CO2 Emissions are First Aggravated and then Alleviated with Economic Growth in China: A New Multidimensional EKC Analysis

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Research Article

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Posted Date: July 20th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-596739/v1

CO_2 emissions are first aggravated and then alleviated with economic growth in China: A new multidimensional EKC analysis

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Abstract: CO_2 emissions have become a topical issue worldwide, but few studies have explored the relationship between CO_2 emissions and income by establishing direct, indirect and total environmental Kuznets curves (EKCs). Using an annual panel dataset collected over the 1997-2017 period in China, this study first analyzed the spatiotemporal evolutionary process of CO_2 emissions and subsequently developed direct, indirect and total EKCs based spatial Durbin model (SDM) and partial derivative approach. These results indicate that, first, CO_2 emissions have characteristic positive spatial autocorrelation, with gravity centers that have shifted westward. Second, the direct EKC forms a line, while the total EKC resembles a lying-S shape as well as the total EKC, which indicates that compared to local economic growth, neighboring growth plays a very different role in impacting local CO_2 emissions. Furthermore, neighboring economic growth seems to have stronger impacts on local emissions, and the turning point of the total EKC comes much earlier than

that of the conventional EKC due to the spillover effects of economic growth. Finally, the growth of the population, as well as the rise of energy intensity, can stimulate CO_2 emissions in both local and neighboring regions. Industrialization seems to have a nonsignificant impact on emissions changes due to the offsetting effects of the positive direct and negative indirect impacts of the share of secondary industry. Improvements in local urbanization may lead to an increase in emissions, while neighboring improvements may have stronger restricting effects; thus, urbanization improvement is beneficial to emissions reduction. This study provides more scientific information from both local and neighboring perspectives, which may differ from conventional results but still be beneficial for emissions reduction policy makers to introduce corresponding measures.

Keywords: CO2 emissions, Environmental Kuznets curve (EKC), Spatial Durbin model (SDM), Spatial weight matrix

1 Introduction

Issues regarding climate change have attracted increasing attention since the Kyoto Protocol came to fruition on February 16, 2005 (Zhang and Sun, 2016). According to Intergovernmental Panel on Climate Change (IPCC) reports, global warming is mainly caused by greenhouse gas emissions, in which carbon dioxide (CO_2) is the most prevalent (Griggs and Noguer, 2006; Karl, 2004). In fact, the energy-related CO_2 emissions of China account for approximately 30% of the global CO_2 emissions in recent years (Shan et al., 2018) due to its greatest amount of energy consumption in the world. As one of the Paris Agreement members, China plays an important role in reducing global greenhouse emissions and mitigating climate change. In the 14th five-year plan, China plans to achieve the peak of carbon emissions by 2030 and encourage some appropriate

regions to reach the peak in advance. However, to achieve CO_2 emission reduction, as well as sustainable economic development, the Chinese government must obtain more detailed information on the CO_2 emission process and the corresponding economic growth with consideration for spatial dependence.

According to the related literature, the environmental Kuznets curve (EKC) is an effective analysis tool to study the relationship between CO_2 emissions and economic growth (Auci and Trovato, 2018; Luzzati et al., 2018). Using different econometric approaches, many scholars have investigated the relationship between CO_2 emissions and economic growth with corresponding datasets and obtained useful conclusions (Lin and Jiang, 2009; Xu et al., 2012; Zou et al., 2014). However, CO_2 emissions have obvious spatial characteristics (Ding et al., 2019; Li, J. et al., 2019) , thus spatial econometric models should be used to explore the so-called inverted-U curve. Indeed, many scholars have studied the relationship between CO_2 emissions and economic growth (Chen and Lee, 2020; Fong et al., 2020; You and Lv, 2018), which is beneficial to understanding the real EKC from different perspectives. However, direct, indirect and total EKCs have not been defined with the partial derivative approach in previous studies. This study attempts to study the relationship between CO_2 emissions and economic growth from direct, indirect and total EKC perspectives.

The novelty of this paper arises from the following three aspects. First, using a spatial panel data model and the principal of partial derivatives, the direct and indirect (spillover) effects as well as the total effect of all explanatory variables are measured, which reveals the spatial interaction effects among all variables in the model. Second, based on the direct, indirect and total effects of Ln(GDP), $(\mathrm{Ln(GDP)})^2$ and $(\mathrm{Ln(GDP)})^3$, this paper develops direct, indirect and total EKCs for CO_2 emissions, which can reveal the relationship between CO_2 emissions and economic growth from

local, neighboring and entire perspectives. Finally, according to the direct, indirect and total effects of other control variables, several key conclusions related to emissions reduction can be obtained from local and neighboring perspectives.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the data descriptions and adopted methods. Section 4 shows the empirical results and analyses. Section 5 provides some conclusions and suggestions resulting from this paper.

