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Differential effects of urbanization on air pollution: Evidences from six air pollutants in mainland China

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ABSTRACT

Rapid urbanization has led to economic growth with inevitable air pollution. There are significant differences in the dominant factors of different air pollutants. However, the influencing mechanism of urbanization on different air pollutants is still unclear. Therefore, exploring the differential effects of urbanization on various air pollutants is of great significance for accelerating local collaborative treatment of air pollutants and improving regional air quality. Based on the analysis of the spatial–temporal pattern evolution, spatial agglomeration, and internal correlation of six air pollutants in mainland China during 2013–2020, namely $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO, we combined the environmental Kuznets theory to build a panel regression model of urbanization on six air pollutants. Except for NO_2 and O_3, the concentrations of the other four air pollutants all decreased to different degrees, among which, SO_2 concentration decreased the most. The spatial pattern of air pollution showed that the concentration of air pollutants in typical areas decreased significantly, while which in areas with higher population density or higher economic development was relatively higher. As a key factor affecting air quality, different aspects of urbanization have significant differences in the direction and intensity of effect on various air pollutants. The relationship between the concentration of six air pollutants and urbanization conforms to the differential environmental Kuznets curve (EKC). There are nonlinear relationships between urbanization and $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO concentrations, which are inverted “U-shaped”, inverted “U-shaped”, inverted “U-shaped”, inverted “*N*-shaped”, “U-shaped”, and inverted “U-shaped” respectively. In addition, urbanization has a spillover effect on $PM_{2.5}$, PM_{10}, SO_2 and CO concentrations, while the direction of whose spillover effect reflects the phased change.

1. Introduction

Since the 21st century, rapid industrialization and urbanization in China has led to a large influx of population into cities and the increasing improvement of production and living infrastructure, which has led to rapid growth in urban economy (Wang et al., 2021a; Li et al., 2022). However, the high population density and the rapid expansion of industrial enterprises have led to a sharp decline in ecological and environmental quality (Wang et al., 2021b; She et al., 2021). The massive emissions of automobile exhaust and industrial waste gases have made serious air pollution problems increasingly serious (Kumar et al., 2020; Xue et al., 2021). In recent years, frequent outbreaks of haze and other air pollution have caused serious impacts on local resident’s production and living, and seriously hindered urban sustainable development (Wei et al., 2021c; Liu et al., 2022a). In particular, existing studies have confirmed that high concentrations of air pollutants can cause serious damage to the human respiratory system (Sui et al., 2021). In 2021, the WHO released the Global Air Quality Guidelines (AQG2021). WHO adjusted the annual average concentration limits and daily average concentration limits for six air pollutants, namely: $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO. This will help to improve China’s air quality by imposing stricter requirements on the concentrations of air pollutants. How to exert the positive effect of urbanization to promote the overall reduction of air pollution and realize urban environmental and socio-economic reciprocal effect is crucial to achieve high-quality development (Fang et al., 2021; Xu et al., 2022a).

Previous studies on air pollution are mainly focused on the evolution of spatial–temporal patterns and factor analysis. The pollutants that characterize air pollution in studies related to spatial–temporal pattern evolution are $PM_{2.5}$ (Chang et al., 2020; Wei et al., 2021b), PM_{10} (Li et al., 2018; Maffia et al., 2020), SO_2 (Jiang et al., 2020; Yuan et al., 2021), NO_2 (Ma et al., 2021; Liu et al., 2021), CO (Liu et al., 2022b) and

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O_3 (Duan et al., 2021; Chen et al., 2022), as well as air quality index (AQI) (Han et al., 2020) and air pollution index (API) (Zhao et al., 2021). The study spaces are mainly focused on national scale (Wei et al., 2021a), climate zone scale (Xu et al., 2022b), urban agglomeration scale (Wang et al., 2021b), and some typical cities (Karimi and Shokrinezhad, 2021). They mainly reveal the characteristics of the time-series evolution (Wei et al., 2021a), spatial distribution (Xu et al., 2022a), and spatial autocorrelation (Qi et al., 2022a) of air pollution. The study of factors mainly includes socio-economic factors and natural factors (Xu et al., 2022b). Existing studies show that natural factors such as wind speed (Duan et al., 2021) and precipitation (Duan et al., 2021) can have a significant effect on the concentration of air pollutants in a short period, and vegetation (Liu et al., 2022a) can hinder the secondary transmission of air pollutants, etc. And socioeconomic factors become the dominant factors affecting air pollutants' concentrations. Most of studies have explored the role of socio-economy on air quality from different perspectives, such as economic development (Wang et al., 2021b), land use (Mo et al., 2021), population agglomeration (Qi et al., 2022b), industrial upgrading (Qi et al., 2022a), and so on. Their research methods mainly include spatial econometric models (Liu et al., 2017), spatial–temporal geographically weighted regression (Yuan et al., 2021), and geographic probes (Xu et al., 2022b), etc.

Although some research results have been achieved, there are still some problems to be investigated. Most of studies have focused on the spatial–temporal evolution of a single air pollutant or the spatial pattern differences of multiple air pollutants in a single year (Xu et al., 2022b; Qi et al., 2022b). There are relatively few studies that integrate multiple air pollutants (Qi et al., 2022a). The explanatory variables in studies of factors also tend to be mostly single variables such as $PM_{2.5}$ (Wang et al., 2021a; Xu et al., 2022b). The core explanatory variables are often socioeconomic factors or natural factors selected separately for analysis, and relatively few studies consider both together. As an integrated process involving population, economy, and industry (Wang et al., 2021a; Wang et al., 2021b), urbanization has a complex inter-feeding mechanism with the environmental system, and its development has posed an inevitable threat to air quality (She et al., 2021). By clarifying the driving mechanism between urbanization and multiple air pollutants, we can help to achieve a harmonious human-land relationship (Li et al., 2022). Meanwhile, with the help of environmental Kuznets theory (Qi et al., 2022a), our findings can be helpful to determine the inflection points between urbanization and air pollution, formulate a more precise plan for local collaborative air pollution management, accelerate the positive coupling of urbanization and ecological environment, and promote urban high-quality development. This is undoubtedly an important empirical analysis and theoretical exploration of harmonious human-land relations in contemporary developing countries. Hopefully, our research results can promote the localization of related disciplines.

In this paper, we used the annual average concentration data of six air pollutants ($PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO), and select 286 prefecture-level administrative cities as the research units to analyze the air pollution situation in China from 2013 to 2020. We analyzed the spatial–temporal evolution characteristics of six air pollutants and the status of air pollution in key regions. And then, we explored the correlation between air pollutants and constructed a panel regression model of the effect of urbanization on six air pollutants, and analyzed the correlation between air pollution and economic development by combining differential EKCs. And then, we analyze the spillover effects of urbanization on different air pollutants by the spatial Dubin model. Finally, we explored the differential effect of different aspects of urbanization on various pollutants, in order to formulate more targeted policies for local joint prevention and control and collaborative management of regional air pollutants.

The remainder of this paper is organized as follows. We presented our data and empirical methodology in Section 2 and our main results in Section 3. In Section 4, we discuss main findings. And then, we conclude and prospect the related research in Section 5.

2. Data and methodology

2.1. Study area and data sources

For the analysis of spatial–temporal patterns, we chose 339 China's cities. However, in the process of factor analysis, we only selected 286 cities (Fig. 1) to build the model because we could not obtain the same amount of socio-economic data. In order to explore the differential effects of urbanization on various air pollutants, we selected per capita GDP, population urbanization rate, population density, index of industrial sophistication, energy consumption index, annual average precipitation, NDVI, ventilation coefficients and temperature. Selected specific index are shown in Table 1. Air pollutants include $PM_{2.5}$, $PM_{10,}$ SO_2, NO_2, O_3 and CO. The descriptive statistics of air pollutant concentrations and influencing factors are shown in Table 2. In order to prevent the phenomenon of spurious regression and ensure the validity of the data measurement model results, we conducted Harris and Tzavalis (HT) test on the variables, and the results showed that all variables passed the significance and stationarity tests.

