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Assessing drivers of coordinated control of ozone and fine particulate pollution: Evidence from Yangtze River Delta in China

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A R T I C L E I N F O

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A B S T R A C T

Previous studies have focused on a certain atmospheric pollutant, and few studies that comprehensively considered the drivers to synergistic impact on multiple pollutants. This study uses panel data of 41 cities in the Yangtze River Delta Urban Agglomeration (YRDUA) from 2005 to 2018. We aim to assess drivers of coordinated control for fine particulate ($PM_{2.5}$) and ozone (O_3) pollution using atmospheric remote sensing and spatial econometric model. Satellite image extraction shows that the key areas of pollution control are concentrated in the eastern coastal areas and northern cities. Here we show the empirical results of the Spatial Durbin Model indicating the drivers that significantly coordinated control of $PM_{2.5}$ and O_3 pollution: economic growth, urbanization, population density and energy intensity. The promotion of urbanization of YRDUA can help mitigate pollution, which proves that the new urbanization approach can improve environmental quality. Other significant drivers have their own adverse effects on $PM_{2.5}$ and O_3 pollution. Besides, the spillover effects of drivers are stronger than their local effects, which means that regional joint prevention and control will significantly improve the ambient air quality. As a result, policy recommendations are finally put forward such as promoting new-type urbanization, further standardizing the regional joint prevention and control mechanism, and exploring source management of $PM_{2.5}$ and O_3 pollution.

1. Introduction

Since the implementation of the National Action Plan on Air Pollution Prevention and Control (2013–2017), fine particulate matter ($PM_{2.5}$) has decreased by around 30–40% in China (Huang et al., 2018; Zhai et al., 2019). Although $PM_{2.5}$ pollution of China has been improved in recent years, the concentration of $PM_{2.5}$ still significantly exceeds the air quality standard (i.e., China's national standard requires that the annual average concentrations of $PM_{2.5}$ should be reduced to 35 μg/m^3 or less). Moreover, ozone (O_3) pollution has become seriously (Li et al., 2019b). In 2019, the average O_3 concentration in 337 cities across the country was 148 μg/m^3, and the number of days with O_3 as the primary pollutant accounted for 41.8% of the total number of days when pollutant exceeded standard, second only to $PM_{2.5}$, which accounted for 45%. In addition, the patterns of $PM_{2.5}$ and O_3 pollution show regional characteristics (Zhang et al., 2021; Zhao et al., 2020). In the Beijing-Tianjin-Hebei region, Yangtze River Delta (YRD) and Fenwei Plain, the O_3 concentration in 2020 increased from 2015 by 24.5%, 18% and 32.1%, respectively(Guan et al., 2021). $PM_{2.5}$ and O_3 pollution have the same source, and volatile organic compounds (VOCs) are their common precursors. The enhancement of atmospheric oxidation will also promote the formation of secondary $PM_{2.5}$ and the increase of O_3 concentration. Enhancing the emission reduction of nitrogen oxides (NO_X) and VOCs has a good synergistic effect on reducing $PM_{2.5}$ and O_3 pollution (Li et al., 2019a). Besides, since the areas with serious $PM_{2.5}$ and O_3 pollution basically coincide in space, the coordinated control of $PM_{2.5}$ and O_3 pollution has become key to controlling air pollution in China (Zhao et al., 2021).

The YRD has the highest level of urbanization and industrialization development in China, and the coal-dominated energy system not only

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supports its urbanization and industrialization development but also causes severe regional air pollution problem (Hong et al., 2021). The formation and development of air pollution events are also significantly affected by the regional transportation of air pollutants within urban agglomerations, and regional transportation accounts for 30–80% of the total O_3 and $PM_{2.5}$ concentration (Chang et al., 2019; Wang et al., 2020). O_3 and $PM_{2.5}$ are the most important air pollutants affecting air quality in the YRD (Gong et al., 2021; Hu et al., 2018). With the integrated development of the YRD becoming a national strategy and accompanied by the new air pollution prevention and control situation, it is necessary to explore the relationship between socio-economic development and air quality. The identification of key drivers will help to find the path of coordinated control of $PM_{2.5}$ and O_3 pollution. Thus, exploring the spatial-temporal distribution and coordinated control paths of $PM_{2.5}$ and O_3 pollution is of great practical significance for promoting the sustainable development of the YRD.

Previous studies have been carried out regarding source apportionment of air pollutants through atmospheric chemical transport models (Li et al., 2021; Liu et al., 2020b; Wang et al., 2019; Wang et al., 2020), temporal and spatial evolution law of air pollution concentration (Liang et al., 2019; Wang et al., 2014), and the econometric study of drivers for air pollution (Dong et al., 2019; Li et al., 2014; Wang et al., 2021).

(Duan et al., 2021) evaluated $PM_{2.5}$ and O_3 changes attributed to meteorological conditions and anthropogenic emissions based on distributed lag nonlinear models coupled Weather Research and Forecasting Model-Community Multi-scale Air Quality Model (WRF-CMAQ). (Wang et al., 2020) also used source-oriented chemical transport model to quantify the source region contributions to surface O_3 in Beijing and Shanghai in 2013. (Sun et al., 2019) measured the temporal and spatial distribution characteristics and influencing factors of $PM_{2.5}$ and O_3 concentrations in 33 cities in the YRD in 2016. However, results of these studies do not dynamically analyze the long-term evolution characteristics of $PM_{2.5}$ and O_3 concentrations. (Huang and Zhao, 2018) analyzed the temporal and spatial evolution characteristics of O_3 pollutants in YRDUA from 2015 to 2017. They obtained the positive and negative directions of relevant drivers by using geographic detector. (Wu et al., 2018) noted that the existence of nexus shapes of $PM_{2.5}$-economic urbanization are inversed-N in China, East China and inversed-U in Middle China. The results suggested that foreign trade contributes the most to air pollution, followed by economic growth, industrial structure, and foreign direct investment.

