. & Mölders, N. Investigations On Meteorological Conditions for Elevated PM2.5 in Fairbanks, Alaska. *ATMOS RES.* 99, 39-49 (2011).
10. Kleine Deters, J., Zalakeviciute, R., Gonzalez, M. & Rybarczyk, Y. Modeling PM2.5 Urban Pollution Using Machine Learning and Selected Meteorological Parameters. *Journal of Electrical and Computer Engineering.* 2017, 1-14 (2017).
11. Wang, S., Zhou, C., Wang, Z., Feng, K. & Hubacek, K. The Characteristics and Drivers of Fine Particulate Matter (PM2.5) Distribution in China. *J CLEAN PROD.* 142, 1800-1809 (2017).
12. DeGaetano, A. T. & Doherty, O. M. Temporal, Spatial and Meteorological Variations in Hourly PM2.5 Concentration Extremes in New York City. *ATMOS ENVIRON.* 38, 1547-1558 (2004).
13. Yin, Q., Wang, J., Hu, M. & Wong, H. Estimation of Daily PM 2.5 Concentration and its Relationship with Meteorological Conditions in Beijing. *J ENVIRON SCI-CHINA.* 48, 161-168 (2016).
14. Bister, M. & Kulmala, M. Anthropogenic Aerosols May Have Increased Upper Tropospheric Humidity in the 20Th Century. *ATMOS CHEM PHYS.* 11, 4577-4586 (2011).
15. Huang, Y., Dickinson, R. E. & Chameides, W. L. Impact of Aerosol Indirect Effect On Surface Temperature Over East Asia. *Proceedings of the National Academy of Sciences - PNAS.* 103, 4371-4376 (2006).
16. Rosenfeld, D. et al. Global Observations of Aerosol-Cloud-Precipitation-Climate Interactions. *REV GEOPHYS.* 52, 750-808 (2014).
17. Zhong, J., Zhang, X., Dong, Y., Wang, Y., Wang, J., Zhang, Y. & Che, H. Feedback effects of boundary-layer meteorological factors on explosive growth of PM2.5 during winter heavy pollution episodes in Beijing from 2013 to 2016. *Atmos. Chem. Phys.* 2017, 1–25 (2017).
18. Yang, Y. R. et al. Characteristics and Formation Mechanism of Continuous Hazes in China: A Case Study During the Autumn of 2014 in the North China Plain. *ATMOS CHEM PHYS.* 15, 8165-8178 (2015).
19. Zhao, Z. et al. Chemical composition of PM2.5 at a high–altitude regional background site over Northeast of Tibet Plateau. *Atmos. Pollut.* Res. 6(5), 815-823 (2015).
20. Li X, F. Y. J. L. The Impact of Meteorological Factors On PM2.5 Variations in Hong Kong. *IOP*

Conference Series: Earth and Environmental Science. (2017).