The data we used on air pollutants came mainly from China High Air Pollutants (CHAP) dataset released by the University of Maryland, USA. It included PM_{10}, SO_2, NO_2, CO, O_3. $PM_{2.5}$ data are obtained from Atmospheric Composition Analysis Group (ACAG) of Washington University in St. Louis, MO, USA. Per capita GDP, population urbanization rate, population density and the index of industrial sophistication all came from the *China Urban Statistical Yearbook (2014–2021)*. The energy consumption index is derived from a nighttime light dataset produced using a deep learning model. We used the sum of gray values of nighttime light data as the energy consumption index. The annual precipitation, temperature the average wind speed and atmospheric boundary data were obtained from the latitude and longitude raster meteorological data published by the ECMWF. NDVI came from NASA.

2.2. Methodology

We used kernel density curve and Global Moran's *I* to investigate the spatial–temporal evolution of six air pollutants' concentrations in mainland China and the differential effects of urbanization on air pollutants. Meanwhile, we used differential EKCs to construct a panel regression model and selected socioeconomic factors and natural factors to explore the differential effects of urbanization on various air pollutants. Finally, we analyze the spillover effects of urbanization on different air pollutants by the spatial Dubin model. Our methodology is shown in Fig. 2.

(1) Kernel density curve.

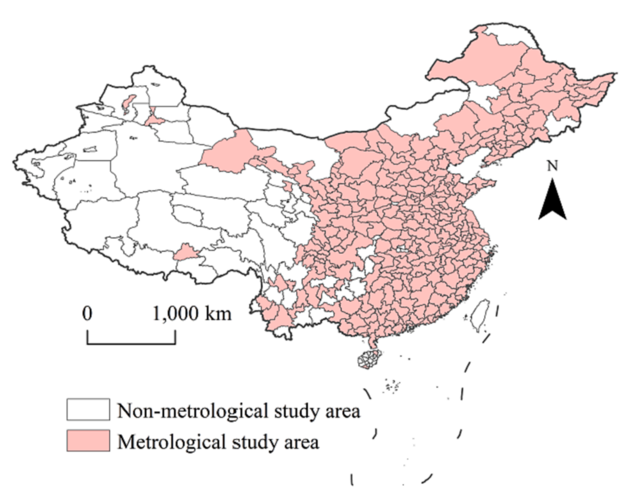

Fig. 1. Map of study area.

Table 1
Index classification, definition and selection basis.

Classification	Index	Definition	Selection basis
Population urbanization	population Urbanization rate (*PU*)	Urban permanent residents/ total population *100 %	Population urbanization is the core of urban development, leading the changes in the urbanization area, including economic development and pollution emissions, such as air pollution.
	Population density (*PD*)	Urban permanent residents/ urban administrative area	
Economic urbanization	Per capita GDP (*VGDP*)	GDP/ total population	The production and living of urban population not only improve their own quality of life, but also directly affect the surrounding environment. This process of effect mostly conforms to the EKC theory.
	Index of industrial sophistication (*Ind*)	Share of tertiary industry in GDP/ share of secondary industry in GDP	
	Energy consumption index (*EC*)	Sum of raster gray values of urban night light data	
Natural environment	Normalized difference vegetation index (*NDVI*)	Detect vegetation growth state and vegetation coverage index by remote sensing data	Natural environment is an important background factor affecting air quality. Local vegetation has a good adsorption effect on air pollutants, and precipitation contributes to the reduction of air pollutants. Local air flow has a significant effect on the transfer of air pollutants. In addition, temperature also affects the diffusion of air pollutants.
	Average annual temperature (*TEMP*)	Average annual temperature in each city	
	Average annual precipitation (*PRCP*)	Average annual precipitation in each city	
	Ventilation coefficients (*VC*)	The product of average annual wind speed and 10 m atmospheric boundary	

Kernel density estimation is used in probability theory to estimate unknown density functions and belongs to one of the nonparametric testing methods (Emanuel, 1962). Kernel density plot is an effective method used to observe the distribution of continuous type variables. We explore the overall distribution and regional clustering differences of air pollution data by plotting the kernel density curves of six air pollutants.

(2) Multiple panel regression model based on urbanization EKCs.

Environmental Kuznets theory (Grossman and Krueger, 1995) is used to describe the correlation and evolutionary pattern of socioeconomic development and environment by regression models. EKC describes that the relationship between economic development and environment quality presents an inverted "U-shaped" curve, which firstly deteriorates and then improves. However, in different countries or regions, the EKC does not follow a strict inverted "U-shaped" curve, and sometimes presents a variety of EKC forms, such as "U-shaped", "*N*-shaped", inverted "*N*-shaped" and monotonous rise (Qi et al., 2023). So, differentiated EKC (Wang et al., 2021d) is more suitable for broader research fields.

The EKC's econometric models mainly include two categories: simplified formulations of primary, secondary, and tertiary functions and structural formulations by adding control variables (Akbostancı et al., 2009). Per capita GDP is the main economic indicator, while environmental quality indicators mainly include air pollutant concentration (Qi et al., 2023), seawater quality (Wang et al., 2021d), etc. Urbanization is a comprehensive process involving population, economy and other aspects. Studies have shown that rapid urbanization in China is the main driving factor for the continuous deterioration of air quality (She et al., 2021). However, different urbanization stages have different effects on air pollution. In order to explore the effect of urbanization on different air pollutants, the average annual concentrations of six air pollutants are used to characterize air pollution and serve as explanatory variables. Comprehensively considering the effect of urbanization on air pollution, we selected population urbanization rate and per capita GDP as the core explanatory variables to represent urbanization stages. Meanwhile, socio-economic factors reflecting urbanization, such as population density, industrial structure upgrading index and energy consumption index, and natural environmental indicators affecting air pollution concentration, such as average annual precipitation and NDVI, are selected as control variables. The model is established as follows.

$$\ln Y_{it} = \sum_{j=1}^{3} \rho_j \left(\ln{}^{j} PU\right)_{it} + \lambda_1 (\ln VGDP)_{it} + \sum \alpha_i X_{it} + cons + \varepsilon \ln Y_{it}$$

$$= \sum_{j=1}^{3} \beta_j \left(\ln{}^{j} VGDP\right)_{it} + \lambda_2 (\ln PU)_{it} + \sum \alpha_i X_{it} + cons + \varepsilon$$

where Y_{it} represents the air pollutants concentrations including the annual average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO in i city in t year. $t \in [2013,..,2020]$, $i \in [1,\ldots,286]$. *PU* represents Population urbanization rate, *VGDP* represents per capita GDP. X_{it} represents the factors affecting the air pollutants concentrations, such as index of industrial sophistication and *NDVI*, etc., which are used as control variables. *cons* is the constant, and ε is the random error. $\rho_3, \rho_2, \rho_1, \beta_3, \beta_2, \beta_1,$

Table 2
Descriptive statistics and stationarity test of variables.

Variables	Units	Samples	Mean	Standard deviation	Minimum	Maximum	HT test Statistic	P	Conclusion
$PM_{2.5}$	μg/m^3	2288	40.637	14.758	3.168	108.872	0.417	0.000	smooth
PM_{10}	μg/m^3	2288	76.731	29.205	25.927	195.326	0.536	0.000	smooth
SO_2	μg/m^3	2288	19.645	12.362	1.395	90.373	0.827	0.000	smooth
NO_2	μg/m^3	2288	26.566	8.847	1.404	53.866	0.946	0.000	smooth
O_3	μg/m^3	2288	87.905	14.279	12.649	122.491	0.586	0.000	smooth
CO	mg/m^3	2288	1.942	0.281	1.048	3.058	0.878	0.000	smooth
PU	%	2288	56.456	14.466	20.738	100.000	0.176	0.000	smooth
PD	person/km^2	2288	441	367	6	3823	0.271	0.000	smooth
VGDP	yuan/person	2288	58831.8	38660.2	8407.0	473335.4	0.122	0.000	smooth
EC	–	2288	44545.2	58125.7	2237.0	490706.5	0.146	0.000	smooth
Ind	–	2288	1.129	0.682	0.207	12.937	0.933	0.000	smooth
NDVI	–	2288	0.717	0.152	0.066	0.905	−0.324	0.000	smooth
TEMP	℃	2288	14.688	5.173	−0.649	25.655	0.000	0.000	smooth
PRCP	mm	2288	1056.6	483.4	198.7	2743.9	−0.039	0.000	smooth
VC	–	2288	7.482	0.641	0.000	8.812	0.909	0.000	smooth