Traditional statistical theory is a theory based on the assumptions of independent observed values. However, when encountering spatial data, independent observed values are not common in real life. According to the First Law of Geography (Tobler, 1970), all attributed values of different indicators on a geographic surface are related to one other, but closer indicators are more strongly related than the more distant ones. The economic and geographical behaviours among regions generally exist spatial interaction to a certain extent. Given the fact that air pollution incidents usually occurred in many areas of China at the same time, so there may exist the spatial correlation within air pollution of neighbouring regions (Hao and Liu, 2016). Only considering the local situation is one-sided, the importance of pollutant transportation between cities should be also considered. Thus, the conventional econometrics techniques like ordinary least square (OLS) method and generalized least squares (GLS) method, which ignore the spatial spillover effect of pollutants may skew the results of driver's analysis (Zhou et al., 2021a). The spatial econometrics model focuses on the interregional interaction of air pollution and it has gradually been accepted to identify the spatial spillover effects between adjacent regions and analyze socioeconomic drivers (Fu and Li, 2020; Liu et al., 2017; Shen et al., 2020). (Feng et al., 2020) used the spatial Durbin model (SDM) to investigate the impact of environmental regulations on the $PM_{2.5}$ concentrations of the local and surrounding cities in the main agglomerations in China. This study revealed that the air pollution was affected not only by local environmental regulations but also by regulations implemented in the surrounding cities. (Fang et al., 2020) explored the spatial-temporal distribution of $PM_{2.5}$ concentrations in 74 nations partnering the Belt and Road Initiative, and identified the socioeconomic and natural drivers by spatial lag model (SLM) and spatial error model (SEM). Notably, its spatial econometric model is subjective choice and has not been judged by model test.

In general, the extant literature provides a crucial theoretical basis and an empirical explanation for the drivers behind the air pollution. However, there is still an existing research gap in this field. Many studies tend to focus on a certain atmospheric pollutant (Wu et al., 2020; Zhan et al., 2021), but few studies that comprehensively considered the drivers to synergistic impact on multiple pollutants. Moreover, due to the lack of atmospheric pollutant data, the spatiotemporal evolution process of pollutant concentration over a long-term scale cannot be easily assessed. Besides, some studies lack the reasonable judgment test of the model in spatial econometric modelling, the subjective selection of econometric model may also lead to biased results.

On the other hand, to overcome the shortcomings of the small sample size of atmospheric pollutant concentration data, studies (Cheng et al., 2017; Li et al., 2016) have recently adopted atmospheric satellite remote sensing data for its extraction. Atmospheric satellite remote sensing data effectively fills the vacancy of long-time series panel data of air pollutant concentration, and thus it is welcomed in the econometric study of drivers for air pollution. Its advantage is based on surface source monitoring rather than measuring data by traditional monitoring points, while comprehensively and accurately identifying the regional pollution situation.

To fill the above gaps, this study extracts $PM_{2.5}$ and surface O_3 satellite remote sensing data in the Yangtze River Delta Urban Agglomeration (YRDUA) from 2005 to 2018, and observe its temporal and spatial evolution characteristics. Spatial autocorrelation of Moran index is used to analyze spatial agglomeration effects. Based on the long-time series panel data of $PM_{2.5}$ and O_3 concentration, a spatial econometric method applying the Spatial Durbin Model can be developed to assess drivers of coordinated control of $PM_{2.5}$ and O_3 pollution and its spatial spillover effect. The main contribution of this paper includes: (1) Based on a developed space-time extra-trees (STET) model, long-term, full-coverage, high-resolution and high-quality datasets of ground-level air pollutants have been extracted to analyze the temporal and spatial evolution of $PM_{2.5}$ and O_3 pollution in the Yangtze River Delta. (2) From the perspective of collaborative influence, the drivers that can realize the coordinated control of $PM_{2.5}$ and O_3 pollution are explored based on spatial econometric model for the first time. (3) Exploring coordinated control of $PM_{2.5}$ and O_3 pollution's socioeconomic path can provide theoretical support for the development of air pollution regional joint prevention and control policies in the YRDUA, and also provide path reference for air pollution control of other large urban agglomerations in China.

2. Methods

2.1. Research area and period

The YRDUA includes 41 cities (with an area of 358,000 km^2) of Shanghai, Jiangsu Province, Zhejiang Province, and Anhui Province (Fig. 1). Shanghai is the central city for the integration of YRD. Hangzhou, Zhejiang Province, Nanjing, Jiangsu Province, and Hefei, Anhui Province are the sub-central cities. The YRDUA is one of the regions with the most active economic development, the highest degree of openness, and the strongest innovation capabilities in China (Zhou et al., 2021b). In 2019, the total Gross domestic product (GDP) of the YRD region was 23.7 trillion-yuan, accounting for 23.9% of the country's total. Moreover, it is a key area for air pollution prevention and control in China, as O_3 and $PM_{2.5}$ are the most prominent air pollutants that affect air quality in the YRD. Therefore, selecting the YRDUA to explore the spatial characteristics of $PM_{2.5}$ and O_3 pollution and assess the drivers for their

Fig. 1. Yangtze River Delta Urban Agglomeration in China.

coordinated governance will provide data for urban agglomerations and regional air pollution control. In addition, to best evaluate the time and space effects of air pollutants, we choose 2005–2018 as the research period to extensively evaluate the impact of China's five-year plan and air pollution control actions on pollutant changes.

2.2. Spatial correlation and weight selection

Exploratory spatial data analysis (ESDA) is widely used in spatial data correlation and the spatial spillover effect. In this study, the global spatial autocorrelation coefficient $Moran^{'} I$ index of ESDA is used to analyze the correlation between $PM_{2.5}$ and O_3 pollution within the YRDUA. The $Moran^{'} I$ is defined as follows:

$$I = \frac{\left[m\sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij}(x_i-\bar{x})(x_j-\bar{x})\right]}{\left[\sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij}\sum_{i=1}^{m}(x_i-\bar{x})^2\right]} \tag{1}$$

Where I is the Moran' I index, which is used to measure the overall spatial correlation of air pollution in urban agglomerations; m is the number of cities within the city group; $w_{ij}$is the spatial weight matrix; x_i and x_j are the air pollution concentrations of i city and j city, respectively ; $\bar{x}$ is the average value of the overall air pollution in each city. The value range of Moran Index I is between $(-1,1)$. If $I > 1$, air pollution has a positive spatial correlation. If $I < 1$, there is a large spatial dispersion across different cities. If $I = 0$, air pollution presents a random distribution characteristic in space.

To strengthen the investigation of spatial correlation characteristics of $PM_{2.5}$ and O_3 pollution, this study selected the economic geography combination weight matrix that considers geographical location and economic level. Previous studies (Dong et al., 2019; Liu et al., 2020a; Zhang et al., 2020) have seen the establishment of two spatial weight matrices and used them for mutual verification: the geographic spatial weight matrix and the economic distance weight matrix. Actually, whether based on the geographic spatial weight matrix or the economic distance weight matrix, the results undoubtedly have certain limitations and deviations. The empirical research shows that changes in the spatial weight matrix will produce new changes in the model estimation results. Hence, verifying the robustness of the model through multiple matrices will eventually affect the reference significance. This study applies the spatial weight matrix based on the reciprocal of the square sum of economic scale and longitude and latitude distance, which not only considers the geospatial distance between cities but also reflects the spillover effect of the regional economic development level. Therefore, it can comprehensively and objectively reflect the spatial correlation characteristics of $PM_{2.5}$ and O_3 pollution in the YRDUA.