2 Literature review

The environmental Kuznets curve (EKC) hypothesis stems from the initial work of Kuznets (1955) and was defined by Panayotou (1993). The concerns of the EKC hypothesis have always been discussed in academic circles due to its importance in pollution reduction policy formulation (Sarkodie and Strezov, 2018). The EKC hypothesis posits that at earlier economic development stages, environmental quality will decrease as economic growth occurs, while after a certain turning point of income per capita, environmental quality will continually improve (Du et al., 2018; Sinha and Shahbaz, 2018). Usama et al. (2016) examined the EKC with the vector error correction model and confirmed that the formulation of the EKC hypothesis was supported by the value of renewable energy consumption. Ilhan and Usama (2015) investigated whether better governance and corruption control helped form the inverted U-shaped EKC of CO_2 emissions in Cambodia during the period of 1996-2012 based on the generalized method of moments and the two-stage least squares and stated that no evidence was provided to confirm the existence of the EKC in this country. Nutakor et al. (2020) examined the causal relationship between economic growth and CO_2 in Rwanda for 1960-2014 data with the vector autoregression (VAR) model and found bidirectional causality between the real GDP and the corresponding CO_2 emissions. In addition, many other

scholars have used such methods to analyze this issue, such as the autoregressive distributed lag (ARDL) approach (Ahmad et al., 2017; Alshehry and Belloumi, 2017; Balaguer and Cantavella, 2016; Sinha and Shahbaz, 2018), cointegration analysis and vector error correction model (VECM) (Ben et al., 2015; Khan et al., 2016; Wang, S. et al., 2017; Zoundi, 2016), fully modified ordinary least squares and pairwise Granger causality method (Alper and Onur, 2016). Using various approaches, these studies have tested the EKC hypothesis and achieved many useful conclusions for policy-makers, but these nonspatial methods could not identify the spatial interaction effect among different variables.

The first law of geography states that all things are related, and nearer things are more related than distant things (Tobler, 1993). Both CO_2 emissions and economic growth have obvious characteristics of spatial dependence (Jorge et al., 2020; Kang et al., 2016). Considering the spatial dependence of household CO_2 emissions, Wang et al. (2018) used a geographically weighted regression (GWR) model to examine the spatial effects of urbanization, energy intensity, energy structure and income on household CO_2 emissions. Similarly, using the dataset of CO_2 emissions in five North African countries during 1990-2014, Mahmood et al. (2020) found significant spatial dependence in the CO_2 emissions distribution. From global and local perspectives, Liu et al. (2021) revealed the spatial aggregation features of CO_2 emissions at the city level and visualized them through mapping. In addition, Meng et al. (2017) noted that the spillover (indirect) effect played an important role in driving regional CO_2 emissions in China, and these results indicated that CO_2 emissions had significant spatial dependence.

Given the notable spatial dependence of CO_2 emissions, spatial econometric models, which can calculate the spatial interaction effects of variables in a model, should be adopted to test the

existence of the EKC (Li, K. et al., 2019; Yang et al., 2019). In recent years, some scholars have indeed discussed the relationship between CO_2 emissions and economic growth with spatial econometric methods. For example, considering the spatial interaction effect, Balado-Naves et al. (2018) employed a panel dataset composed of 173 countries over the 1990-2014 period to examine the EKC for CO_2 emissions and found that most countries supported the standard EKC and that some areas appeared to have an inverted-U relationship between neighboring per capita income and national per capita emissions. Munir et al. (2020) found that some previous results about the EKC for CO_2 emissions were biased due to their exclusion of cross-sectional dependence, and Munir et al. applied a new panel test of Granger noncausal relationships to obtain much different conclusions (Munir et al., 2020). Additionally, using a spatial panel model to avoid the coefficient estimation error, Kang et al. (2016) stated that the shape of the relationship between CO_2 emissions and economic growth followed an inverted-N trajectory and confirmed that spatial spillover effects significantly affected the EKC shape.

Previous studies on the EKC for CO2 emissions with spatial econometric models have supported many beneficial explorations and obtained scientific results by considering the spatial interaction effects (Wang and Ye, 2017). However, these papers do not pay enough attention to calculating the direct, indirect and total effects of real GDP per capita on CO_2 emissions per capita. Moreover, most previous studies still obtained the EKC only from the estimated coefficients of spatial econometric models; for instance, Balado-Naves et al. (2018) estimated the spatial EKC with the coefficients of the spatially lagged GDP and $(GDP)^2$ based the spatial lag of X model (SLX) and the spatial Durbin error model (SDEM). For SLX and SDEM, the direct and indirect effects of an explanatory variable are equal to the coefficients of this variable and its spatially lagged variable,

while for other models, such as SDM and spatial autoregressive (SAR) models, the direct and indirect effects are not equal to corresponding coefficients (Elhorst, 2014). Thus, we should develop the general direct, indirect and total EKCs based on the direct, indirect and total effects of GDP, $(GDP)^2$ and $(GDP)^3$, but not their coefficients, and these three types of effects can be calculated with a partial derivative approach (Elhorst, 2014).

Under this circumstance, considering the importance of the spatial interaction effects of GDP and other influential factors on CO_2 emissions, this paper first calculates the direct, indirect and total effects of GDP on CO_2 emissions based on econometric models and the partial derivative approach and then develops the direct, indirect and total EKCs. This study is a critical supplement to the existing literature related to the EKC hypothesis because the conclusions of the paper can provide more information to policymakers focusing on CO_2 emission reduction from local, neighboring and nation-wide perspectives.

3 Data and methodologies

3.1 Data

3.1.1 Dependent variables

As the dependent variable of this study, the measure of CO_2 emissions is a key step to examine the EKC hypothesis, and many scholars have tried to calculate such factors in China by employing different methods, such as constructing carbon inventories (Shan et al., 2016), input-output analysis and computing based on nighttime light data (Chen et al., 2020). CO_2 emissions are closely related to fossil energy consumption (Shan et al., 2016); thus, this study calculates CO_2 emissions with carbon inventory-based energy consumption. Furthermore, we used the emission coefficients

proposed by Mi et al. (2017), which are based on 602 coal samples from the largest coal-mining regions in China, and these coefficients are more suitable for conditions in China than that of the IPCC (Mi et al., 2017). The CO_2 emissions data can be obtained from the China Emission Accounts and Datasets (CEADS) website (http://www.ceads.net/(Mi et al., 2017)).