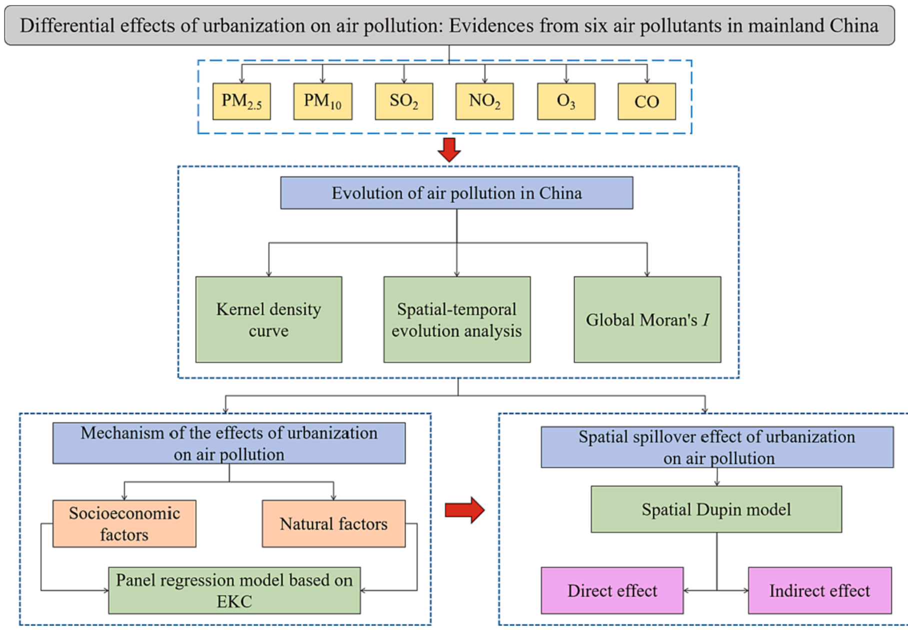

Fig. 2. Flow chart of the methodology.

λ_1, λ_2 and α_i are the estimated coefficients of corresponding independent variables.

(3) Spatial Dubin model.

The spatial Dubin model is a kind of spatial econometric model. Compared with ordinary OLS regression, the spatial econometric model further considers the effect of spatial interaction factors, which can effectively reduce the effect of endogenous factors and determine whether there is positive or negative spillover effect of some factors. We select the spatial Dubin model to analyze the effect of urbanization on the air pollutant concentration in the region and its neighboring areas. The specific model is as follows.

$\ln Y_{it} = \eta\sum_{j=1}^{n} W_{ij}\ln Y_{it} + \sum_{g=1}^{2}\rho_g(\ln {}^{g}PU)_{it}$ - $+\sum_{g=1}^{2}\phi_g(\sum_{j=1}^{n} W_{ij}(\ln {}^{g}PU)_{it}) + \lambda_1(\ln VGDP)_{it} + \theta_1\sum_{j=1}^{n} W_{ij}(\ln VGDP)_{it}$ - $+\alpha_i X_{it} + \omega_i \sum_{j=1}^{n} W_{ij}X_{it} + \varepsilon \ln Y_{it} = \eta\sum_{j=1}^{n}W_{ij}\ln Y_{it} + \sum_{g=1}^{3}\beta_g(\ln {}^{g}VGDP)_{it}$ - $+\sum_{g}^{3}\upsilon_g(\sum_{j=1}^{n}W_{ij}(\ln {}^{g}VGDP)_{it}) + \lambda_2(\ln PU)_{it} + \theta_2\sum_{j=1}^{n}W_{ij}(\ln PU)_{it} + \alpha_i X_{it}$ - $+\omega_i\sum_{j=1}^{n}W_{ij}X_{it} + \varepsilon$ where W_{ij} is the space weight matrix, η, φ, θ, υ and ω are the influence coefficient of the spatial weight term.

3. Results

3.1. Spatial-temporal evolution of different air pollutants

The Chinese government promulgated the Action Plan for *the Prevention and Control of Air Pollution (Atmospheric Ten)* in 2013. Since then, government has gradually strengthened the monitoring of air pollutants. From 2013 to 2020, the concentrations of six air pollutants have decreased significantly, except for NO_2, which has remained relatively stable, and O_3, which has increased year by year (Fig. 3). Among them, SO_2 concentration decreases most significantly, by 62.19 %, PM_{10}, $PM_{2.5}$, and CO concentrations decrease by 43.05 %, 35.97 %, and 29.32 %, respectively. Overall, air quality in China has improved significantly, while O_3 pollution concentration remains high.

We plotted the kernel density curves of six air pollutants in China to compare their clustering trends and changes (Fig. 4) by Stata16. We found that compared with 2013, the kernel density curves of $PM_{2.5}$, PM_{10}, SO_2 and CO converge to the left in 2020, and the kernel density tends to move towards lower concentrations in general, while the kernel density curve of O_3 concentration shows a small shift to the right, indicating that the pollution concentration has increased, which is

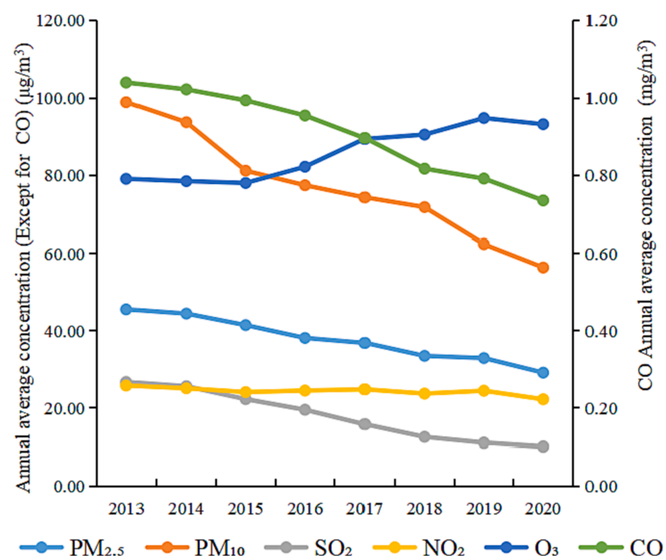

Fig. 3. Temporal evolution of different air pollutants in China during 2013–2020.

consistent with the results in Fig. 3. The right trailing edge is significantly shorter than that of 2013, and the distribution extension is tightened to a certain extent, indicating that the number of cities with low concentration increases and the number of cities with high concentration decreases. From the evolution of the kernel density curves of each pollutant, the curves of $PM_{2.5}$, PM_{10}, SO_2 and CO change from the "short and fat" type in 2013 to the "thin and tall" type in 2020 (Fig. 4). O_3 concentration is shifting from "tall and thin" to "short and fat", with the waveform shifting to the right, the vertical height of the peak decreasing and the horizontal width increasing, indicating that the regional disparity of O_3 concentration is widening. The kernel density curve of NO_2 concentration in 2020 has produced another waveform compared with that of 2013, and the phenomenon of double waveform appears, which indicates that there is a typical bifurcation of NO_2 concentration.