2.3. Variable and data source

2.3.1. Data of annual mean $PM_{2.5}$ and O_3 concentrations

In this study, annual mean $PM_{2.5}$ and O_3 data from 2005 to 2018 that covers YRDUA are obtained from the long-term, full-coverage, high-resolution and high-quality datasets of ground-level air pollutants for China (ChinaHighAirPollutants, CHAP, https://weijing-rs.github.io/product.html), which are averaged from the daily data. The CHAP dataset is generated using a developed STET model from big data, including ground measurements, remote sensing products, and atmospheric reanalysis (Wei et al., 2020; Wei et al., 2021; Wei et al., 2022). CHAP $PM_{2.5}$ is the MODIS/Terra+Aqua Level 3 (L3) yearly 0.01 degree (≈1 km) gridded ground-level $PM_{2.5}$ products of Eastern China (ECHAP_P-$M_{2.5}$_Y1K) from 2005 to 2018, which are averaged from the Level 2 daily products. The annual $PM_{2.5}$ estimates are highly related to ground-based measurements (R^2 = 0.94), with an average root-mean-square error (RMSE) of 5.07 μg/m^3 (Wei et al., 2020, 2021). Particularly, CHAP O_3 is a new dataset and first generated from OMI Total-column O_3 products, together with other auxiliary data that uses artificial intelligence by considering the spatiotemporal heterogeneity of air pollution. This is the OMI Level 3 (L3) annually, which are 0.25-degree (≈25 km) gridded ground-level O_3 products in China, measured from 2005 to 2018 (Wei et al., 2022). They are averaged from the Level 2 daily (local time 13:30) products. We found that CHAP O_3 has high accuracy with a cross-validation coefficient of determination (CV-R^2) of 0.84 and RMSE of 20.11 μg/m^{-3} daily.

2.3.2. Data of drivers

Considering the existing literature and data availability, ten socio-economic drivers were selected as explanatory variables, to test the spatial interaction mechanism of $PM_{2.5}$ and O_3 pollution in YRDUA. The selected drivers are as follows and the details explanations are shown in the Supplementary materials: (1) Per capita GDP (GDP). We use the primary and squared terms of per capita GDP to conduct empirical research on the relationship between $PM_{2.5}$ and O_3 pollution and economic growth. (2) Urbanization level (URBAN). The proportion of the urban population in the total population is used to indicate the level of urbanization. (3) Normalised difference vegetation index (NDVI). (4) Population density (POP). (5) Technical level (TL). R&D investment costs are used to reflect the technological level of each city. (6) Industrial structure (IS). The proportion of the secondary industry in GDP is used to express the industrial structure. (7) Energy intensity (EI). EI is expressed as the ratio of total social electricity consumption to GDP. (8) Traffic pressure (TP). TP is expressed by the number of civil vehicle ownerships per unit of road history. (9) Investment in fixed assets (IIFA). (10) Opening up (OPEN). The actual foreign direct investment (FDI) reflects the degree of opening up.

The driver data of this study is composed of panel data from 41 cities in YRD from 2005 to 2018. NDVI comes from the Resource and Environmental Data Cloud Platform (http://www.resdc.cn/) and population density comes from Worldpop (http://www.worldpop.org/). The is remaining, above mentioned driver data comes from the 'China City Statistical Yearbook' and the annual statistical yearbooks of each city. Table 1 shows the statistical description of the variables.

2.4. Spatial econometric model settings

Static panel data models were established for $PM_{2.5}$ and O_3, respectively. According to the spatial econometric model determination method proposed by (Elhorst, 2012), one must first check whether to use the spatial lag model (SLM) or spatial error model (SEM) through the Lagrange multiplier test. Thereafter, a likelihood ratio (LR) test is employed to judge whether to use the fixed-effect model or random-effect model. Finally, the Wald test is used to judge whether the spatial Dubin model (SDM) is degraded. Based on the above three tests and research needs, we can determine the model that is finally suitable for empirical research.

As shown in Table 2, the LM, robust LM and LM (error) reject the null hypothesis at the significance level of 1%. The robust LM (error) fails to pass the significance test. Therefore, the spatial effect of the explained variable exists and the SLM can be used for econometric analysis. Thereafter, the SDM was established for regression. The LR test showed that the hypothesis of the random-effect model was rejected at the 1% significant level, so the fixed-effect model was selected. The Wald (SLM) and Wald (SEM) tests reject the null hypothesis at the 1% significant level, so SDM cannot be simplified. In conclusion, the fixed effect SDM should be applied for the $PM_{2.5}$ and O_3 econometric modelling in this paper.

Referring to the research of (Lesage and Pace, 2009), the SDM is established for $PM_{2.5}$ and O_3, respectively. The SDM can be expressed as follows:

$$Y_{it\,PM2.5} = \rho W y_{it\,PM2.5} + X_{it}\beta + WX\theta + \varepsilon_{it} \tag{2}$$

$$Y_{it\,O3} = \rho W y_{it\,O3} + X_{it}\beta + WX\theta + \varepsilon_{it} \tag{3}$$

Where $Y_{itPM2.5}$ and Y_{itO3} are the annual mean $PM_{2.5}$ and O_3 concentration of cities i over the years t ; ρ is the spatial autoregressive coefficient ; W is the weight matrix of economic geography combination; X_{it} represents the explanatory variable; β is the estimated explanatory variable coefficient ; θ is the estimated parameter of the spatial lag term of the explanatory variable; $\varepsilon_{it}$is the error term.

Due to the existence of the spatial spillover effects, the partial derivative (total effect) of an explanatory variable on air pollution cannot be equal to the coefficient of the explanatory variable. The reason for this is that the change of the explanatory variable will not only affect the air pollution in the region but also the air in the neighbouring area. Local (direct) effects and spillover (indirect) effects are thus produced. The direct and indirect effects of the SDM model are calculated as follows. Use eq. (2) as an example to convert to the general form:

$$Y_{it\,PM2.5} = (I - \rho W)^{-1}(X_{it} + WX\theta) + (I - \rho W)^{-1}\varepsilon_{it} \tag{4}$$

Where $(I - \rho W)^{-1}$ is the spatial multiplier matrix. The partial derivative differential equation matrix of $Y_{itPM2.5}$ with respect to t explanatory variables can be expressed as follows:

$$\left[\frac{\partial y}{\partial x_{1t}}, \dots, \frac{\partial y}{\partial x_{it}}\right] = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1t}} & \cdots & \frac{\partial y_n}{\partial x_{it}} \\ \vdots & \cdots & \vdots \\ \frac{\partial y_n}{\partial x_{1t}} & \cdots & \frac{\partial y_n}{\partial x_{it}} \end{bmatrix} = (I - \rho W)^{-1} \begin{bmatrix} \beta_t & w_{12}\theta_t & \cdots & w_{1n}\theta_t \\ w_{21}\theta_t & \beta_t & \cdots & w_{2n}\theta_t \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1}\theta_t & w_{1n}\theta_t & \cdots & \beta_t \end{bmatrix} \tag{5}$$

This defines the average value of diagonal elements in the matrix on the right of eq. (5) to measure the direct effect, and the average value of rows or columns of non-diagonal elements to measure the indirect effect. Therefore, the direct and indirect effect formulas of SDM can be expressed as follows:

$$Direct\ effect = \frac{(3 - \rho^2)}{3(1 - \rho^2)}\beta_t + \frac{2\rho}{3(1 - \rho^2)}\theta_t \tag{6}$$

Table 1
Statistical description of variables.

