RESEARCH ARTICLE



Spatial and temporal changes analysis of air quality before and after the COVID-19 in Shandong Province, China

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Abstract

Due to the COVID-19 pandemic outbreak, the home quarantine policy was implemented to control the spread of the pandemic, which may have a positive impact on the improvement of air quality in China. In this study, Google Earth Engine (GEE) cloud computing platform was used to obtain CO, NO₂, SO₂ and aerosol optical depth (AOD) data from December 2018-March 2019, December 2019-March 2020, and December 2020-March 2021 in Shandong Province. These data were used to study the spatial and temporal distribution of air quality changes in Shandong Province before and after the pandemic and to analyze the reasons for the changes. The results show that: (1) Compared with the same period, CO and NO₂ showed a decreasing trend from December 2019 to March 2020, with an average total change of 4082.36 mol/m² and 167.25 mol/ m², and an average total change rate of 4.80% and 38.11%, respectively. SO₂ did not have a significant decrease. This is inextricably linked to the reduction of human travel production activities with the implementation of the home quarantine policy. (2) The spatial and temporal variation of AOD was similar to that of pollutants, but showed a significant increase in January 2020, with an average total amount increase of 1.69×10^7 up about 2.54% from December 2019 to March 2020. This is attributed to urban heating and the reduction of pollutants such as NO_x. (3) Pollutants and AOD were significantly correlated with meteorological data (e.g., average temperature, average humidity, average wind speed, average precipitation, etc.). This study provides data support for atmospheric protection and air quality monitoring in Shandong Province, as well as theoretical basis and technical guidance for policy formulation and urban planning.

Keywords Air quality · COVID-19 · Google Earth Engine · Shandong Province

Introduction

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Jingge Niu njgsdjzu@163.com With the improvement of urbanization and the increase of human activities, air pollution has become an increasingly serious problem (Azuma et al. 2020; Zhou et al. 2020; Song et al. 2021). Especially, many cities in northern winter have

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serious haze pollution, which affects human health and daily life. Scientific and effective exploration of air quality changes is of great importance for government decision making. Owing to the COVID-19 pandemic outbreak, the Chinese government adopted a home quarantine policy, which largely improved air quality in China. Therefore, this outbreak and lockdown period may be an excellent time to explore the driving factors of air quality change.

Many scholars have explored the impact of the pandemic lockdown initiative on air quality in China. The station data was frequently used to analyze the spatial and temporal changes of pollutant concentrations. For example, Zhu et al. (2020) studied the relationship between six air pollutants (i.e., PM_{2.5}, PM₁₀, CO, O₃, NO₂ and SO₂) and confirmed COVID-19 cases in 120 cities of China from January 23, 2020 to February 29, 2020 (Zhu et al. 2020). Yao et al. (2020) analyzed the association between PM_{25} and PM₁₀ concentrations and COVID-19 case fatality rates in 49 cities of China from January 15, 2020 to March 22, 2020 (Yao et al. 2020). However, station data could not well demonstrate the spatial distribution of pollutant changes, and are not easily collected and obtained. The application of remote sensing data has increasingly developed into a key technical tool for global atmospheric environment monitoring compared with traditional air pollution monitoring technology. Remote sensing data can provide data support for air quality monitoring with certain accuracy and relatively easy access (Zhao et al. 2017; Asokan and Anitha 2019). For example, Prakash et al. (2021) used the GEE platform to obtain Sentinel-5P and MCD19A2 data for March and April 2019 and 2020 to assess the major pollutants in major Indian cities during the pandemic lockdown period (Prakash et al. 2021). Meng et al. (2021) obtained CO, NO₂, O₃ and SO₂ concentrations from January 23, 2020 to May 31, 2020 by Sentinel-5P data to exploit the non-linear relationship between annual and daily global air pollution concentrations and daily confirmed cases (Meng et al. 2021). Dutheil et al. (2020) compared NO₂ concentrations in some regions of China from January-March 2019 and January-March 2020 by Sentinel-5P data (Dutheil et al. 2020). Ghasempur et al. (2021) explored the spatial and temporal distribution of NO₂ and SO₂ in Sentinel-5P data and AOD in MODIS data from January 2019 to September 2020 in Turkey through the GEE platform and discovered that Sentinel-5P data were strongly correlated with station data (Ghasempour et al. 2021). Zheng et al. (2019) used NO₂ data from Sentinel-5P to explore the spatial and temporal characteristics and influencing factors of NO₂ concentrations in mainland China from February 2018 to January 2019, where NO₂ concentrations from Sentinel-5P were highly correlated with NO2 concentrations from urban surface monitoring (p < 0.05, $R^2 = 0.72$) (Zheng et al. 2019). In the above-mentioned studies, the pollutant data from Sentinel-5P data were employed to detect air quality changes with favorable effects and highly correlated with pollutant station data.