We visualized the spatial–temporal distribution patterns of $PM_{2.5}$,

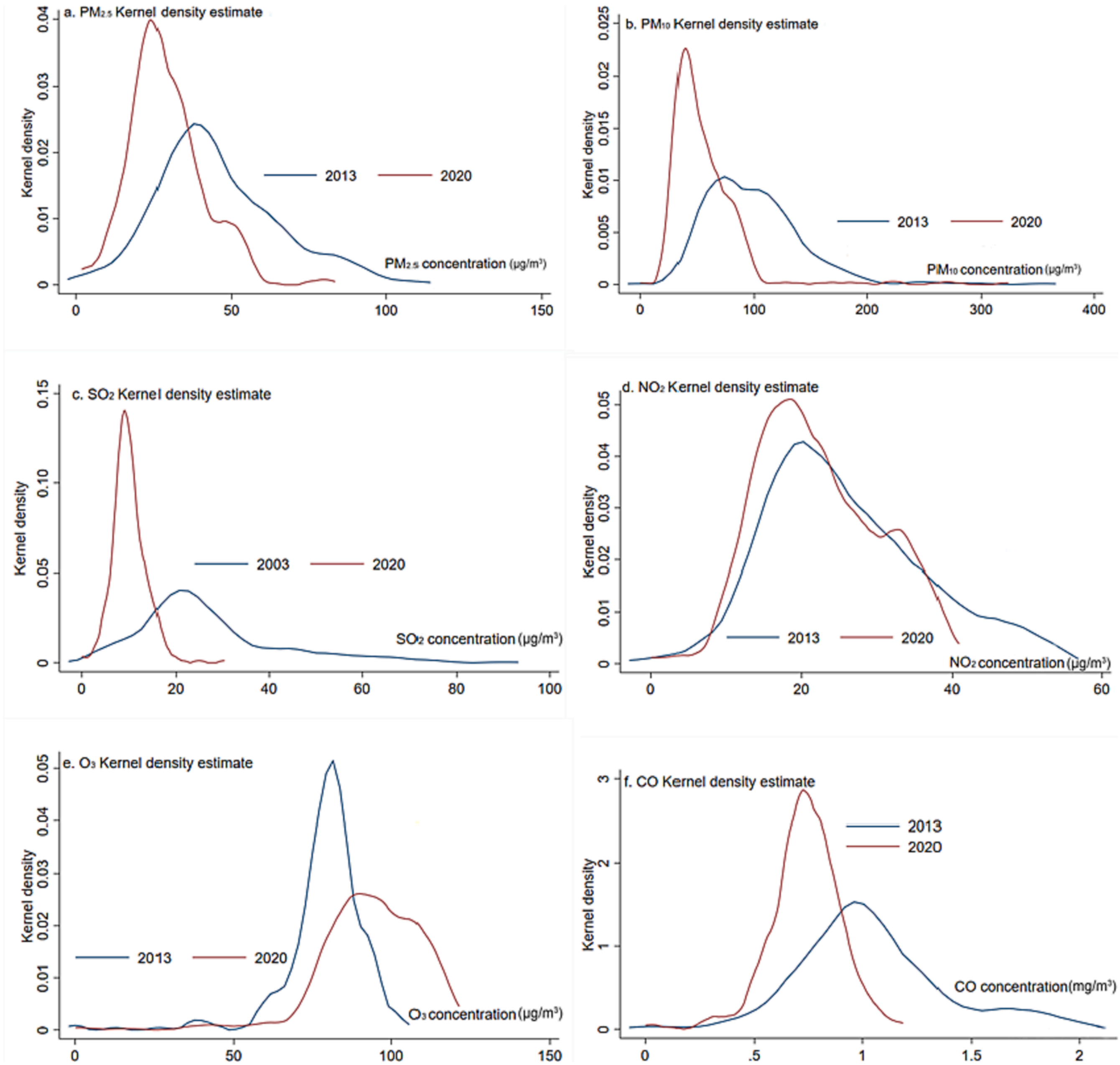

Fig. 4. Kernel density distribution of different air pollutants.

PM_{10}, SO_2, NO_2, O_3 and CO concentrations in China during 2013–2020 by ArcGIS10.4 (Fig. 5). $PM_{2.5}$ concentration and PM_{10} concentration in the spatial distribution pattern shows a certain coupling. The North China Plain and southern Xinjiang become the two major centers of gravity of particulate pollution, showing an obvious "heavier in the north than in the south" pattern. In 2020, cities with high $PM_{2.5}$ concentration or high PM_{10} concentration significantly reduced, especially Beijing-Tianjin-Hebei and its surrounding areas, as well as Shandong, Henan and other places to significantly reduce pollutants' concentration. In 2013, the spatial distribution pattern of SO_2 concentration shows that the areas with high concentration are agglomerated and distributed near resource-based industrial cities, such as Zibo, Dongying, Zaozhuang, Wuhai, etc. In 2020, SO_2 concentration in China decreases significantly, while which in only individual cities such as Wuhai, Shizuishan and Shuozhou exceed 20 $\mu g/m^3$. The overall spatial variation of areas with higher NO_2 concentration is small during 2013–2020. The whole area has improved significantly. NO_2 concentration in urban agglomerations with higher economic development or higher population density is higher than that in the rest of the regions, e.g., Beijing-Tianjin-Hebei urban agglomeration, Yangtze River Delta urban agglomeration, Pearl River Delta urban agglomeration, Chengdu-Chongqing urban agglomeration, Shandong Peninsula urban agglomeration, etc. The distribution of O_3 concentration in 2013 shows a relatively homogeneous distribution, with higher concentration only in Haibei, Hainan and Zhangye in the northwest, while which substantially increases in 2020. O_3 concentration in China's northern region is significantly higher than that in the southern region with the Qinling-Huaihe as the dividing line. Meanwhile, O_3 concentration in North China and Northwest China is significantly higher than that in Northeast China. In 2013, the areas with high CO concentration are mainly located in the middle and lower reaches of the Yellow River and some resource-based industrial cities. In 2020, the traditional CO typical pollution areas are significantly improved. The areas with high concentration are significantly reduced, while which in the old industrial base cities such

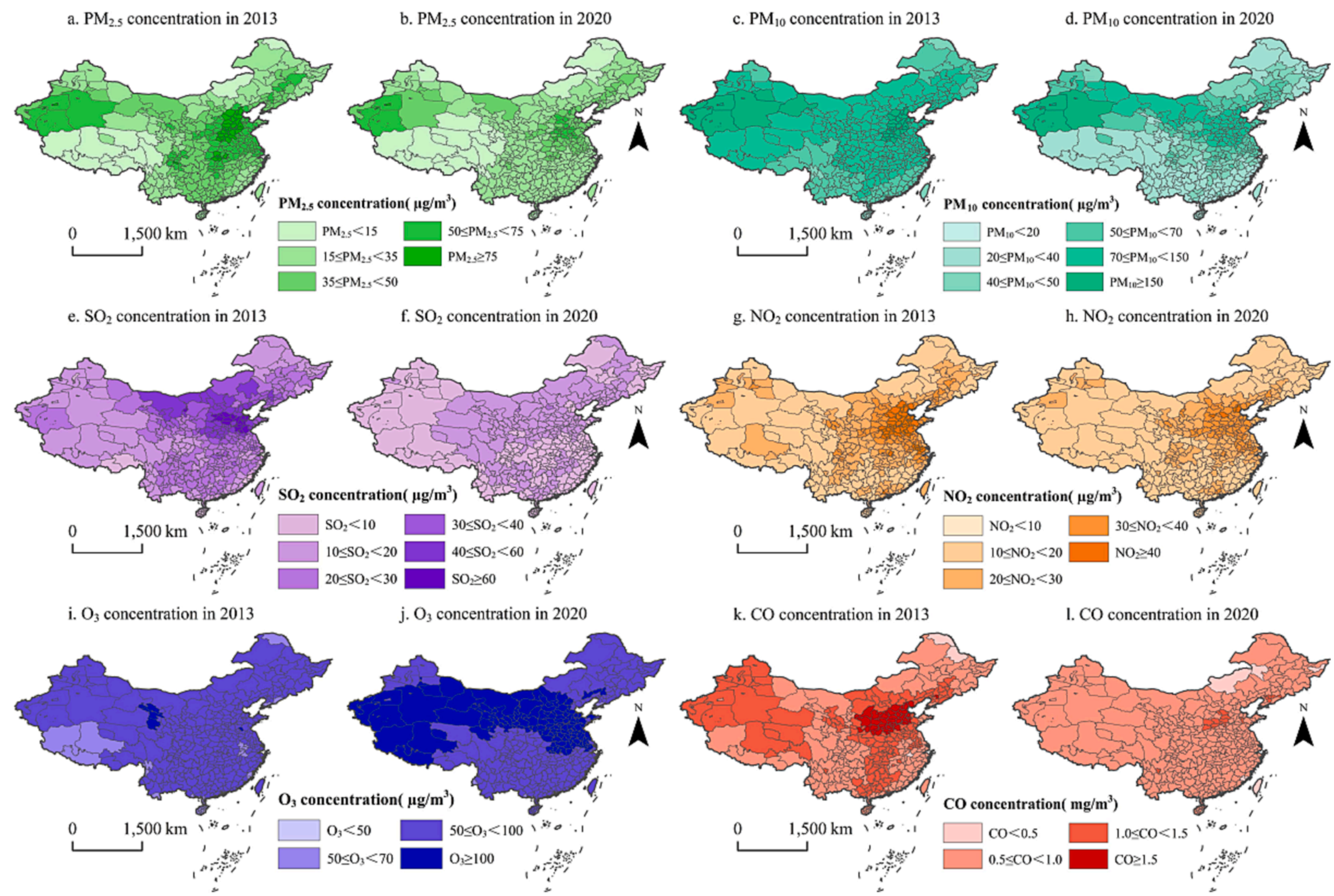

Fig. 5. Spatial distribution of six air pollutants in China during 2013–2020.

as Jincheng, Changzhi and Panzhihua still maintain high.