Variable	Unit	Max	Min	Mean	Std.dev
$PM_{2.5}$	ug/m^3	91.341	25.580	62.255	14.149
O_3	ug/m^3	114.122	57.185	92.840	10.758
GDP	yuan/ person	169,409.247	3761.410	48,374.536	32,680.898
URBAN	%	89.607	25.582	56.023	13.518
NDVI	–	0.868	0.429	0.738	6.474
POP	person/ km^2	4415.255	121.376	742.159	591.181
TL	10^8yuan	426.366	0.008	16.088	114.516
IS	%	74.735	23.910	49.133	8.480
EI	kW·h/ yuan	0.183	0.019	0.084	36.708
TP	10^4/km	322.852	3.436	53.909	59.581
IIFA	10^8yuan	7623.423	75.610	1632.371	1540.724
OPEN	10^8dollar	185.140	0.055	14.498	24.557

Table 2
Results of LM, LR and Wald tests.

$PM_{2.5}$		O_3	
Variable	Value	Variable	Value
LM	269.5304***	LM	401.9419***
Robust LM	106.7889***	Robust LM	74.6264***
LM (error)	162.7486***	LM (error)	329.1505***
Robust LM (error)	0.0071	Robust LM (error)	1.8349
LR (time)	290.2167***	LR (time)	68.292***
LR (spatial)	316.3107***	LR (spatial)	110.118***
Wald (SLM)	372.477***	Wald (SLM)	$7_{2.5}$433***
Wald (SEM)	419.8032***	Wald (SEM)	137.3053***

Note: ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

$$Indirect\ effect = \frac{(3+\rho^2)}{3(1-\rho^2)}\beta_t + \frac{3+\rho}{3(1-\rho^2)}\theta_t \quad (7)$$

Finally, for the parameter estimation method, we apply maximum likelihood estimation (ML) to estimate the SDM parameters. Its advantage is that ML estimation can avoid the biased estimation caused by the variable endogeneity problem of traditional OLS estimations (Wang et al., 2018). Moreover, it can scientifically reflect the correlation of elements between regions.

MATLAB R2018b software was conducted to complete the process of calculating the Moran index and spatial econometric modelling. ENVI 5.3 and ArcGIS 10.8 completed the analysis and grid processing of $PM_{2.5}$ and O_3 satellite remote sensing data and generated visual maps.

2.5. Limitations of data collection

In this study, the spatial econometric model was applied to assessing drivers of coordinated control of $PM_{2.5}$ and O_3 pollution. However, we had to face the issue of data availability. First, the data is only available between 2005 and 2018 because of the lack of new urban socio-economic data after 2018. Even though the pollution emission data (2005–2020) is existing, it doesn't match the complete panel data required by the study. Only the latest data (after 2018) of the city is officially and completely released, further analysis can be carried out.

3. Results and discussion

3.1. Temporal variation and spatial correlation

The satellite remote sensing data set is used to extract $PM_{2.5}$ and O_3 concentration grid images of YRDUA from 2010 to 2018. Fig. 2 is the spatial distribution map of annual $PM_{2.5}$ and O_3 concentration in YRDUA. For $PM_{2.5}$, from 2010 to 2013, its spatial distribution pattern has the characteristics of high in the north, low in the south, high in the East and low in the West. The heavily polluted areas are concentrated in the inland of the central and western North and the northeast coast of YRDUA. These cities have large industrial scales, denser populations and larger pollution emissions, resulting in relatively high average $PM_{2.5}$ concentrations in inland cities. After 2013, China began paying attention to haze pollution and adopted a series of effective policies and technical means to control air pollution. From 2013 to 2018, the $PM_{2.5}$ pollution of urban agglomeration in YRD improved significantly, and the heavily polluted cities in the east coast and the North showed a trend of retreating from space to the north. In addition, remote sensing images show that the concentration of $PM_{2.5}$ along both banks of the Yangtze River Basin in the YRD from 2010 to 2018 is higher than on land.

For O_3, from 2010 to 2013, the O_3 concentration in Jiangsu in the north, Shanghai in the East and Zhejiang in the South was high, instead of Anhui Province centred on Hefei was low. $PM_{2.5}$ and O_3 pollution were also significant. From 2014 to 2015, with the implementation of the clean action, the O_3 concentration decreased significantly, but the O_3 concentration in eastern coastal cities was significantly different from western cities, due to the large NOx and VOCs emissions. From 2013 to 2018, the O_3 concentration in YRDUA first decreased and then increased, roughly increasing from northeast to southwest. Shanghai, Jiangsu Province, and cities in northern Anhui are predominant O_3 pollution areas of YRDUA.

The air quality in YRDUA from 2010 to 2013 was poor, with high $PM_{2.5}$ and O_3 concentrations. After 2013, the $PM_{2.5}$ concentration decreased significantly, and the O_3 concentration first decreased and then increased again. To comprehensively assess the spatial agglomeration effect of pollution, Table 3 shows the Moran index based on the economic geographic combination weight matrix for the $PM_{2.5}$ and O_3 concentrations of YRDUA from 2005 to 2018. The Moran index of $PM_{2.5}$ concentration ranges from 0.413 to 0.534 with a mean value of 0.472, and all values are significant at the 1% level. Annual changes show an increasing trend of upward and downward fluctuations, which imply that $PM_{2.5}$ exhibits significant spatial autocorrelation and aggregation effects. The Moran index of O_3 concentration ranges from 0.389 to 0.518 and the mean value is 0.484. Similarly, all values pass the 1% significance level. The results indicate that the O_3 concentration has a more significant spatial autocorrelation than the $PM_{2.5}$ concentration.