Therefore, this paper utilized the Google Earth Engine (GEE) platform to explore the air quality changes in different years during the same period of the pandemic outbreak and lockdown (i.e., December 2018 to March 2019, December 2019 to March 2020, December 2020 to March 2021). GEE (https://code.earthengine.google.com) is a free, cloud-based platform that allows for in-cloud data access, processing and management (Tamiminia et al. 2020). Its strength lies in the combination of petabyte-scale satellite imagery and geospatial datasets with planetary-scale analysis capabilities, allowing for easy analysis and mapping at the global level, with easy access to data and 'unlimited' and stable processing power (Hu et al. 2018; Chen et al. 2021). Furthermore, the driving factors of air quality changes before and after the COVID-19 outbreak were explored to investigate the sources influencing air quality change.

The contributions of this paper are as follows: (1) This study understands the changes in air pollution levels from the coexistence of multiple pollutants after the implementation of the COVID-19 home quarantine policy in Shandong Province. We used satellite remote sensing data and compared the three times of the non-pandemic period, the pandemic period, and the basic end of pandemic to explore the impact of pandemic on air quality from a relatively comprehensive perspective. (2) This study quantifies the relationship between meteorological observations and air pollution, and explores the extent to which industrial, daily life and other activities affect air pollution in Shandong Province. We examined a few spatial regression models for identifying meteorological factors as explanatory variables to explain air quality changes during the pandemic. The driving factors of air quality changes from economic and social statistics were discussed in depth from the perspectives of mobile sources, industrial sources, and domestic sources.

The objective of this study is to analyze the air quality in Shandong Province during the pandemic lockdown from the perspective of air pollution. The dynamic changes of air quality in Shandong Province were studied from a more comprehensive perspective by comparing the air quality with the non-pandemic period and the approximate end of the pandemic. Meanwhile, due to the complex influences of emissions and meteorology, the impacts of natural and anthropogenic factors on air quality changes were systematically and quantitatively analyzed to understand the reasons why serious air pollution was not avoided in previous years and to provide theoretical support for scientific and effective air pollution control in the future.

Data and methods

Study area

The study area was Shandong Province, located in the Bohai Sea region of eastern China (see Fig. 1), between 34°22.9'-38°24.01' N and 114°47.5'-122°42.3' E (Zhang et al. 2016). Shandong province has a large population, with a resident population of 100,702,100 at the end of 2019. Shandong Province is one of the most economically developed provinces in China, with a gross domestic product of 7,312.90 billion yuan in 2020.



Fig. 1 Study area location map

 Table 1
 Description of datasets involved in the study

Datasets

Sentinel-5P is a global atmospheric pollution monitoring satellite launched by European Space Agency on October 13, 2017. The satellite carries tropospheric monitoring instruments and is capable of effectively observing trace gas constituents in the global atmosphere, including important indicators closely related to anthropogenic activities, e.g., NO₂, O₃, SO₂, CH₄ and CO (Vîrghileanu et al. 2020; Schneider et al. 2021). Aerosol optical depth (AOD) from moderate resolution imaging spectrometer (MODIS) data and Sentinel-5P air pollution data were acquired from the GEE platform (see Table 1). The time intervals for the study data were December 2018 to March 2019 (referred to as Period 1), December 2019 to March 2020 (referred to as Period 2), and December 2020 to March 2021 (referred to as Period 3). In addition, the factors affecting the changes in air quality before and after the COVID-19 pandemic were analyzed using meteorological station data from major cities in Shandong Province and statistical data from the National Bureau of Statistics. Among them, meteorological station data (e.g., average temperature, average humidity, average wind speed, etc.) were used as natural factors, and statistical data (e.g., industrial value added, cement, thermal power, gasoline, road passenger volume, natural gas, and gas, etc.) were used as anthropogenic factors.