3.2. Characteristics of the spatial correlations among air pollution

We used GeoDa1.16 to calculated the Global Moran's I estimates of the annual average concentrations of six air pollutants in China during 2013–2020 (Fig. 6). We found that the Global Moran's I estimates of the annual average concentrations of six air pollutants were all greater than 0.5 at the significance level of 0.1 %. The status of air pollutants in each city is significantly affected by similar pollution in neighboring cities. Air pollution in cities around cities with more serious air pollution is also more serious, while the air pollution in cities around cities with better air quality is also relatively good. There is a significant spatial spillover effect for six air pollutants. However, from 2013 to 2020, the Moran's I of $PM_{2.5}$, PM_{10}, SO_2 and CO concentrations show significant decreases of 5.49 %, 8.06 %, 18.79 % and 18.94 % respectively, which indicates that although the spatial concentration of these four air pollutants is weakening, whose Moran's I is still higher than 0.5 and has a high spatial spillover. Moran's I of NO_2 remains relatively stable, fluctuating 0.798–0.815. Moran's I of O_3 shows a significant increase during 2013–2017, while which remains relatively stable during 2017–2020.

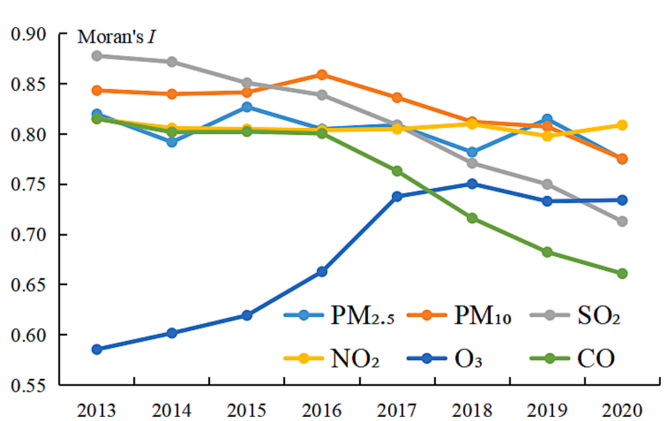

Fig. 6. Global Moran's I of six air pollutants during 2013–2020.

3.3. Changes in air pollution in key areas

In 2013, the promulgation of *the Atmospheric Ten* was issued by Chinese government. And then, a series of measures to improve air quality gradually began to be implemented. The "Three-Year Action Plan for Winning the Blue Sky Defense"[1] clearly defines Beijing-Tianjin-Hebei and its surrounding areas, the Yangtze River Delta region and the Fenwei Plain as the key areas. In response to the differences in the prevention and control of various air pollutants, the joint prevention and control of air pollution in key regions has been deepened and continued to promote the transformation of thermal power plants with ultra-low emissions. Enterprises undergo "coal to gas, coal to electricity" transformation.[2] The pilot cities for clean heating in the northern region have achieved full coverage in Beijing-Tianjin-Hebei and surrounding areas and the Fenwei Plain (Chu et al., 2020). Industrial pollution control and

[1] https://www.gov.cn/zhengce/content/2018–07/03/content_5303158.htm?trs=1.

[2] https://www.gov.cn/zhengce/content/2018–07/03/content_5303158.htm?trs=1.

carried out collaborative efforts to improve the quality of motor vehicles and oil products has been collaborated to strengthen in the Yangtze River Delta (Geng et al., 2021). A series of environmental regulations have played an important role in the governance of air pollution (Qi et al., 2022a). We compare the amount and change rate of six air pollutants' concentrations in key areas and with China's average from 2013 to 2020 to reflect whether there is a significant improvement in air quality after the promulgation of *the Atmospheric Ten* (Table 3). The amount of change in $PM_{2.5}$ concentration improvement in the three key regions is higher than China's average (-16.38 μg/m^3), the rate of change in the Yangtze River Delta and Beijing-Tianjin-Hebei and its surrounding areas is also faster than the Chinese average, while which in the Fenwei Plain is slightly lower than China's average. For PM_{10} and SO_2 concentrations, the amount and rate of change in key regions are both higher than China's average, especially for SO_2 concentration, where whose improvement is very strong. The improvement of NO_2 concentration in Beijing-Tianjin-Hebei and its surrounding areas is much higher than China's average, while whose improvement in the Yangtze River Delta and Fenwei Plain is lower than China's average. As traditional bituminous coal pollution, CO and SO_2 concentrations in northern China is more serious than that in southern China (Qi et al., 2022b), so the improvement of CO and SO_2 concentrations in Beijing-Tianjin-Hebei and surrounding areas as well as in Fenwei Plain is far higher than Yangtze River Delta and China's average. At present, O_3 concentration in China show a gradual increase. Meanwhile, the results show that the increase in O_3 concentration in key areas exceeds China's average in both amount and rate of increase. Environmental regulation has a significant control effect on five air pollutants, except O_3. However, as a typical secondary air pollutant with a wide range of precursor sources (Gong et al., 2022), O_3 interaction with $PM_{2.5}$ makes the synergistic control resistant (Wu et al., 2021).

4. Discussion

4.1. Interrelationships among various air pollutants

To further understand the spatial–temporal coupling effects and to explore the correlations of different air pollutants among cities, we chose Pearson correlation coefficients and Spearman correlation coefficients to verify and quantify the interrelationships among air pollutants. Fig. 7 shows the correlations among six air pollutants concentrations, with Pearson correlation coefficient in the upper triangle and Spearman correlation coefficient in the lower triangle. The positive correlation between O_3 concentration and NO_2 concentration is much higher than the rest of air pollutants, especially the Spearman correlation coefficient between O_3 and SO_2 is only 0.05. $PM_{2.5}$ and PM_{10} are both particulate matter pollution, and their concentrations are coupled. The correlation coefficients of SO_2 and CO, which are both traditional smoky air pollutants, also exceed 0.7, showing a tendency to change at the same frequency. Another existing study shows that there is a significant correlation effect and enhancement effect between air pollutants (Chu et al., 2020). Especially, there is a significant interaction between particulate matter concentration and SO_2 and NO_2 concentrations, and even there is a significant secondary transformation process

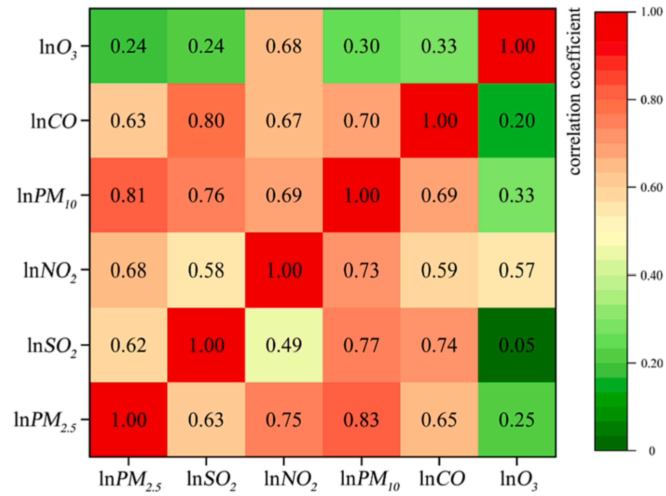

Fig. 7. Intercorrelation coefficients of six air pollutants.

(Chu et al., 2020). Therefore, the mechanism of air pollution evolution is complex, and systematic control of various pollutant concentrations is essential to improve air quality (Gong et al., 2022).

4.2. Effects of urbanization on air pollution based on differential EKCs

We conducted a panel regression analysis of the factors affecting six air pollutants' average concentration in mainland China during 2013–2020 by random effects models and fixed effects models (Table 4). Population and economy are the core of urbanization. To test whether there is an EKC between air pollution and urbanization, we selected population urbanization rate and per capita GDP as core explanatory variables respectively, and added the squared and cubed terms of population urbanization rate and per capita GDP. Finally, we chose the individual fixed effects model as the explanatory model based on the Hausman test results. The regression results show that urbanization has a significant effect on the concentration of air pollutants. However, there are obvious differences in the effects of urbanization on different air pollutants.