3.1.2 Independent variables

The influential factors on the EKC for CO_2 emissions include income elasticity, scale, composition and technique effects and international trade factors (Sarkodie and Strezov, 2018). Table 1 presents the specific factors affecting environmental variables in the selected previous studies. According to these results, the explanatory variables (shown in

Table 2

Description statistics of key variables.

Variables	Description	Data for 1997-2017			
		Max	Min	Mean	Std. dev.
Ln(CO_2)	Per capita CO_2 emissions (kg/people)	3.245	-0.031	1.512	0.637
Ln(GDP)	Per capita real GDP (Yuan/people)	11.442	7.712	9.641	0.778
Ln(POP)	Population (people)	9.321	6.207	8.143	0.763
Ln(URB)	Urbanization rate (%)	4.495	2.642	3.710	0.438
Ln(IND)	Proportion of secondary industry (%)	-0.527	-1.66	-0.818	0.204
Ln(ENER)	Energy consumption per GDP (kg standard coal per ten thousand Yuan)	8.840	6.243	7.258	0.518
Ln(TRAD)	Trade openness (trade volume per GDP)	0.493	-4.091	-1.868	1.018

Note: Variables are in the formation of natural logarithm.

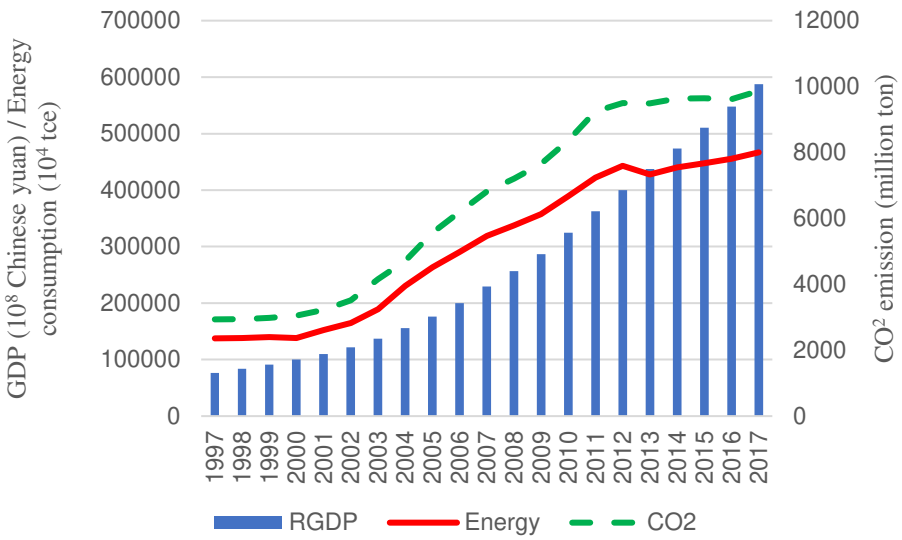

Fig. 1. Total energy consumption, real GDP and CO_2 emissions in China, 1997-2017.

) include the per capita real gross domestic product (GDP) as income elasticity, population as scale effect, urbanization rate as composition effect, proportion of secondary industry as composition effect, energy consumption per GDP as technique effect and trade openness as a proxy for international trade.

Table 1

Selected previous studies of variables for EKC.

Authors (year)	Dependent variables	Independent variables
Wang et al. (2017)	CO_2	Per capita GDP, Population, Proportion of secondary industry, Capital investments, Foreign direct investment
Xu (2018)	SO_2	Real GDP/GDP^2 per capita, Real FDI per capita, Trade openness (Ratio of foreign trade to GDP), Financial development (Ratio of savings to GDP)

Ulucak and Bilgili (2018)	Ecological footprint	Per capita GDP/GDP^2, Trade openness (Ratio of foreign trade to GDP), Human capital, Biocapacity
Talbi (2017)	CO2	Energy consumption of fuel, Intensity energy of road transport, Real per capita GDP, Urbanization, Fuel rate
Sinha and Shahbaz (2018)	CO2	Per capita GDP/GDP^2, Per capita renewable energy generation, Per capita energy consumption, Volume of foreign trade, Total factor productivity (TFP)
Charfeddine (2017)	Ecological footprint	GDP, Energy use, Urbanization, Fertility, Life expectancy
(Olale et al., 2018)	CO_2	Per capita GDP/GDP^2, Real trade openness (Ratio of foreign trade to GDP)

3.1.3 Data preprocessing and description

Data from 30 Chinese provinces for 1997 to 2017 were collected. Due to a lack of data available in some regions in China, including Tibet, Taiwan, Hong Kong and Macao, we removed these regions from our empirical analyses. Moreover, the data for our variables are all presented in a natural logarithmic form to eliminate heteroscedasticity.

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Description statistics of key variables.