Methods

Acquisition of pollution data using GEE

The GEE platform is widely used in many large-scale, long time series remote sensing applications (Mandal et al. 2018; Dlamini and Xulu 2019). In this study, all data acquisition and processing steps were performed online on the GEE platform using code. The original Sentinel-5P Level 2 (L2) data was time-graded, not latitude/longitude graded. To be able to incorporate the data into GEE platform, each Sentinel-5P L2 product was converted to Level 3 (L3) using the bin_spatial operation of the harpconvert tool (Gorelick et al. 2017). The source data was filtered to remove pixels with Quality Assurance (QA) values less than 75% for NO₂ and 50% for CO (Butz et al. 2012). Finally, NO₂, SO₂, CO, and AOD data

Datasets	Sensor	Study interval	Units	Spatial resolution	Image collection ID
NO ₂ SO ₂ CO AOD	Sentinel-5P Sentinel-5P Sentinel-5P MODIS	2018/12/01-2019/03/31 2019/12/01-2020/03/31 2020/12/01-2021/03/16	mol/m ² mol/m ² mol/m ²	0.01 arc degrees 0.01 arc degrees 0.01 arc degrees 1 km	COPERNICUS/S5P/NRTI/L3_NO2 COPERNICUS/S5P/NRTI/L3_SO2 COPERNICUS/S5P/NRTI/L3_CO MODIS/006/MCD19A2_GRANULES

were obtained for different years from December to March and monthly averages were calculated using the GEE platform.

Driving force analysis methods for Shandong Province

In this study, Pearson correlation analysis was performed using Statistical Product and Service Solutions (SPSS 25) software (Shi and Shi 2020). Pearson correlation analysis was used to explore the degree of correlation between air quality and driving factors before and after the COVID-19 pandemic (Baeza and Paruelo 2020; Özelkan 2020).

In addition, spatial regression analysis was performed using GeoDa software, and ordinary least squares linear regression model (OLS), spatial lag model (SLM), and spatial error model (SEM) were compared to select the most appropriate method for constructing the air quality-meteorological model (Lina and Lixun 2019). The following are the mathematical expressions of the OLS model, SLM model and SEM model, respectively (Liu et al. 2015; Mollalo et al. 2020).

$$Y = \beta_0 + \beta X + \epsilon \tag{1}$$

$$Y = \beta_0 + \rho \omega Y + \beta X + \epsilon \tag{2}$$

$$Y = \beta_0 + \beta X + \varphi, \varphi = \lambda \omega \varphi + \epsilon$$
(3)

where Y is the dependent variable; X is the independent variable; ω is the spatial adjacency matrix; β_0 is the constant intercept; β is the independent variable coefficient; ϵ

is the normally distributed error vector; ρ and λ are the spatial autoregressive and spatial autocorrelation coefficients. respectively. First-order Queen contiguity was used to establish the spatial relationship in Shandong province.

As shown in Fig. 2, the optimal regression model selection is judged by the Moran's I, Lagrange multiplier-lag (LM-lag), Lagrange multiplier-error (LM-error), goodness of fit (R^2) , natural log-likelihood function value (LogL), Akaike info criterion (AIC), etc. The model applicability is greater when the LM test passes with higher R² and LogL values and lower AIC value (Lina and Lixun 2019).