21. Lin, G. et al. Spatial Variation of the Relationship Between PM2.5 Concentrations and Meteorological Parameters in China. *BIOMED RES INT.* 2015, 1-15 (2015).
22. Pu, W., Zhao, X., Zhang, X. & Ma, Z. Effect of Meteorological Factors On PM2.5 During July to September of Beijing. *Procedia Earth and Planetary Science.* 2, 272-277 (2011).
23. Huang, F. et al. PM2.5 Spatiotemporal Variations and the Relationship with Meteorological Factors During 2013-2014 in Beijing, China. *PLOS ONE.* 10, e141642 (2015).
24. Pearce, J. L., Beringer, J., Nicholls, N., Hyndman, R. J. & Tapper, N. J. Quantifying the Influence of Local Meteorology On Air Quality Using Generalized Additive Models. *ATMOS ENVIRON.* 45, 1328-1336 (2011).
25. Granger, C.W.J. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica.* 37 (3), 424–438 (1969).
26. Li, G., Fang, C., Wang, S. & Sun, S. The Effect of Economic Growth, Urbanization, and Industrialization on Fine Particulate Matter PM2.5 Concentrations in China. *Environ. Sci. Technol.* 50 (21), 11452-11459 (2016).
27. Sfetsos, A. & Vlachogiannis, D. A new approach to discovering the causal relationship between meteorological patterns and PM10 exceedances. Atmos. Res. 98 (2-4), 500-511 (2010).
28. Sugihara, G. et al. Detecting Causality in Complex Ecosystems. *Science (American Association for the Advancement of Science).* 338, 496-500 (2012).
29. Xu, X. & Ren, W. Application of a Hybrid Model Based on Echo State Network and Improved Particle Swarm Optimization in PM2.5 Concentration Forecasting: A Case Study of Beijing, China. *Sustainability-Basel.* 11 (11), 3096 (2019).
30. Sethi, J.K. & Mittal, M. A new feature selection method based on machine learning technique for air quality dataset. Journal of Statistics and Management Systems. 22 (4), 697-705 (2019).
31. Chen, Z. et al. Detecting the Causality Influence of Individual Meteorological Factors On Local PM2.5 Concentration in the Jing-Jin-Ji Region. *SCI REP-UK.* 7, (2017).
32. Chen, Z. et al. Understanding meteorological influences on PM2.5 concentrations across China: a temporal and spatial perspective. ATMOS CHEM PHYS. 18, 5343-5358 (2018).
33. Chen, Z. et al. Influence of Meteorological Conditions On PM2.5 Concentrations Across China: A Review of Methodology and Mechanism. *ENVIRON INT.* 139, 105558 (2020).

34. Hu, X. et al. Temporal and Spatial Variation of PM2.5 in Xining, Northeast of the Qinghai–Xizang (Tibet) Plateau. *ATMOSPHERE-BASEL.* 11, 953 (2020).
35. Engling, G. et al. Characterization and sources of aerosol particles over the southeastern Tibetan Plateau during the Southeast Asia biomass-burning season. *Tellus Ser. B Chem. Phys. Meteorol.* 63, 117–128 (2011).
36. Zhuzi Zhao, J. C. Z. S. Chemical Composition of PM2.5 at a High–Altitude Regional Background Site Over Northeast of Tibet Plateau. *ATMOS POLLUT RES.* 5, 815-823 (2015).
37. Chen, L., Zhu, J., Liao, H., Yang, Y. & Yue, X. Meteorological Influences On PM2.5 and O3 Trends and Associated Health Burden Since China's Clean Air Actions. SCI TOTAL ENVIRON. 744, 140837 (2020).
38. Zhang, X., Gu, X., Cheng, C. & Yang, D. Spatiotemporal Heterogeneity of PM2.5 and its Relationship with Urbanization in North China From 2000 to 2017. *SCI TOTAL ENVIRON.* 744, 140925 (2020).
39. Yang, Q., Yuan, Q., Li, T., Shen, H. & Zhang, L. The Relationships Between PM2.5 and Meteorological Factors in China: Seasonal and Regional Variations. *INT J ENV RES PUB HE.* 14, 1510 (2017).
40. Wu, X., Cheng, C., Zurita-Milla, R. & Song, C. An Overview of Clustering Methods for Geo-Referenced Time Series: From One-Way Clustering to Co- and Tri-Clustering. *International journal of geographical information science : IJGIS*. 34, 1822-1848 (2020).
41. Dong-Lin, Q. I. et al. Characteristics of Air Quality and its Relationship with Meteorological Factors From 2001 to 2011 in Xining. *Journal of Meteorology and Environment*. (2014).
42. Chen, T., He, J., Lu, X., She, J. & Guan, Z. Spatial and Temporal Variations of PM2.5 and its Relation to Meteorological Factors in the Urban Area of Nanjing, China. *INT J ENV RES PUB HE*. 13, 921 (2016).
43. Li, Y., Chen, Q., Zhao, H., Wang, L. & Tao, R. Variations in PM10, PM2.5 and PM1.0 in an Urban Area of the Sichuan Basin and their Relation to Meteorological Factors. *ATMOSPHERE-BASEL*. 6, 150-163 (2015).
44. Lin, G. et al. Spatial Variation of the Relationship Between PM2.5 Concentrations and Meteorological Parameters in China. *BIOMED RES INT*. 2015, 1-15 (2015).