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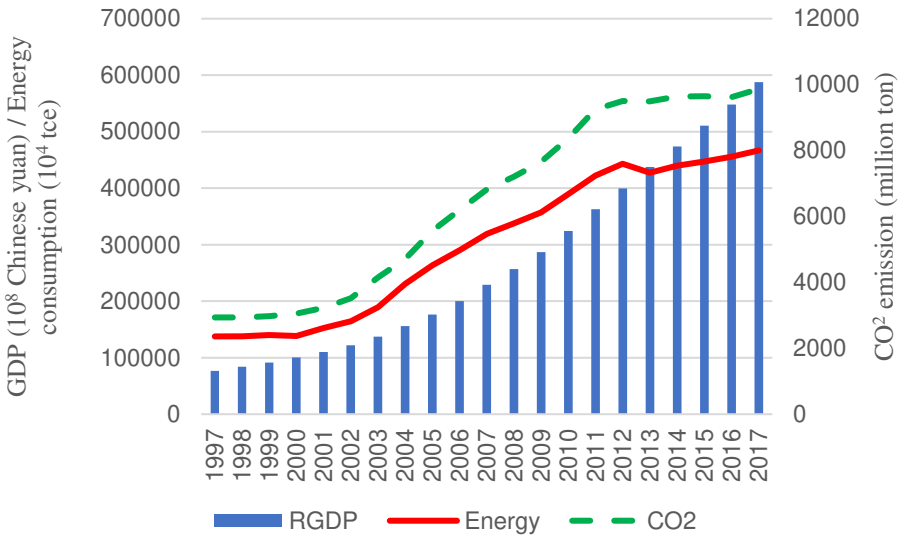

Fig. 1. Total energy consumption, real GDP and CO_2 emissions in China, 1997-2017.

shows the descriptive statistics of all variables used in the study.

Table 2

Description statistics of key variables.

Variables	Description	Data for 1997-2017			
		Max	Min	Mean	Std. dev.
Ln(CO_2)	Per capita CO_2 emissions (kg/people)	3.245	-0.031	1.512	0.637

Ln(GDP)	Per capita real GDP (Yuan/people)	11.442	7.712	9.641	0.778
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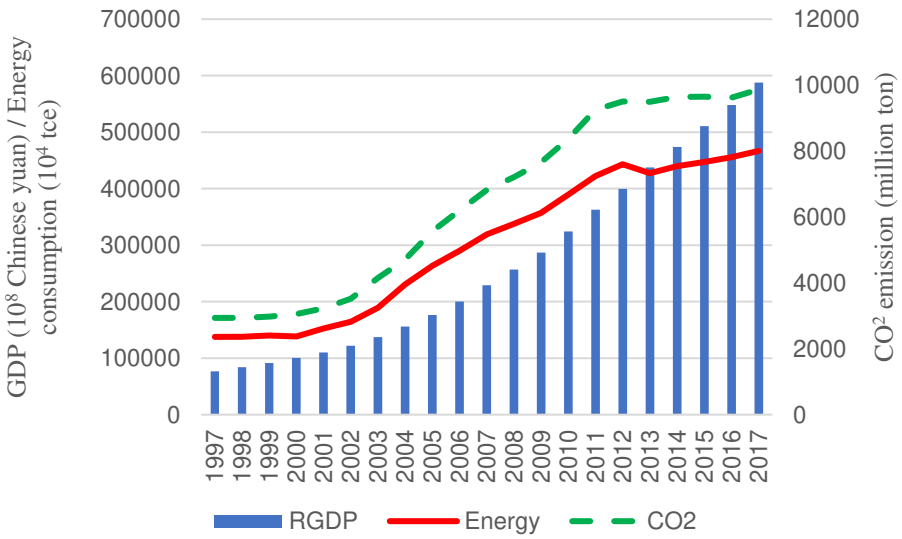

Fig. 1. Total energy consumption, real GDP and CO_2 emissions in China, 1997-2017.

Fig. 1 shows the real GDP, energy consumption and CO_2 emission data collected in China. The real GDP grew exponentially from 1997 to 2017, while the fossil energy consumption and CO_2 emissions grew with the economic growth of China. During the period of 1997-2000, CO_2 emissions and energy consumption changed gradually and then increased sharply until 2012. It should be noted

that the energy consumption of China first decreased in 2013, and after 2013, both CO_2 emissions and energy consumption gently increased, mainly due to the implementation of the CO_2 emissions reduction strategy.

Table 3

Results of unit root test for variables.

Variables	Levin-Lin-Chu	Im-Pesaran-Shin	Breitung	Fisher
	Statistic	Statistic	Statistic	Statistic
Ln(CO_2)	-3.093***	-2.915***	-4.963***	7.811***
Ln(GDP)	-3.763***	-1.699**	-7.917***	5.449***
Ln(POP)	-12.093***	-2.795***	-3.653***	8.158***
Ln(URB)	-30.311***	-6.976***	-1.852**	10.358***
Ln(IND)	-10.065***	1.257	-4.937***	6.998***
Ln(ENER)	-2.699***	-2.019**	-2.613***	8.450***
Ln(TRAD)	-3.338***	-1.695**	-5.151***	6.542***

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3 shows the results of 4 types of unit root tests for all variables. From the results, we can find that only the variable of Ln(IND) does not pass the Im-Pesaran-Shin test, while it passes the other 3 types of unit root tests, so we can conclude that all data in logarithmic form are stable. Therefore, using these stable data, we can perform empirical analyses with spatial econometric models.