The specific judgment steps are as follows: first run the OLS model, and if the Moran's I test is not significant, the OLS model is used as the optimal model. If the Moran's I test is significant, the LM-lag test and LM-error test are compared. If both LM-lag test and LM-error test are insignificant, the OLS model is used as the optimal model. If only the LM-lag test is significant, then the SLM model is used as the optimal model. If only the LM-error test is significant, the SEM model is used as the optimal model. If both LM-lag test and LM-error test are significant, the indicators of robust LM-lag test and robust LM-error test are compared. If the robust LM-lag test is significant, the SLM model is used as the optimal model. If the robust LM-error test is significant, the SEM model is used as the optimal model.

Fig. 2 Flow chart of optimal model selection



Results and analysis

Spatial and temporal changes analysis of air quality in Shandong Province

Spatial and temporal analysis of pollutant concentrations

According to the relevant literature (Xu et al. 2018), it is clear that the pollutant concentrations have a clear cyclical variation. Figures 3, 4 and 5 show the spatial and temporal

From the monthly perspective, it can be seen that the concentration of these pollutants was higher from December to the following February. During the study period, the highest CO concentrations were observed in



Fig. 3 Spatial distribution of CO concentration



Fig. 4 Spatial distribution of NO₂ concentration

January 2019 and the highest NO_2 concentrations were observed in December 2020, while no significant changes were observed in SO_2 concentrations. There was a more significant increase in pollutant concentrations in March 2021 compared to the same period in 2019-2020. From the annual perspective, CO and NO_2 were significantly lower in Period 2 compared to Period 1, with an average total amount of CO decreased by 4082.36 mol/m² and an average total change rate of 4.80%, an average total amount of NO₂ decreased by 167.25 mol/m² and an average total change rate of 38.11%. There was a significant increase between Period 2 and Period 3, with the average total amount of CO and NO₂ increased by 730.46 mol/ m^2 and 167.93 mol/ m^2 , respectively, and the average total change rate was 0.90% and 61.84%. As shown in Fig. 5, SO₂ exhibited little variation over the study interval, which is somewhat related to the missing data. Comparing Period 1 and Period 2, the average total amount of SO₂ increased by 72.08 mol/ m^2 up about 10.44%, and decreased by 2.41 mol/ m^2 in Period 2 and Period 3. The central region of Shandong Province, namely Jinan City, Binzhou City and Zibo City, had high concentrations of



Fig. 5 Spatial distribution of SO₂ concentration

pollutants in the year-round. Pollutant concentrations in the eastern coastal areas of Shandong Province such as Weihai City, Yantai City, and Qingdao City were at low levels year-round.

Spatial and temporal analysis of AOD

AOD data can also effectively reflect the ground pollution (Lee et al. 2011; Ranjan et al. 2020). As shown in Fig. 7, in Period 1-Period 2, the average total change in AOD had a significant increase of about 1.69×10^7 , with an

average total change rate of 2.54%. In Period 2-Period 3, the average total amount of AOD decreased by 4.49×10^7 , with an average total change rate of 6.58%. As shown in Fig. 8, AOD in December 2019-January 2020 showed a more pronounced increase compared to December 2018 to January 2019, mainly concentrated in the western part of Shandong Province, namely Heze City, Liaocheng City, and Dezhou City. AOD in February-March 2020 presented a decreasing trend compared to the same period in 2019, and the most obvious areas were the southern regions of Shandong Province, namely Zaozhuang City,



Fig. 6 Spatial change of pollutants in Period 1-Period 2 and Period 2-Period 3



Fig. 7 Spatial change of AOD in Period 1-Period 2 and Period 2-Period 3

Linyi City, and Jining City. However, AOD for December 2020 to February 2021 displayed another marked decline compared to December 2019 to February 2020. AOD returned to previous levels and increased significantly in March 2021.

Analysis of the driving factors in air quality changes before and after COVID-19

Pollutant concentration changes are influenced by a combination of factors (e.g., natural factors, anthropogenic factors) (Pei et al. 2021; Sahoo 2021; Zhou et al. 2021). In order to study the driving factors of air quality changes in Shandong Province before and after the COVID-19 pandemic, meteorological data from 16 prefecture-level cities in Shandong Province were considered as natural factors data and relevant data released by the National Bureau of Statistics were taken as anthropogenic factors.