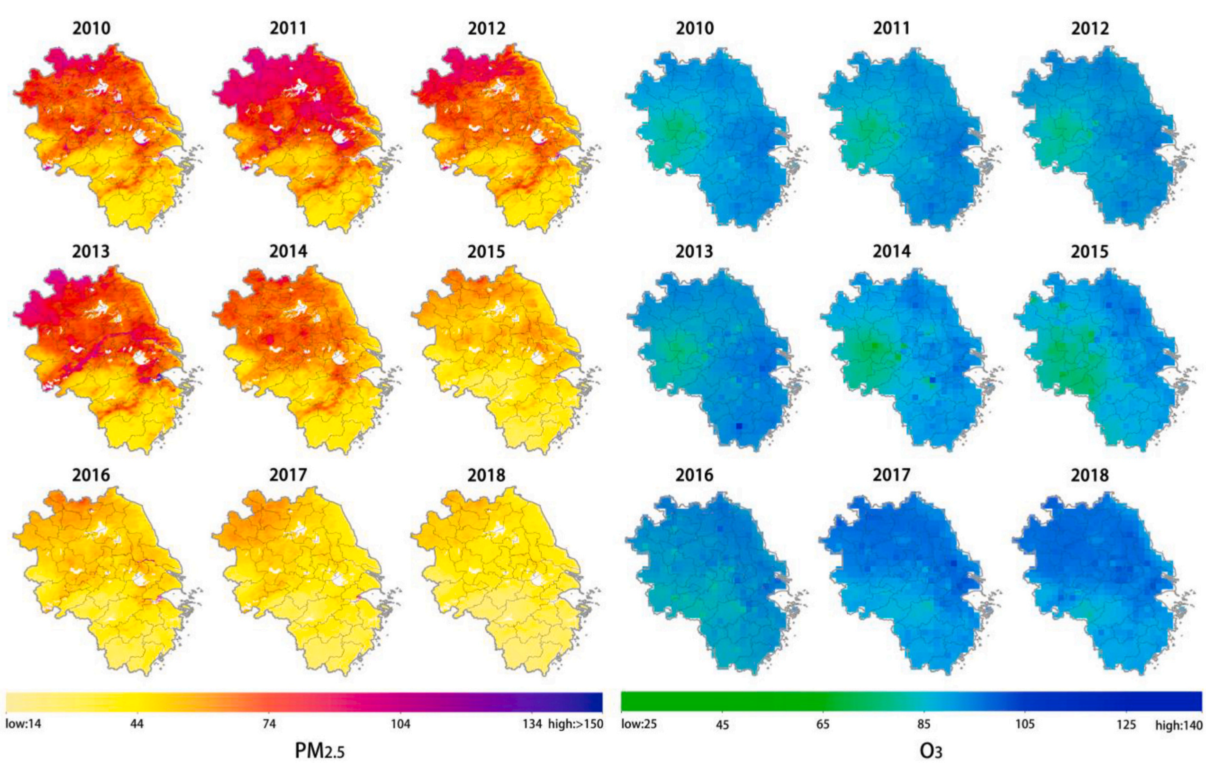

Fig. 2. Spatial distributions of $PM_{2.5}$ and O_3 concentration per year (2010–2018).

Table 3
Estimation Moran' I result of $PM_{2.5}$ and O_3.

Year	$PM_{2.5}$		O_3	
	Moran' I	z	Moran' I	z
2005	0.425***	9.090	0.509***	10.437
2006	0.465***	11.002	0.502***	10.860
2007	0.433***	9.527	0.518***	11.090
2008	0.459***	9.427	0.531***	11.429
2009	0.508***	12.504	0.502***	10.803
2010	0.484***	10.809	0.493***	10.804
2011	0.500***	12.294	0.518***	11.843
2012	0.494***	13.862	0.487***	10.674
2013	0.413***	8.094	0.511***	11.573
2014	0.484***	10.938	0.491***	12.146
2015	0.465***	10.488	0.477***	11.427
2016	0.432***	9.084	0.389***	8.348
2017	0.510***	13.242	0.424***	9.617
2018	0.534***	16.066	0.425***	9.090

Note: ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

3.2. Estimation results of spatial econometric models

Based on the model comparison and testing, we use the fixed effect SDM to estimate parameters. Table 4 shows that the spatial autocorrelation coefficients W*dep.var. of the SDM model are 0.877 and 0.920, respectively, which are significant at the 1% level. The results imply that $PM_{2.5}$ and O_3 have positive spatial spillover effects. It also proves the rationality of applying spatial econometric analysis. Table 4 shows that for $PM_{2.5}$ and O_3, the primary term of economic growth is positive, the secondary term is negative, and both pass the 1% significance level. $PM_{2.5}$ and O_3 pollution show a significant inverted U curve relationship with economic growth. Namely, the degree of air pollution increases first and then decreases with the improvement of the economic growth level. However, the overall $PM_{2.5}$ and O_3 pollution of YRDUA is in a positive correlation stage with economic growth, and the 'decoupling' state is unknown. For $PM_{2.5}$, the spatial lag coefficient of economic growth is negative, indicating that the increase in economic growth in surrounding cities can reduce local $PM_{2.5}$ pollution. However, the coefficient of the spatial lag of economic growth for O_3 is positive, with a 10% significance level, meaning that the economic increase in the surrounding areas aggravated O_3 pollution. The rapid economic development will inevitably lead to the consumption of fossil energy and air quality deterioration. It is imperative to achieve environmentally friendly and stable economic development. This result was also obtained in by (Feng et al., 2020) and (Du et al., 2018) revealed that the impact of per capita GDP on $PM_{2.5}$ concentration is positive, which is explained as the increased energy consumption and human activities brought by economic development.

The urbanization coefficients are −0.154 and − 0.113, which are significant at the 1% and 5% levels, respectively. This indicates that the level of urbanization has a significant negative impact on $PM_{2.5}$ and O_3 pollution. Namely, YRDUA will significantly improve $PM_{2.5}$ and O_3 pollution with the promotion of urbanization. Besides, the spatial lag coefficient of urbanization shows that the urbanization of surrounding cities is also conducive to the mitigation of O_3 pollution in this city.

The population density also has a significant positive effect on $PM_{2.5}$ and O_3 pollution. Population density has an impact on urban air pollution through scale and agglomeration effects. The estimation results show that the scale effect of population density in YRDUA is greater than the agglomeration effect. The coefficient of population density for $PM_{2.5}$ is 0.212 and significant at 1%. The spatial lag coefficient of population density is still positive. The coefficient of population density for O_3 is 0.273 and significant at 1%. The spatial lag coefficient of population density is also positive.

The technical level has a significant negative impact on $PM_{2.5}$ pollution, but it has an insignificant negative impact on O_3 pollution. The estimation results show that the technological progress of the YRDUA can promote productivity developments and allow new technologies that treat $PM_{2.5}$ pollution. But for the new problem of O_3 pollution, the improvement of technical level has not achieved the reduction of O_3 pollution.