3.2 Methodologies

3.2.1 Standard deviation elliptic-gravity center model

A standard deviational ellipse (SDE) can present the overall characteristics of the spatial distribution of geographical elements (Du et al., 2019; Lefever, 1926), such as the CO_2 emissions in China. SDE has four main basic parameters: mean center, major axis, minor axis and azimuth. The mean center is the gravity center (GC) of all points of CO_2 emission data, which reveals their relative positions, while the movement of the GC can show the dynamic evolutionary trajectories of CO_2 emissions over time. The major and minor axes denote their directions and scopes, and the azimuth represents the emissions' main trend. The formulas for these parameters of the SDE-GC model are as follows:

$$X = \sum_{i=1}^{n} \omega_i x_i / \sum_{i=1}^{n} \omega_i ; \qquad Y = \sum_{i=1}^{n} \omega_i y_i / \sum_{i=1}^{n} \omega_i$$

(1)

$$\sigma_x = \sqrt{\sum_{i=1}^{n} (\omega_i x_i^* \cos\theta - \omega_i y_i^* \sin\theta)^2 / \sum_{i=1}^{n} \omega_i^2} ; \quad \sigma_y = \sqrt{\sum_{i=1}^{n} (\omega_i x_i^* \sin\theta - \omega_i y_i^* \cos\theta)^2 / \sum_{i=1}^{n} \omega_i^2}$$

(2)

$$\tan\theta = \left(\left(\sum_{i=1}^{n} \omega_i^2 x_i^{*2} - \sum_{i=1}^{n} \omega_i^2 y_i^{*2} \right) + \sqrt{\left(\sum_{i=1}^{n} \omega_i^2 x_i^{*2} - \sum_{i=1}^{n} \omega_i^2 y_i^{*2} \right)^2 - 4 \sum_{i=1}^{n} \omega_i^2 x_i^{*2} y_i^{*2}} \right) \Big/ 2 \sum_{i=1}^{n} \omega_i^2 x_i^* y_i^* \quad (3)$$

where (X, Y) represents the coordinate of the GC for CO_2 emissions; (x_i, y_i) is the geographical coordinate of province i in China; (x_i^*, y_i^*) denotes the coordinate deviation between province i and the GC; ω_i, as the weight, denotes the per capita CO_2 emissions in province i; σ_x, σ_y denotes the standard deviations along the X axis and Y axis, respectively; and θ denotes the elliptic

azimuth defined by rotating clockwise in the direction due north to the long axis of the ellipse.

3.2.2 Global Moran's Index (GMI)

The global Moran's index (GMI) can be used to measure the spatial autocorrelation of CO_2 emissions. The results of the GMI ranges from -1 to 1. If its value is significantly positive, CO_2 emissions have a positive spatial autocorrelation, denoting that regions with high or low emissions are located close together. By contrast, if the value is significantly negative, CO_2 emissions have a negative spatial autocorrelation, denoting that highly and less polluted regions are located close together. If the value of the GMI is 0, no spatial autocorrelation exists in the emissions data, indicating that CO_2 emissions are stochastic. In addition, if the absolute value of the GMI is closer to 1, the degree of spatial autocorrelation is stronger. The GMI model can be described by Eqs. (1) and (2).

$$GMI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\times\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2} \tag{1}$$

$$\mathrm{z} = \frac{\mathrm{GMI-E(GMI)}}{\sqrt{VAR(GMI)}} \tag{2}$$

$$W_g = \begin{bmatrix} w_{11}^g & w_{12}^g & \cdots & w_{1n}^g \\ w_{21}^g & w_{22}^g & \cdots & w_{2n}^g \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1}^g & w_{n2}^g & \dots & w_{nn}^g \end{bmatrix} \quad W_e = \begin{bmatrix} w_{11}^e & w_{12}^e & \cdots & w_{1n}^e \\ w_{21}^e & w_{22}^e & \cdots & w_{2n}^e \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1}^e & w_{n2}^e & \dots & w_{nn}^e \end{bmatrix} \quad W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{3}$$

where x_i and x_j are the CO_2 emissions values for the ith and jth provinces, respectively, and $\bar{x}$ is the average value of emissions for all provinces. w_{ij} is the element of W, and W is a $n \times n$ comprehensive spatial weight matrix defined based on a spatial geographic distance weight matrix and spatial economic distance weight matrix. We apply the comprehensive spatial weight

matrix of the geographic and economic distance (W) as our spatial weight matrix due to its geographic and economic features. The matrix can be defined as follows. W_g and W_e are the $n \times n$ spatial geographic distance and economic distance weight matrices, respectively, while w_{ij}^g and w_{ij}^e are their elements between provinces i and j, respectively. w_{ij}^g can be defined as the reciprocal of the distance between provinces i and j, while w_{ij}^e is the reciprocal of the GDP (2016) difference between provinces i and j. Thus, w_{ij} can be determined from the dot product of w_{ij}^g and w_{ij}^e. In addition, we also use the z score, defined as Eq. (2) to test the significance of the spatial autocorrelation.

3.2.3 Spatial panel model

Given the spatial dependence of CO_2 emissions, spatial econometric models other than nonspatial regression models should be proposed. We use a spatial panel model to quantitatively investigate the relationships between the dependent and independent variables (Lesage and Pace, 2009; Shao et al., 2020; Zeng et al., 2019). Using spatial panel models to achieve the direct, indirect and total EKCs, our analysis involves three steps: introducing the adopted spatial econometric model (SDM); estimation methods and tests; measuring the direct, indirect and total effects of Ln(GDP), Ln(GDP)^2 and Ln(GDP)^3; and developing direct, indirect and total effect EKCs. Specifically, the process is as follows. First, introducing the SDM, both spatially lagged dependent and independent variables are included in the SDM proposed by Lesage and Pace (2009). The SDM can be written as Eqs. (3)-(5).