Correlation analysis and regression analysis of meteorological factors and air pollutants

The main meteorological data used to explore the correlation between meteorological data and air quality were average temperature (AT), average humidity (AH), average wind speed (AWS), average precipitation (AP), average barometric pressure (ABP), average total cloud cover (ATCC), and average visibility (AV).

Table 2 shows the Pearson correlation coefficients between air pollutants and natural factors (i.e., meteorological data). The air pollutants were more significantly correlated with each other. CO had a more significant correlation with AT, AWS, ATCC, and AV. NO_2 was correlated with AT, AWS, and AV. SO_2 showed a correlation with AT and AV. There was a significant correlation between AOD and AH, AWS, ATCC and AV. Therefore, these meteorological factors are affecting the air quality changes to some extent.



Fig. 8 Spatial distribution of AOD

As shown in Table 3, the Moran's I value for both the COmeteorological model and the NO₂-meteorological model were less than 0.05, the LM-lag values were less than 0.05, and the LM-error values were greater than 0.05, so the optimal CO-meteorological model and the NO₂-meteorological model were SLM models. The Moran's I value for both the SO₂-meteorological model and the AOD-meteorological model were greater than 0.05, and the LM-lag and LM-error values were greater than 0.05, thus the optimal SO₂-meteorological model and the AOD-meteorological model were OLS models. The R² values showed that the regression models of each pollutant and meteorological factors were well fitted and could provide a general reference for pollutant concentrations.

Analysis of anthropogenic factors in air quality change before and after COVID-19

The anthropogenic factors affecting air quality can be classified as industrial factors, mobile factors and domestic factors. The industrial factors were industrial value added, cement, thermal power, crude oil processing, coke,

	СО	NO ₂	SO ₂	AOD	AT	AH	AWS	AP	ABP	ATCC	AV
СО	1										
NO_2	0.600**	1									
SO_2	0.136	0.363**	1								
AOD	0.408**	0.084	-0.228**	1							
AT	-0.467**	-0.572**	-0.456**	0.042	1						
AH	0.141	-0.077	0.049	0.397**	-0.224**	1					
AWS	-0.407**	-0.254**	-0.127	-0.191*	-0.071	-0.160*	1				
AP	-0.063	-0.115	0.111	0.031	-0.245**	0.419**	0.074	1			
ABP	0.116	0.012	0.080	-0.012	0.279**	0.190*	-0.691**	-0.206**	1		
ATCC	0.248**	-0.004	-0.074	0.376**	-0.241**	0.343**	-0.060	0.210**	-0.044	1	
AV	-0.471**	-0.280**	-0.152*	-0.495**	0.168*	-0.599**	0.584**	-0.055	-0.378**	-0.139	1

Table 2 Correlation analysis of air quality and meteorological factors

* p<0.05, ** p<0.01

non-ferrous metals, flat glass and crude steel. The mobile factors were gasoline, diesel, road passenger volume and road freight volume. The domestic factors were raw coal, liquefied natural gas, natural gas and gas.

Industrial activity in Shandong Province declined significantly during the outbreak and lockdown period due to the combined effects of the Chinese New Year holiday and the pandemic control. As shown in Fig. 9, the value added of industry in Shandong Province dropped significantly by 34.34% year-on-year from Period 2. Shandong Province's coke, cement, thermal power, non-ferrous metals, crude steel and other industry output year-on-year declined by 10.866%, 2.461%, 3.713%, 7.801% and 5.912%. Crude oil processing and flat glass industry output rose year-on-year, respectively, 1.660% and 4.902%. The production process of coking, steel and glass companies cannot be interrupted, so the