The results of the model with population urbanization rate as the core explanatory variable (Table 4) show that there are differences in the direction and intensity of the effects of urbanization on six air pollutants. For $PM_{2.5}$, PM_{10}, SO_2, O_3, NO_2 and CO, population urbanization rate and its squared terms pass the 1 % significance level test. The relationship between $PM_{2.5}$, PM_{10}, SO_2, CO concentrations and urbanization conforms to the classical EKC theory, showing an inverted "U-shaped" curve. However, there is a "U-shaped" relationship between O_3 and urbanization. Combined with mathematical models, NO_2 is different from other air pollutants, while whose curve is an inverted *N*-shaped (Fig. 8). $PM_{2.5}$, PM_{10}, SO_2 and CO concentrations gradually decrease by urbanization, while air quality is improved. Before crossing the inflection points, for every 1 % increase in population urbanization rate, $PM_{2.5}$, PM_{10}, SO_2, and CO concentrations will increase by 3.24 %, 3.62

Table 3
Changes of six air pollutants in China's key regions in 2020 compared with 2013.

Classification	Areas	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)	SO_2 (μg/m^3)	NO_2 (μg/m^3)	O_3 (μg/m^3)	CO (mg/m^3)
Change amount	Beijing-Tianjin-Hebei and its surrounding areas	−35.39	−75.86	−44.76	−11.05	27.74	−0.79
	Yangtze River Delta	−21.49	−48.82	−16.97	−4.09	20.29	−0.20
	Fenwei Plain	−17.89	−56.92	−31.67	−2.72	25.62	−0.76
	China's average	−16.38	−42.61	−16.62	−3.55	14.16	−0.31
Change rate(%)	Beijing-Tianjin-Hebei and its surrounding areas	−42.81	−47.54	−77.33	−23.40	32.39	−45.35
	Yangtze River Delta	−39.29	−46.97	−67.79	−12.63	25.26	−22.44
	Fenwei Plain	−33.88	−44.32	−71.14	−7.71	32.06	−46.30
	China's average	−35.97	−43.05	−62.19	−13.75	17.90	−29.33

Table 4
Regression results of population urbanization effects on air pollution.

Variables	$PM_{2.5}$	PM_{10}	SO_2	NO_2	O_3	CO
ln*PU*	3.243***	3.619***	10.188***	−7.234**	−1.888***	1.162***
$\ln^2 PU$	−0.478***	−0.553***	−1.480***	1.904**	0.271***	−0.176***
$\ln^3 PU$	–	–	–	−0.168**	–	–
ln*VGDP*	−0.070***	−0.135***	−0.120***	0.025***	0.068***	−0.003
ln*EC*	−0.358***	−0.340***	−0.878***	−0.068**	0.167***	−0.148***
ln*PD*	−0.017	−0.015	−0.064*	0.037***	0.058***	−0.003
Ind	−0.037***	−0.055***	−0.026**	−0.004	0.011***	−0.007**
NDVI	0.316***	0.417***	0.386***	0.253***	0.012	0.095***
ln*PRCP*	−0.220***	−0.251***	−0.217***	−0.134***	−0.062***	−0.037**
VC	−0.020**	−0.051***	−0.101***	−0.031***	0.036***	−0.026***
TEMP	−0.028***	−0.039***	−0.105***	−0.033***	0.041***	−0.008**
cons	4.723***	6.127***	−0.006***	14.145***	4.413***	0.905**
R^2	0.725	0.749	0.742	0.281	0.584	0.541
F	526.050	594.170	571.730	70.690	279.690	234.540
N	2288	2288	2288	2288	2288	2288

Note: "*", "**", "***" indicate significant at the levels of 0.1, 0.05 and 0.01, respectively; "-" indicates no item.

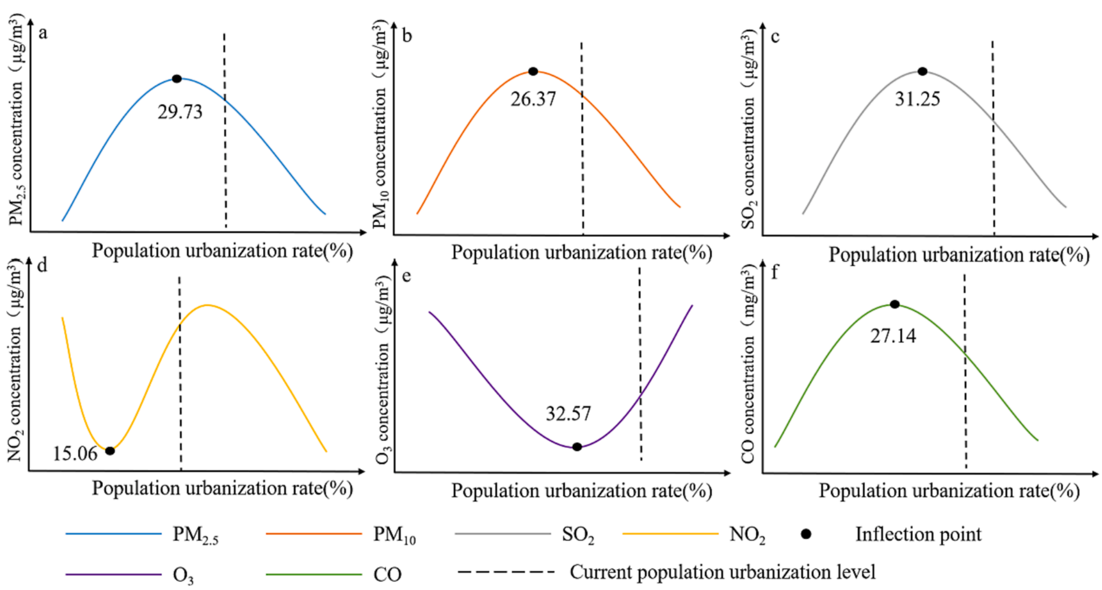

Fig. 8. The EKCs between population urbanization and six air pollutants in China.

%, 10.19 %, and 1.16 %, respectively. Urban ecological bearing threshold can hardly bear the huge pressure. The concentration of air pollutants rises obviously. After crossing the inflection points, for every 1 % increase in population urbanization rate, $PM_{2.5}$, PM_{10}, SO_2, and CO concentrations will decrease by 0.48 %, 0.55 %, 1.48 %, and 0.18 %, respectively. After certain capital and technological innovation advantages accumulated, green transformation of urban production and life style has been realized. The upgrading of industrial structure has greatly improved the treatment efficiency of air pollutants. Air quality has improved.

At this stage, NO_2 and O_3 concentrations are still increasing rapidly with urbanization, namely, NO_2 and O_3 concentrations will increase by 1.90 % and 0.27 % for every 1 % increase in population urbanization rate. Automobile exhaust emission is one of the main sources of NO_2. Excessive population agglomeration increases the scale of motor vehicles, aggravates the degree of urban road congestion, and then produces much more air pollutants such as $PM_{2.5}$ and NO_2. So, the conversion between O_3 and various air pollutants is intensified, which further aggravates O_3 concentration.

Population density has a significant positive effect on NO_2 and O_3 concentrations. The excessive agglomeration of population leads to a gradual increase of air pollutants produced in the daily life of urban residents. With the widespread use of clean energy, the energy consumption index has a significant inhibitory effect on the improvement of air pollution, namely, for every 1 % increase in the energy consumption index, $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO concentrations decrease by 0.36 %, 0.34 %, 0.88 %, 0.07 %, and 0.15 % (Table 4), respectively. However, O_3 concentration responds positively to energy consumption index. Industry, as an important indicator of economic urbanization, is crucial for air pollution governance, while which has an important impact on particulate matter pollution and bituminous coal pollution (Qi et al., 2022a). Industrial pollution emissions are the most important source of air pollution. By reducing the proportion of heavy chemical industry and increasing the proportion of tertiary industry, industrial upgrading has a significant contribution to reduce energy consumption and exhaust emissions (Qi et al., 2022b). The results showed that for each 1 % increase in index of industrial sophistication, $PM_{2.5}$, PM_{10}, SO_2, and CO concentrations will decrease by 0.04 %, 0.06 %, 0.03 %, and 0.01 % (Table 4), respectively. Industrial enterprises, especially heavy chemical enterprises, mainly consume coal and emit particulate matter, SO_2 and CO, posing a serious threat to air quality. Since the promulgation of *the Atmospheric Ten* in 2013, the transformation and upgrading of polluting industries, a series of clean-ups of heavy chemical industries and the use of clean energy have led to a gradual improvement in air quality under government environmental regulations in recent years (Guo et al., 2022).