The increase in the proportion of the secondary industry has a positive and significant impact on urban $PM_{2.5}$ pollution, but the decline in the proportion of the secondary industry has shown a significant aggravation effect on urban O_3 pollution levels. The spatial lag coefficient of the industrial structure indicates that the increase in the proportion of the secondary industry in surrounding cities is conducive to the improvement of $PM_{2.5}$ pollution. The estimation results show that with the decline of the proportion of secondary production, $PM_{2.5}$ pollution slows down but O_3 pollution increases.

The rise of energy intensity has significantly exacerbated urban $PM_{2.5}$ and O_3 pollution. The estimation coefficient of energy intensity for O_3 is 0.167 and passes the 1% significance level. The estimation coefficient of energy intensity for $PM_{2.5}$ is 0.029 at a 10% significance level. The reduction of O_3 pollution caused by the reduction of energy intensity is greater than that of $PM_{2.5}$ pollution.

The increase of investment in fixed assets will aggravate O_3 pollution (estimated coefficient 0.042, 10% significance level). However, it has no significant weak positive effect on $PM_{2.5}$ pollution. Similarly, the improvement of the degree of opening up will significantly alleviate O_3 pollution (coefficient − 0.189, 1% significant level). This shows that the increase of foreign capital utilisation will be conducive to O_3 pollution control in YRDUA.

Finally, NDVI and traffic load have no significant effects on $PM_{2.5}$ and O_3 pollution. Transportation is one of the main sources of air pollution. At present, the YRD and China are vigorously promoting new energy vehicles and quality upgrades of oil products. Assessing the impact of traffic load on $PM_{2.5}$ and O_3 pollution has not produced the expected mitigation effect, and the policy still needs time to be tested.

Table 4
Estimation results of SDM with fixed effects.

Variable	$PM_{2.5}$		O_3	
	Coefficient	t	Coefficient	t
GDP	0.316***	4.151	0.348***	2.985
$(GDP)^2$	−0.240***	−3.477	−0.322***	−3.043
URBAN	−0.154***	−5.074	−0.113**	−2.439
NDVI	−0.047	−1.588	−0.007	−0.159
POP	0.212***	4.890	0.273***	4.107
TL	−0.130***	−3.483	−0.014	−0.254
IS	0.132***	7.354	−0.144***	−5.220
EI	0.029*	1.700	0.167***	6.409
TP	−0.013	−0.402	0.040	0.815
IIFA	0.017	1.130	0.042*	1.807
OPEN	0.025	0.576	−0.189***	−2.838
W*GDP	−1.965***	−10.067	0.536*	1.798
$W^*(GDP)^2$	1.676***	10.052	−0.424*	−1.667
W*URBAN	0.102	1.123	−0.292**	−2.106
W*NDVI	0.365***	4.037	0.194	1.403
W*POP	0.538***	4.315	0.858***	4.522
W*TL	−0.731***	−5.522	−0.488**	−2.414
W*IS	−0.137***	−2.733	0.090	1.178
W*EI	−0.090*	−1.621	−0.112	−1.318
W*TP	−0.545***	−5.913	0.096	0.684
W*IIFA	0.168	1.550	0.346**	2.084
W*OPEN	0.601***	4.500	−0.034	−0.165

Note: ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

3.3. Local and spillover effects of drivers

Table 5 shows the local and spillover effects of the SDM model. The total effect of the three drivers (including economic growth, population density and technical level) have a significant impact on $PM_{2.5}$ and O_3 pollution. Economic growth has no significant negative effect on local $PM_{2.5}$ but can improve $PM_{2.5}$ pollution in surrounding cities and

Table 5
Estimations of local and spillover effects based on direct, indirect and total effects by SDM model.

Variable	$PM_{2.5}$						O_3					
	Direct	t	Indirect	t	Total	t	Direct	t	Indirect	t	Total	t
GDP	−0.101	−1.085	−13.550***	−6.138	−13.651***	−6.034	0.732***	4.134	10.707***	2.784	11.439***	2.876
URBAN	−0.163***	−3.676	−0.311	−0.408	−0.474	−0.595	−0.294***	−2.982	−5.011**	−2.496	−5.305**	−2.532
NDVI	0.031	0.718	2.556***	3.128	2.587***	3.047	0.074	0.842	2.301	1.267	2.375	1.255
POP	0.389***	6.312	5.790***	4.751	6.179***	4.895	0.759***	5.517	13.668***	4.538	14.427***	4.605
TL	−0.339***	−5.948	−6.795***	−4.816	−7.134***	−4.905	−0.236*	−1.892	−6.190**	−2.199	−6.426**	−2.196
IS	0.128***	4.978	−0.151	−0.354	−0.024	−0.053	−0.159***	−3.174	−0.472	−0.484	−0.631	−0.620
EI	0.012	0.430	−0.543	−1.069	−0.531	−0.999	0.185***	3.116	0.533	0.450	0.718	0.580
TP	−0.150***	−3.347	−4.443***	−4.932	−4.593***	−4.933	0.105	1.159	1.745	0.987	1.850	1.003
IIFA	0.062*	1.687	1.463	1.551	1.525	1.560	0.213**	2.385	4.798**	2.142	5.011**	2.154
OPEN	0.178**	2.533	4.989***	3.616	5.167***	3.594	−0.283*	−1.784	−2.687	−0.883	−2.971	−0.931

Note: ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

demonstrates a significantly strong negative spillover effect. By observing the decomposition effect, the local and spillover effects for technical level improvements on $PM_{2.5}$ pollution are positive and pass the 1% significance level. The decomposition effect demonstrates that the spillover effect of economic growth and technology are significantly stronger than the local effect, which proves the existence of a 'demonstration effect'. However, for O_3 pollution, the local effect and spillover effect of economic growth are 0.732 and 10.707, respectively; both pass the 1% significance level. Hence, economic growth not only contributes to local O_3 pollution but also aggravates O_3 pollution in surrounding cities. The local effect and spillover effect of population density on $PM_{2.5}$ and O_3 pollution are positive. Similarly, the spillover effect of population density on $PM_{2.5}$ and O_3 is significantly stronger than the local effect, indicating that the scale effect of the population still significantly aggravates air pollution. The improvement of the urbanization level has a negative local effect on $PM_{2.5}$ pollution, but the spillover effect on surrounding cities is insignificant. However, for O_3 pollution, urbanization level improvement will significantly alleviate O_3 pollution holistically, and its spillover effect is stronger than its local effect. Hence, the current urbanization process in YRD will effectively improve $PM_{2.5}$ and O_3 pollution. Increased secondary industries have a positive effect on the local $PM_{2.5}$ pollution and pass the 1% significance level.