$$Y = \alpha + \rho(W \cdot Y) + X\beta + (W \cdot X)\theta + \psi^i + \varphi^t + \varepsilon \tag{3}$$

$$Y = [\mathrm{Ln}(\mathrm{CO_2})] \tag{4}$$

$$X = [\mathrm{Ln(GDP)}, (\mathrm{Ln(GDP)})^2, (\mathrm{Ln(GDP)})^3, \mathrm{Ln(POP)}, \mathrm{Ln(URB)}, \mathrm{Ln(IND)}, \mathrm{Ln(ENER)}, \mathrm{Ln(TRAD)}] \tag{5}$$

where Y, the dependent variable (shown as Eq. (4)), represents CO_2 emissions, and α is a constant parameter. W is the comprehensive spatial weight matrix, $(W \cdot Y)$ is the spatial interaction effect of CO_2 emissions, and ρ is the coefficient of $(W \cdot Y)$. The independent variable vector X (shown as Eq. (5)) denotes factors affected on CO_2 emissions, and β is the coefficient of these factors. Similarly, $(W \cdot X)$ denotes the spatial interaction effects of influential factors found in neighboring/related provinces on local dependent variables (Y), and θ is the coefficient of these interactive effects. In specification (3), i is an index for the cross-sectional dimension (province) with $i = 1,2,\cdots,30$, and t is an index for the time dimension (year) with $t = 1997,1998,\cdots,2017$. ψ^i and $\varphi^t$are the individual- and time-specific effects, respectively. ε is the error term, which is an independently and identically distributed error term with a zero mean and variance of σ^2.

Second, estimation methods are preformed and a process is selected. The ordinary least square (OLS) cannot be used in spatial econometric models due to its biased and inconsistent estimator (Anselin, 1988), so the maximum likelihood (ML) method was proposed by Anselin (1988) to estimate spatial econometric models. For the model selection procedure, we first determine whether nonspatial models (OLSs) or spatial models (spatial lag model (SLM) or spatial error model (SEM)) are more suitable (shown as Fig. F2) with Lagrange multiplier (LM) and robust LM tests. Then, we compare SDM with SLM and SEM based on the Wald and likelihood ratio (LR) test (shown as Fig. F3). Consequently, the optimal model can be determined; then, on the basis of the optimal model,

we estimated the pooled, individual, time-period and two-way fixed models and found the best model by comparison.

Third, we measured the direct, indirect and total effects of Ln(GDP), Ln(GDP)^2 and Ln(GDP)^3 and developed direct, indirect and total effect EKCs. While calculating these three effects is our main focus, the direct effect is not necessarily the value of the estimated parameters (β), and the indirect effect is not necessarily the value of the parameters (θ) due to the nonlinear features of the economic system (Elhorst, 2014). As the volatility of dependent and/or independent variables can spread to neighboring or related regions through a special path, they may affect other provinces' dependent variables (Anselin, 1988). On the other hand, interaction effects may increase or decrease and then return to other provinces. According to the above analyses, direct, indirect and total effects should be estimated correctly. While these could not be calculated based on the estimated parameters, we tried to measure them using partial differential methods (Elhorst, 2014; Lesage and Pace, 2009). Thus, we must address two problems: measuring the three effects and testing their significance.

To calculate direct, indirect and total effects, Eq. (3) is changed to the following:

$$Y = (I - \rho \cdot W)^{-1}(X\beta + W \cdot X\theta) + R \qquad (6)$$

where R is a rest term containing a constant parameter, error term, and individual and/or time-period specific effects. The matrix of partial derivatives of the expected value of y with respect to the kth independent variable of X is determined by Eq. (7).

$$\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdots \frac{\partial E(Y)}{\partial x_{nk}}\right] = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{nk}} \\ \vdots & \vdots & \vdots \\ \frac{\partial E(y_n)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_n)}{\partial x_{nk}} \end{bmatrix} = (I - \rho \cdot$$

$$STW)^{-1}\begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_{1n}\theta_k & \\ w_{21}\theta_k & \beta_k & \cdots & w_{2n}\theta_k & \\ \vdots & \vdots & \vdots & & \vdots \\ w_{n1}\theta_k & w_{n2}\theta_k & \cdots & \beta_k & \end{bmatrix} \quad (7)$$

where w_{ij} is the element of W, elements of the diagonal line in the matrix denote direct effects, and nondiagonal elements denote indirect effects. In general, we only estimate the average value of diagonal and nondiagonal elements as direct and indirect effects, respectively. Thus, the direct effect (DE), indirect effect (IDE) and total effect (TE) of x_k are defined by Eqs. (8)-(10), respectively.

$$DE = (\frac{\partial E(y_1)}{\partial x_{1k}} + \frac{\partial E(y_2)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_n)}{\partial x_{nk}})/n = A/n \quad (8)$$

$$IDE = (\frac{\partial E(y_1)}{\partial x_{1k}} + \frac{\partial E(y_1)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_1)}{\partial x_{nk}} + \frac{\partial E(y_2)}{\partial x_{1k}} + \frac{\partial E(y_2)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_2)}{\partial x_{nk}} + \frac{\partial E(y_n)}{\partial x_{1k}} + \frac{\partial E(y_n)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_n)}{\partial x_{nk}} - A)/(n \times n - n) \quad (9)$$

$$TE = (\frac{\partial E(y_1)}{\partial x_{1k}} + \frac{\partial E(y_1)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_1)}{\partial x_{nk}} + \frac{\partial E(y_2)}{\partial x_{1k}} + \frac{\partial E(y_2)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_2)}{\partial x_{nk}} + \frac{\partial E(y_n)}{\partial x_{1k}} + \frac{\partial E(y_n)}{\partial x_{2k}} + \cdots + \frac{\partial E(y_n)}{\partial x_{nk}})/(n \times n)$$

(10)

where $y_{1,}y_{2,}\cdots y_n$ $(n = 30)$ denotes the CO_2 emissions in the 1st, 2nd, ⋯, and 30th provinces in China, while $x_{1k,}$ $x_{2k,}\cdots x_{nk}$ $(n = 30)$ represents the kth dependent variable in the 1st, 2nd, ⋯, and 30th provinces. Here, we mainly focus on the dependent variables of Ln(GDP), $(\text{Ln(GDP)})^2$ and $(\text{Ln(GDP)})^3$.