Table 3 Regression analysis of air quality and meteorological factors

Variable	Coefficient								
Pollutants	SLM model		OLS model						
	СО	NO ₂	SO ₂	AOD					
AT	-1.254×10^{-4}	-3.100×10^{-7}	-2.824×10 ⁻⁵	26.615					
AH	6.825×10^{-5}	3.080×10^{-6}	3.759×10^{-6}	-2.751					
AWS	-7.259×10^{-4}	-2.630×10^{-5}	-4.964×10^{-5}	26.583					
AP	-1.814×10^{-4}	-3.166×10^{-6}	-1.734×10^{-5}	-0.438					
ABP	-1.315×10^{-5}	-8.333×10^{-7}	-4.933×10^{-7}	-1.277					
ATCC	-4.473×10^{-6}	-6.509×10^{-7}	-1.604×10^{-6}	3.412					
AV	6.896×10^{-5}	5.553×10^{-6}	2.555×10^{-5}	-23.557					
Constant inter- cept	0.033	7.953×10 ⁻⁴	0.001	1871.12					
ρ	0.633	0.710	-	-					
\mathbb{R}^2	0.899	0.906	0.699	0.905					
Moran's I	0.004	0.001	1	0.606					
LM-lag	0.037	0.029	0.653	0.265					
LM-error	0.316	0.129	0.425	0.498					

actual pollution emissions from these industries do not change much (Zhu et al. 2021). As a result, pollution from different industrial sectors has different impacts on air quality.

Mobile source emissions also showed a significant decline. Figure 9 shows that the national road passenger volume decreased by 59.370% year-on-year from Period 2. The national road freight volume increased by 1.810% year-on-year. Shandong Province is in the vicinity of the capital economic circle and has a large volume of cargo transportation. The output of gasoline and diesel products in Shandong Province dropped 24.954% and 12.872% year-on-year, respectively. According to changes in NO₂ concentrations, there was a significant decrease in emissions from road motor vehicles and a significant reduction in other mobile sources.

Emissions from domestic sources increased somewhat. Liquefied natural gas and gas in Shandong Province increased by 71.875% and 7.351% respectively compared to the same period. Raw coal and natural gas in Shandong Province decreased by 2.258% and 12.500%, respectively. The increase in the amount of gas used by residents in Shandong Province made an important contribution to air pollution. Moreover, the heating season in the cities extended by about 2 weeks, with a corresponding increase in pollutant emissions caused by residential heating, which will have a certain negative impact on the air quality (Zhu et al. 2021).

Discussion

Analysis of the causes in air quality changes before and after COVID-19

Based on the above results, it can be noted that CO and NO_2 decreased significantly during the outbreak and lockdown period compared to the same period, and SO₂ did not change significantly. It is worth noting that the sources of CO are mainly



Fig. 9 The change in air quality, industrial sources, mobile sources and domestic sources from Period 2 compared to the same period in Period 1

incomplete combustion of fossil fuels and motor vehicle exhaust emissions (Kang et al. 2019). NO₂ comes mainly from vehicle exhaust, fuel combustion in industry and industrial production processes of nitric acid, nitrogen fertilizer and explosives, as well as lightning (Yu et al. 2020). SO₂ mostly originates from the smelting of sulfur-containing ores, the burning of fossil fuels, or industrial emissions from sulfuric acid and phosphate fertilizer production (Torbatian et al. 2020). Human travel activities and production operations have been greatly reduced due to pandemics and home quarantine policies, thereby resulting in a reduction in CO and NO₂ (Yang et al. 2018; Copat et al. 2020).

AOD had a significant increase in January 2020. Combining the relevant literature, the reasons for the increase in AOD may be as follows: the reduction of pollutants like NO_x leads to an increase in ozone formation, which enhances the oxidation capacity of the atmosphere and promotes condensation around existing or new particles, leading to the production of particulate compounds (e.g., sulfates, nitrates, and organic compounds) (Huang et al. 2020; Nichol et al. 2020). Figure 10 shows the comparison of meteorological data (i.e., AT, AH, ABP, and AWS) for some typical cities in December-March. Meteorological data during the lockdown period varied within acceptable ranges from contemporaneous data. However, the typical city had greater AH from December 2019 to February 2020 than during the same period. Higher AH also promotes the formation of particulate compounds. These particulate compounds are less absorbed in nature and prone to form $PM_{2.5}$, which in turn also leads to an increase in AOD (Zhao et al. 2019; Wang et al. 2020; Zhang et al. 2020). On the other hand, urban heating in winter is also responsible for the increase in AOD.