When evaluating the effect of energy intensity on $PM_{2.5}$ and O_3 pollution, only the local O_3 pollution displayed a significant positive local effect. For O_3 pollution, the local and spillover effects of the increase in fixed-asset investment are both positive, and its effect for aggravating O_3 pollution in surrounding cities is significantly stronger than aggravating local O_3 pollution. This result is related to the production and transportation of raw construction materials from surrounding to local cities, so O_3 pollution to surrounding cities is stronger than pollution during local construction.

Table 4 shows that the impact of NDVI, traffic load, fixed asset investment and opening to the outside world for $PM_{2.5}$ pollution did not pass the significance test, so it will not show in the decomposition effect analysis. Notably, among the drivers of $PM_{2.5}$ and O_3 pollution, the spillover effect is significantly stronger than the local effect, which confirms that $PM_{2.5}$ and O_3 pollution in the YRDUA have the characteristics of cross-regional interaction and neighbouring cities mutually influence their air quality to a large extent. This means that YRDUA must further deepen the joint prevention and control mechanism to control regional $PM_{2.5}$ and O_3 pollution.

3.4. Discussion for drivers of coordinated control

Fig. 3 demonstrates the influence direction of parameter estimation, and its show that drivers that can significantly coordinate control of $PM_{2.5}$ and O_3 pollution are economic growth, urbanization, population density and energy intensity, and other significant drivers have adverse

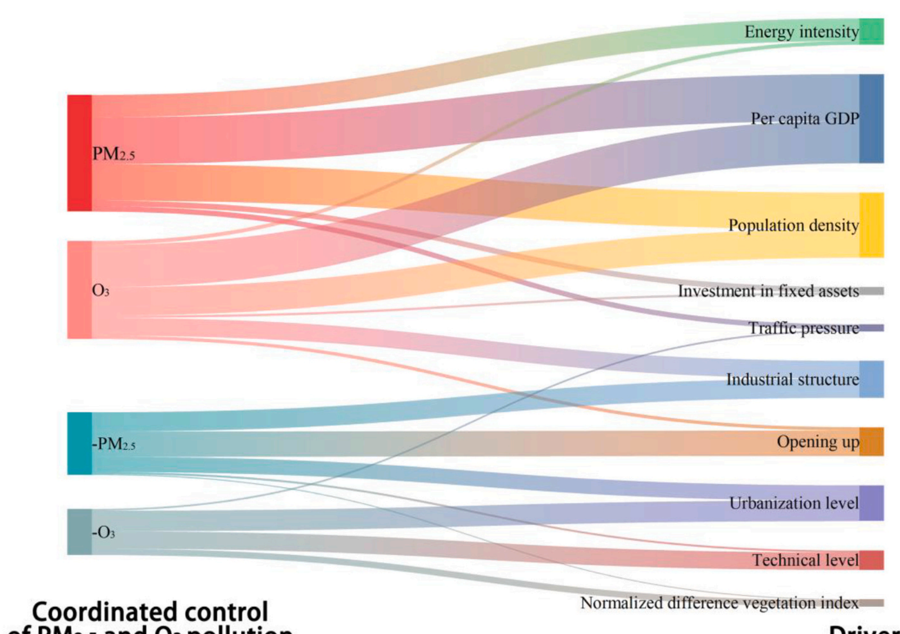

Fig. 3. The influence direction of various drivers.

effects on $PM_{2.5}$ and O_3 pollution. Specifically, population density, industrial structure and energy intensity are the driving factors that can aggravate $PM_{2.5}$ pollution in descending order, while urbanization and technological level are the driving factors that can decrease $PM_{2.5}$ pollution in descending order. The drivers that aggravate O_3 pollution from large to small are economic growth, population density, energy intensity and fixed asset investment, while opening to the outside world, the proportion of secondary industry and urbanization are the drivers that can slow down O_3 pollution in descending order. $PM_{2.5}$ and O_3 pollution and economic growth show a significant inverted U curve relationship. At present, pollution is aggravated as the level of economic growth increases. The finding is consistent with (Feng et al., 2020) and (Du et al., 2018). (Feng et al., 2020) found the impact of per capita GDP on $PM_{2.5}$ pollution is positive. In addition, this study finds that the promotion of urbanization in YRDUA can reduce $PM_{2.5}$ and O_3 pollution. Some studies from the perspective of China's national level (Li et al., 2016; Wang et al., 2018) showed that the development of urbanization in the early stage was an important cause of increasing regional air pollution. In contrast to our findings, the results obtained by (Du et al., 2018) and (Liu et al., 2020a) showed that the impact of urbanization on $PM_{2.5}$ pollution is positive, which is explained as the increased human activities brought by urbanization. The impact of urbanization on $PM_{2.5}$ pollution can be attributed to multiple reasons. Mature urbanization may produce the energy-saving effect and the Improvement of urban governance capacity (Li et al., 2020). At present, the YRDUA has got rid of the extensive urbanization development path, and has effectively improved the air quality through the implementation of a series of emission reduction policies and environmental policies, and embarked on a green intensive urbanization development path. The scale effect of population density is still less than the agglomeration effect, which aggravates $PM_{2.5}$ and O_3 pollution. This result is consistent with (Cheng et al., 2017) and (Wang et al., 2017). With a number of people swarm into the YRDUA, population gathering bring excessive energy demand and environmental pollution as well as in the production and consumption. Hence, to enhance the agglomeration effect, urban governance should focus on the role of population agglomeration in resource utilisation. The rise of energy intensity has significantly exacerbated urban $PM_{2.5}$ and O_3 pollution. This result was also found in previous studies (Liu et al., 2015), which revealed the correlation between energy intensity and pollutant emissions are positive due to more energy use accompanied by economic development. If the YRDUA replaces the traditional fossil energy with renewable and clean energy and realizes energy structure optimisation and energy intensity reduction, it will undoubtedly significantly control $PM_{2.5}$ and O_3 pollution. The improvement of the technical level can significantly reduce $PM_{2.5}$ pollution but does not play a role in O_3 pollution control. Similar to our results, (Liu et al., 2020a) also identified the negative effect of the increase of technical level on $PM_{2.5}$ pollution. It requires us to consider realizing the coordinated control of $PM_{2.5}$ and O_3 and developing a multi-pollutant joint treatment system when developing green technology. The decline in the proportion of secondary industry can decrease $PM_{2.5}$ pollution but increase O_3 pollution, indicating that the accuracy of coordinated treatment of $PM_{2.5}$ and O_3 pollution need to be improved during structural transformation. (Yan et al., 2018; Yan et al., 2020) also proved the positive correlation between the industrial structure and $PM_{2.5}$ pollution. As the main energy-consuming industry, the secondary industry is also the main driving force of economic development and a major source of air pollution. China has recently invested manpower and material resources to upgrade the industrial structure to carry out green upgrades, eliminate outdated production capacity, and transform traditional technologies. YRDUA has been continuously optimised as a test site for reforms, and the proportion of the secondary industry has been decreasing annually. Therefore, the $PM_{2.5}$ concentration has dropped significantly. However, O_3 pollution becomes more serious, leading to a situation where $PM_{2.5}$ and O_3 dual pollution keep worsening. NOx and VOCs mostly come from industrial coal-fired sources (Li et al., 2019a). At present, focusing on the breakthrough of VOCs and NOx treatment technology, and carrying out collaborative treatments are key to the reduction of $PM_{2.5}$ and O_3 pollution. Some studies (Cheng et al., 2020; Yan et al., 2020; Zhu et al., 2019) have argued that FDI have significantly deteriorated environmental quality based on the pollution haven hypothesis. This study finds that the increase of FDI can significantly decrease O_3 pollution but it has no significant positive effect on $PM_{2.5}$ pollution. The increase of fixed asset investments will slightly increase O_3 pollution and it has no significant positive effect on $PM_{2.5}$ pollution. This requires the YRDUA to strengthen the investment of environmentally friendly technologies and products, carry out green screening and improve the environmental access threshold. NDVI and traffic load have no significant effects on $PM_{2.5}$ and O_3 pollution, indicating that YRDUA should focus on urban greening and traffic system construction.(Zhao et al., 2019) and (Kumar et al., 2014) found that exhaust of motor vehicles could contribute greatly to the emissions of primary $PM_{2.5}$ and the form of secondary $PM_{2.5}$ and O_3 pollution, including NO_X and VOC_S. In term of the analysis of local and spillover effects, similar to our results, (Feng et al., 2020) and (Du et al., 2018) also found that the spillover effects of drivers are significantly stronger than the local effects, which means that regional joint prevention and control will significantly improve the ambient air quality in the YRDUA.