While it is also important to test the significance of direct, indirect and total effects, as there is no way to compute these values from the estimated parameters or their T-values, we attempt simulation from variance-covariance matrices based on the results of maximum likelihood

estimation for Eq. (3). We can simulate the parameter formation process due to their presumed normal distribution. We simulated this 1000 times to obtain these three interaction effects and their response T-values with MATLAB.

Finally, another key goal is to develop direct, indirect and total effect EKCs. Based on the direct effects of Ln(GDP), $(Ln(GDP))^2$ and $(Ln(GDP))^3$, the direct EKC can be developed, and the graph of the direct EKC can be obtained with the MATLAB program. Similarly, the indirect and total effect EKCs can also be developed based on the indirect and total effects of Ln(GDP), $(Ln(GDP))^2$ and $(Ln(GDP))^3$. Moreover, the long-run direct, indirect and total EKCs can be achieved by expanding the sample period through which all features of the three types of EKCs can be observed clearly.

4. Empirical analyses and results

Based on the above data and adopted methods in this study, we can achieve the spatial dependence features of CO_2 emissions with GMI, their spatiotemporal evolutionary characteristics with the SDE-GC model, and the direct, indirect and total EKC formations with SDM.

4.1 Spatial characteristics of CO_2 emissions in China

4.1.1 Spatiotemporal evolutionary process

We mapped the gravity centers and standard deviation ellipses of per capita CO_2 emissions in China from 1997 to 2017 with the SDE-GC model to analyze their dynamic spatiotemporal evolutionary process (Fig. 2).

As shown in Fig. 2, the GC geographical coordinates of per capita CO_2 emissions in China 1997 to 2017 ranged from 111.338° E~113.665° E and 35.806° N~36.214° N, from Changzhi city in

1997 to Linfen city in 2017. During the 1997-2005 period, the GC vibrated strongly, and the transfer direction was not clear; after that, it moved northwest. The long axis of the ellipse extended from 1153.158 km in 1997 to 1186.588 km in 2017, while the short axis extended from 1020.422 km to 1059.361 km. The total moving distance of the gravity center is 354.91 km, and the average annual shift speed is 17.75 km/a. Thus, we can obtain three results as follows. First, CO_2 emissions are mainly concentrated in eastern China because they are developed regions and most energy-intensive industries are distributed there. Second, during the 1997-2017 period, the GC of CO_2 emissions moved toward the west. In 2000, China implemented the strategy of developing the western region, and some industries, especially energy-intensive industries, moved to western China; thus, the GC of the CO_2 emissions moved west. Last, the extension of the long and short axes of the ellipses reveals that the CO_2 emissions have been increasing continuously, and the range is also expanding.

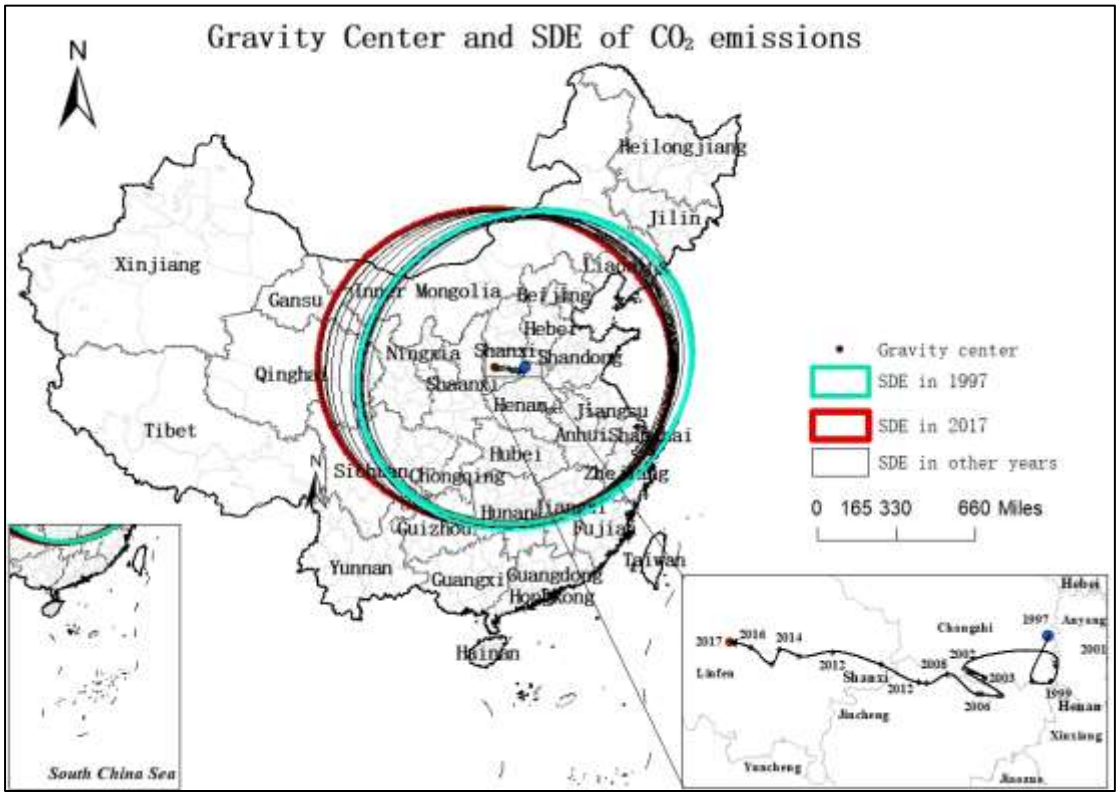

Fig. 2. Spatiotemporal evolutionary process of per capita CO_2 emissions of China 1997-2017.