Implications and recommendations of air quality change research

This study is important for understanding the current status of air quality qualitatively and quantitatively, and exploring the extent of natural and anthropogenic factors influencing air quality changes. It is significant for informing decisions on relevant policies to achieve the ultimate goal of improving air quality. From the perspective of anthropogenic factors, controlling anthropogenic emissions (especially industrial and mobile sources) is a fundamental measure to improve air quality. Natural factors (i.e., meteorological factors) have a strong correlation with air quality, and air quality-meteorological models have a good fit. Therefore, relevant departments can combine the air quality spatial and temporal distribution maps to selectively regulate and block the local areas with high pollutant concentrations (e.g., Zibo City, Binzhou City, and Jinan City) in making relevant government decisions. On this basis, it is necessary to understand meteorological information of cities with air pollution sources and design a reasonable industrial production layout and effective environmental planning. Then, it is desirable to change the energy structure and promote the use of clean fuels and clean production processes, thereby reducing pollutant emissions.



Fig. 10 Comparison of meteorological factors

This study has certain implications for remote sensing image data to conduct atmospheric monitoring studies. It demonstrates to some extent the usefulness of using the GEE platform to obtain Sentinel-5P data for spatial and temporal analysis in air pollution at different regional scales (Schneider et al. 2021). First, Sentinel-5P data is a free, high spatial resolution product that provides offline and near realtime air pollution data. Second, compared to ground-based air quality stations that provide only punctual information, Sentinel-5P data is a continuous data surface with daily global coverage. It grids a large amount of spatial data and is able to present the spatial distribution of different pollutants at a given time. However, there are some problems with Sentinel-5P data, such as cloud coverage and limitations in the number of observations, which hinder exhaustive air pollution monitoring (Vîrghileanu et al. 2020).

Conclusions

In this paper, pollutant concentrations and AOD data in Shandong Province were obtained from December 2018-March 2019, December 2019-March 2020, and December 2020-March 2021 using the GEE cloud platform. The spatial and temporal distributions of air quality changes in Shandong Province before and after the COVID-19 pandemic were studied, and the reasons for the changes were analyzed. Specific conclusions are presented below.

 Shandong Province had the highest CO concentration in January 2019 and the highest NO₂ concentration in December 2020, while SO₂ concentration did not change significantly. A significant increase in AOD existed in Period 2. Pollutant concentrations increased more significantly in March 2021 compared to the same period in 2019-2020.

- (2) Compared with Period 1, the average total amount of CO and NO₂ decreased by 4082.36 mol/m² and 167.25 mol/m² in Period 2, with an average total change rate of 4.80% and 38.11%, respectively. Between Period 2-Period 3, the average total amount of CO and NO₂ increased by 730.46 mol/m² and 167.93 mol/ m², respectively, with the average total change rate of 0.90% and 61.84%. The average total amount of SO₂ and AOD increased by 72.08 mol/m² and 1.69 × 10⁷ up about 10.44% and 2.54% between Period 1-Period 2, respectively, while decreased by 2.41 mol/m² and 4.49 × 10⁷ in Period 2-Period 3.
- (3) Pollutant concentrations show significant correlation with meteorological data. CO was significantly related to AT, AWS, ATCC and AV, NO₂ was relevant to AT, AWS and AV. SO₂ was correlated with AT and AV, and AOD was significantly associated with AH, AWS, ATCC and AV.
- (4) The significant decrease in CO and NO₂ from December 2019-March 2020 compared to the same period was mainly due to the reduction in human travel activities and production operations. AOD showed an increasing trend during January 2020, which was associated with urban heating and decreases in pollutants such as NO_x.

The GEE platform can help more countries and regions to understand the spatial and temporal changes of air quality and offer the theoretical basis for the management and protection of atmospheric environmental quality. In the future, air quality changes will be studied in a larger study area.

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