The above discussion proves that the coordinated control of $PM_{2.5}$ and O_3 pollution is key when solving future atmospheric environmental governance and its socio-economic roots. In the future, the coordinated control of $PM_{2.5}$ and O_3 pollution will not only focus on transforming the economic development mode, enhancing the population agglomeration effect, and improving the quality of urbanization, while adhering to the green road in the adjustment of industry and energy structure, and comprehensive technological innovation in energy conservation and emission reduction. When considering the coordinated management of multiple pollutants, strengthening foreign investment for 'green' identification and technology introduction can promote the realisation of coordinated control regarding $PM_{2.5}$ and O_3 pollution in YRDUA, from the perspective of social and economic drivers.

4. Conclusion and policy implications

This study uses atmospheric remote sensing technology to observe the spatial evolution characteristics of $PM_{2.5}$ and O_3. The Moran index indicates that air pollution has a significant spatial agglomeration effect. Based on the fixed effect SDM, positive and negative effects of key $PM_{2.5}$ and O_3 drivers are identified, and then local and spillover effects are assessed to analyze the socio-economic roots of coordinated control for $PM_{2.5}$ and O_3 pollution.

Firstly, remote sensing images indicates that the key areas of pollution control in the YRDUA will be concentrated in the eastern coastal areas and the northern cities. Secondly, the decoupling stage between $PM_{2.5}$ and O_3 pollution and economic growth in YRDUA is yet to arrive. The concentration of $PM_{2.5}$ has recently decreased but O_3 pollution problems have become apparent, which means that atmospheric environmental control will be a protracted war. The urbanization process of YRDUA significantly decreased $PM_{2.5}$ and O_3 pollution. There is a significant positive effect on $PM_{2.5}$ and O_3 pollution by population density and energy intensity. The technical level played a significant role in decreasing $PM_{2.5}$ pollution, with no significant effect on O_3 pollution. The decline in the proportion of secondary industries will effectively reduce $PM_{2.5}$ pollution, but boost O_3 pollution. Fixed asset investment exacerbates O_3 pollution and has no significant impact on $PM_{2.5}$ pollution. The increase in opening up significantly reduced O_3 pollution but has no significant impact on $PM_{2.5}$ pollution. Both NDVI and traffic loads failed the significance test on $PM_{2.5}$ and O_3 pollution. The drivers that can significantly coordinate the control of $PM_{2.5}$ and O_3 pollution are economic growth, urbanization, population density and energy intensity, while other significant drivers have their own reverse effects on $PM_{2.5}$ and O_3 pollution. Third, the spillover effects of $PM_{2.5}$ and O_3

drivers are significantly stronger than the local effects, which further indicates that the joint prevention and control can significantly improve the overall air quality.

Based on the empirical results of this study, the following policy recommendations are put forward:

The promotion of unique and high-quality urbanization. Improving the urban ecological carrying capacity through overall planning of land and space, optimisation of traffic roads, rational population distribution and optimisation of energy-saving infrastructure. Introducing green/environmental protection concepts, strengthening publicity and education, increasing the supply of green travel service facilities, and promoting the coordinated development of low-carbon, green and environmentally friendly urban agglomerations.

The regional joint prevention and control mechanisms should be standardised and the joint force of air pollution control should be enhanced. The spatial spillover effect of $PM_{2.5}$ and O_3 pollution requires the necessity of regional joint prevention and control. The integrated development of YRD will further break the administrative boundaries of regional joint prevention and control in organisation, system and evaluation. Through the design of a comprehensive air pollution control technological system, accurate predictions and fine diagnoses, we can share environmental information and form a unified environmental pollution monitoring platform, to establish a regional law enforcement and supervision system.

In terms of source management of $PM_{2.5}$ and O_3 pollution, it is necessary to strengthen the emission reduction of VOCs and nitrogen oxides. Stringent air pollutant concentration limit standards should be designed. This requires comprehensive measures, such as industrial, energy and transportation structural adjustments. This can be done through promoting comprehensive pollution control in industrial parks, replacing products that contain VOCs, and improving pollution control technology. Coal and oil consumption should be controlled strictly and the replacement of clean energy should be accelerated. Controlling motor vehicle pollution emissions is key to reducing VOCs and nitrogen oxide emissions, which requires rail transportation structures, electrification of vehicle and ship transportation, and promoting oil product upgrades.

CRediT authorship contribution statement

Huaxin Lin: Methodology, Software, Writing – original draft. **Jingan Zhu:** Software, Visualization, Investigation. **Ping Jiang:** Conceptualization, Investigation, Writing – review & editing. **Zhongyao Cai:** Data curation, Validation. **Xinyu Yang:** Data curation. **Xiaohui Yang:** Data curation. **Ziqian Zhou:** Data curation. **Jing Wei:** Software, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

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