Economic development is one of the main manifestations of urbanization. In order to explore its effect on air pollution, we built a model with per capita GDP as the core explanatory variable. The regression results (Table 5) show that the relationship between economic urbanization and $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO presents inverted "U-shaped", inverted "U-shaped", "*N*-shaped", inverted "U-shaped", inverted "*N*-shaped", and "*N*-shaped" (Fig. 9), respectively. At present, the inflection points between $PM_{2.5}$, SO_2, CO and other air pollutants and economic urbanization have reached, and the clean and green transformation of heavy chemical industry has greatly reduced industrial pollution emissions. Urban domestic air pollutants, such as PM_{10}, NO_2 and O_3, are mainly due to the intensification of housing and public infrastructure construction, resulting in a large amount of construction dust. Meanwhile, the increase in the scale of motor vehicles makes NO_2 concentrations increase day by day.

4.3. Spatial spillover effect of urbanization on air pollution

Considering the strong spatial correlation between air pollutants and their factors, we explore the spatial spillover effect of urbanization on air pollution by the spatial econometric model. By calculating Global Moran's *I*, LM(lag) and LM(error) tests and Robust LM(lag) and Robust LM(error) tests, we found that the parameters of $PM_{2.5}$, PM_{10}, SO_2, O_3 and CO pass the 0.001 significance level test, indicating that $PM_{2.5}$, PM_{10}, SO_2, O_3 and CO are suitable for spatial measurement, while NO_2 fails to pass the test and is not suitable for spatial measurement. Meanwhile, by comparing Log-likelihood, R^2, LR tests, we found that the spatial Dubin model is better than the spatial error model and the spatial lag model. The regression results of the spatial Dubin model are shown in Table 6. The regression results show that urbanization not only has a significant effect on local air pollutants, but also does in neighboring areas, with typical phased characteristics.

The effect of population urbanization on local $PM_{2.5}$ and SO_2 concentrations shows a significant trend of first increasing and then decreasing, while whose effect on O_3 concentrations is the opposite. However, urbanization has no significant effect on $PM_{2.5}$, SO_2 and O_3 concentrations in neighboring areas. Population urbanization has a significant negative spillover effect on PM_{10} and CO concentrations in neighboring areas before crossing the inflection points, and a significant positive spillover effect after crossing the inflection points. Both per capita GDP and population density have a significant positive spillover effect on $PM_{2.5}$ and PM_{10} concentrations in neighboring areas. The intensification of human activities and particulate matter pollution emissions have a positive effect on $PM_{2.5}$ and PM_{10} concentrations in neighboring areas. Industrial structure upgrading index has a significant negative spillover effect on PM_{10} concentration. Industrial upgrading and cleaning reform greatly reduce disposable particle pollutants such as industrial dust, fly ash and soot. The reduction of pollutant sources reduces the concentration of particulate matter in neighboring areas. The energy consumption index has a negative spillover effect on traditional industrial pollutants such as $PM_{2.5}$, SO_2 and CO concentrations. The adjustment of energy consumption structure and the use of clean energy reduce the emission of air pollutants, which also reduces the effect on the concentration of air pollutants in neighboring areas.

The estimation of the coefficients characterizing the exogenous interaction effect (*WX*) (Table 6) can show that $W \times \ln PU$ and $W \times \ln^2 PU$ pass all significance level test. Therefore, in order to deeply analyze the spatial interaction of urbanization, we further present the results of direct and indirect effects of SDM model (Table 7). According to the significance and elasticity coefficient of urbanization and its square term, the contribution degree of urbanization to different air pollutants can be roughly compared. The indirect effect of urbanization on the concentration of air pollutants is main in neighboring areas. $PM_{2.5}$, PM_{10} and CO concentrations in neighboring areas decrease first and then increase in a "U-shaped" curve. However, urbanization only passes the 10 % significance test for SO_2 concentration in neighboring areas. Every 1 % increase in population urbanization rate will decrease SO_2 concentration by 18.82 % in neighboring areas. At this stage, the improvement of SO_2 concentration by urbanization is weaker than that of PM_{10} concentration, but stronger than that of $PM_{2.5}$ and CO concentrations. The direct effect of urbanization on local O_3 concentration shows an "U-shaped" curve of first decreasing and then increasing, while whose indirect effect does not pass the significance test, indicating that there is no significant spatial spillover effect of urbanization on O_3 concentration.

4.4. Research limitations and future research directions.

In terms of research methods and data, our greatest innovation is the utilization of remote sensing data to investigate the differential effects of urbanization on different air pollutants. Our greatest contribution is the comprehensive comparative analysis of the spatial–temporal evolution of six air pollutants and the effect of urbanization on them. We also explore the spatial spillover effects of urbanization on different pollutants by the spatial econometric model. Our findings can help future scholars to better understand the relationship between urbanization and air pollution, and can also help local governments to better control air pollution in a concerted manner. Although some results are achieved in this paper, the study period is relatively short, limited to 2013–2020 due to data limitations, and it is not possible to compare the differential effects of different aspects of urbanization on air pollutants before the promulgation of *the Atmospheric Ten* in 2013. The key areas such as Beijing-Tianjin-Hebei and surrounding areas, Yangtze River Delta region, and Fenwei Plain only explore the change trends in terms of the amount and rate of change of six air pollutants without the heterogeneity analysis of their dominant factors. So, spatial heterogeneity of factors of multiple air pollutants can be considered in the future.

Table 5
Regression results of economic urbanization effects on air pollution.

Variables	$PM_{2.5}$	PM_{10}	SO_2	NO_2	O_3	CO
ln*VGDP*	0.380**	−0.726***	27.664***	0.340***	−10.799***	5.013***
$\ln^2$*VGDP*	−0.021***	0.027***	−2.499***	−0.014***	0.980***	−0.454***
$\ln^3$*VGDP*	–	–	0.0745***	–	−0.029***	0.014***
ln*PU*	−0.380***	−0.542***	−1.019***	−0.096***	0.169***	−0.166***
ln*EC*	−0.382***	−0.355***	−0.934***	−0.070***	0.175***	−0.154***
ln*PD*	−0.033**	−0.027	−0.080**	0.032***	0.056***	−0.003
Ind	−0.037***	−0.057***	−0.036***	−0.003	0.015***	−0.010***
NDVI	0.346***	0.466***	0.497***	0.254***	−0.009	0.109***
ln*PRCP*	−0.219***	−0.244***	−0.213***	−0.135***	−0.062***	−0.036***
VC	−0.026***	−0.055***	−0.114***	−0.032***	0.039***	−0.027***
TEMP	−0.030***	−0.046***	−0.108***	−0.033***	0.039***	−0.008**
cons	9.508***	17.406***	−80.750***	3.619***	40.485***	−14.927***
R^2	0.714	0.739	0.724	0.282	0.584	0.536
F	497.22	562.86	475.190	78.160	254.480	209.300
N	2288	2288	2288	2288	2288	2288

Note: "*", "**", "***" indicate significant at the levels of 0.1, 0.05 and 0.01, respectively; "-" indicates no item.

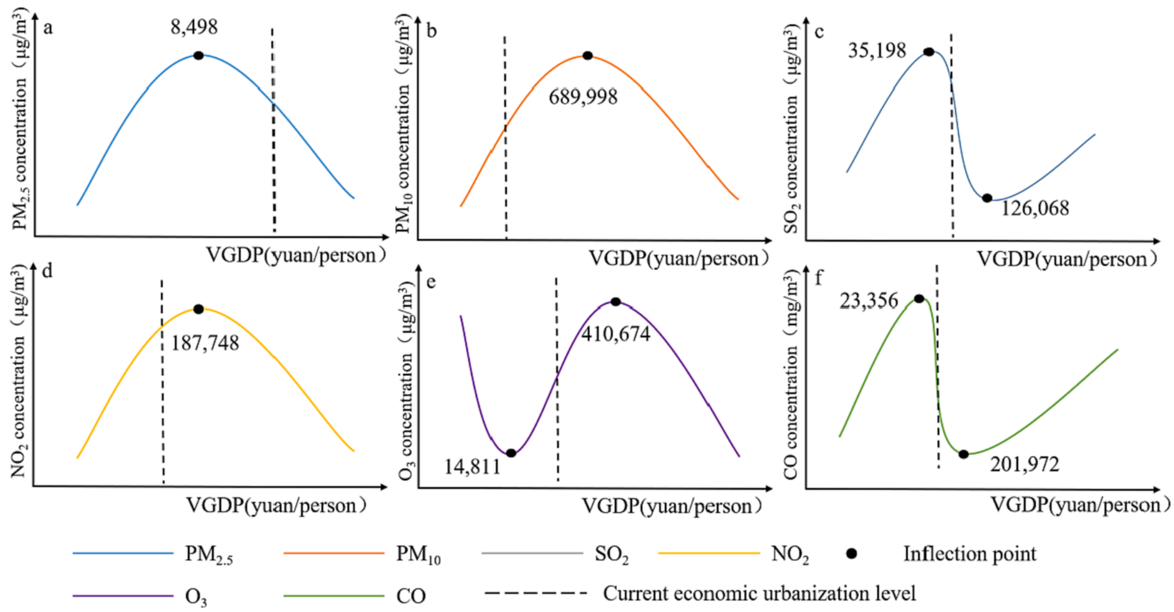

Fig. 9. The EKCs between economic urbanization and six air pollutants in China.

Table 6
The spatial Dubin model results of population urbanization effects on air pollution.

Variables	$PM_{2.5}$	PM_{10}	SO_2	O_3	CO
lnPU	0.924***	0.339	3.730***	−0.554***	0.020
$\ln^2 PU$	−0.126***	−0.049	−0.517***	0.077***	−0.006
ln*VGDP*	−0.007	−0.031***	0.061***	0.029***	0.034***
ln*PD*	−0.003	0.003	−0.002	0.038***	0.008
ln*EC*	−0.103***	−0.078***	−0.218***	0.007	−0.028
Ind	−0.015***	−0.015***	0.060***	−0.011***	0.007***
NDVI	−0.251***	−0.133	−0.022	−0.024	−0.061***
ln*PRCP*	−0.107***	−0.036***	−0.091***	−0.063***	−0.015*
VC	0.013**	−0.009	−0.055***	0.044***	−0.020***
TEMP	−0.001	0.038***	−0.014	0.024***	0.006*
W × ln*PU*	−12.233***	−6.888**	−14.062*	−1.623	−5.327**
$W \times \ln^2 PU$	1.446***	0.797**	1.487	0.154	0.615**
W × lnVGDP	0.179***	0.195***	0.130	0.046	0.010
W × ln*PD*	0.353***	0.177*	0.084	0.082	0.018
W × ln*EC*	−0.355***	0.070	−0.400**	0.288***	−0.269***
W × *Ind*	0.047	−0.117**	−0.020	−0.023	0.007
W × *NDVI*	0.451***	0.164	−0.016	0.083	0.174***
W × ln*PRCP*	−0.204***	−0.010	0.082	0.178***	−0.027
W × *VC*	−0.034	0.002	0.075	−0.031	−0.010
W × *TEMP*	−0.046	−0.070	−0.060	0.035	−0.028
R^2	0.860	0.927	0.874	0.709	0.660
Log-likelihood	3119.4	3456.2	1348.6	3592.9	4020.7
LM(error)	5106.0***	1.50E + 04***	1.50E + 04***	3195.6***	2042.7***
Robust LM(error)	5085.3***	1.50E + 04***	1.50E + 04***	3190.4***	2009.4***
LM(lag)	29.74***	64.22***	201.73***	7.96***	36.88***
Robust LM(lag)	9.00***	18.37***	14.14***	2.74*	3.54***
N	2288	2288	2288	2288	2288

Note: "*", "**", "***" indicate significant at the levels of 0.1, 0.05 and 0.01, respectively.

Urbanization is a process involving population, economy, land and other aspects. In the face of the new development goals of carbon peak and carbon neutral, we can try to study the relationship between carbon emission reduction and air pollution governance to quickly achieve high-quality development. There are significant differences in air pollution in cities with different urbanization, and even local different leading industries in cities can make differences in the leading air pollutants. In future research, more detailed classification studies can be conducted for cities in different stages, cities with different economic levels and cities with different dominant air pollutants, so that the general patterns and differential driving mechanisms of urbanization on air pollution can be explored in a more localized and site-specific manner, thus facilitating the formulation of governance policies for air pollution.

5. Conclusions

In order to identify the effect of urbanization on different air pollutants and formulate more targeted policies for local joint prevention and control and collaborative management of regional air pollutants, we investigated the effect of urbanization on six air pollutants' concentrations. The main findings are as follows. From 2013 to 2020, $PM_{2.5}$, PM_{10}, SO_2, and CO concentration in China decrease substantially, while NO_2 concentration remains relatively stable, and O_3 concentration shows a

Table 7
The direct and indirect effect of spatial Dubin model.

Variables		$PM_{2.5}$	PM_{10}	SO_2	O_3	CO
PU	ln*PU*	0.924***	0.339	3.730***	−0.554***	0.020
	$W \times$ ln*PU*	−12.233***	−6.888**	−14.062*	−1.623	−5.327**
	LR_Direct	0.894***	0.268	3.721***	−0.552***	0.044
	LR_Indirect	−14.647***	−24.107**	−18.816*	−3.407	−3.680***
	LR_Total	−13.752***	−23.839**	−15.094	−3.959	−3.636**
*PU*2	ln2*PU*	−0.126***	−0.049	−0.517***	0.077***	−0.006
	$W \times$ ln2*PU*	1.446***	0.797**	1.487	0.154	0.615**
	LR_Direct	−0.121***	−0.041	−0.516***	0.076***	−0.009
	LR_Indirect	1.722***	2.786*	1.926	0.341	0.424**
	LR_Total	1.600***	2.745*	1.410	0.417	0.415**
Control variables	–	Yes	Yes	Yes	Yes	Yes
Spatial rho		0.201	0.712**	0.323***	0.450***	−0.436**
Variance sigma2_e		0.004***	0.003***	0.018***	0.003***	0.002***

Note: "*", "**", "***" indicate significant at the levels of 0.1, 0.05 and 0.01, respectively.

rapid growth trend year by year. The spatial distribution of $PM_{2.5}$ and PM_{10} concentrations are similar, with high concentrations mainly agglomerated in Beijing-Tianjin-Hebei and its surrounding areas, as well as in southern Xinjiang. The areas with higher CO concentration are mainly agglomerated in resource-based cities. Meanwhile, six air pollutants show significant clustering effects, while the clustering degree of the remaining five air pollutants is decreasing, except for O_3. During 2013–2020, air pollution improvement in Beijing-Tianjin-Hebei and its surrounding areas, Yangtze River Delta region, Fenwei Plain and other key regions are better than China's average. There is a strong correlation between six air pollutants, and more attention should be paid to the synergistic control of pollutants in the process of joint prevention and control. Different aspects of urbanization have different effects on various air pollutants. Combined with the EKCs' shape, there are non-linear relationships between population urbanization and $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3, and CO concentrations with inverted "U-shaped", inverted "U-shaped", inverted "U-shaped", inverted "*N*-shaped", "U-shaped", and inverted "U-shaped" respectively. The relationship between economic urbanization and six air pollutants concentrations is inverted "U-shaped", inverted "U-shaped", "*N*-shaped", inverted "U-shaped", inverted "*N*-shaped", and "*N*-shaped". Additionally, urbanization has a spillover effect on $PM_{2.5}$, PM_{10}, SO_2 and CO concentrations, while whose direction of spillover effect reflect the stage change. Our findings clarify the effect of urbanization on different air pollutants and spillover effects, and find the inflection point between urbanization and air pollution. These will help to formulate more precise air pollution prevention policies, accelerate the positive coupling between urbanization and the ecological environment, and promote high-quality urban development.

CRediT authorship contribution statement

Guangzhi Qi: Writing – original draft, Methodology. **Jiahang Che:** Writing – original draft. **Zhibao Wang:** Writing – original draft, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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