4.1.2 Spatial distribution of CO_2 emissions

Fig. 3 presents the distribution of CO_2 emissions of China in 2017. High CO_2 emissions are mainly concentrated in Beijing-Tianjin-Hebei (BTH), Yangtze River delta, the Pearl River Delta and Xinjiang Province. The high emission regions in the BTH region include Hebei and Hebei's neighboring provinces, such as Liaoning, Inner Mongolia, Shanxi, Henan and Shandong provinces, and those in Yangtze River delta contain Jiangsu and Zhejiang provinces. It should be noted that Beijing city and Tianjin city, which are distributed in BTH, are low-CO_2-emission regions, and Shanghai city, which is distributed in the Yangtze River delta, also has low CO_2 emissions. Pearl River delta mainly refers to Guangdong Province. BTH, the Yangtze River Delta and the Pearl River Delta are the most developed regions in China, and most of the CO_2 emissions are produced therein. Xinjiang Province is considered a high-emission regions mainly due to the transfer of energy-intensive industries from eastern China.

The ten low CO_2 emissions regions can be divided into three categories. The first category contains municipalities directly under the Central Government, including Beijing, Tianjin, Shanghai and Chongqing, whose energy-intensive industries have been transferred out. The second category contains Qinghai, Gansu, and Ningxia provinces located in Northwest China and Jilin Province located in Northeast China, which are less-developed regions. The last category includes Yunnan and Hainan provinces, which have excellent ecological environments and developed tourism industries.

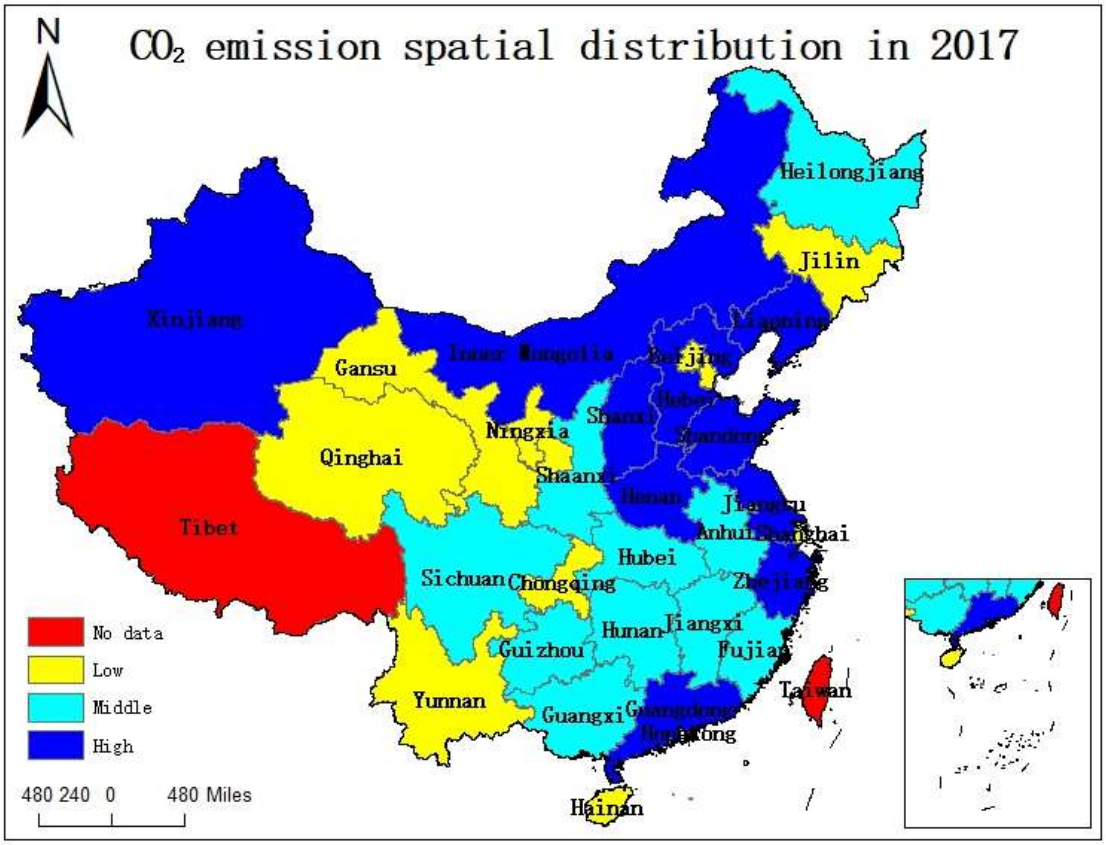

Fig. 3. CO2 emissions spatial distribution in China of 1997 and 2017.

Note：Cluster of Low, Middle and High contain 10 provinces or cities, respectively.

4.1.3 Spatial dependence of CO_2 emissions

Another spatial feature of CO_2 emissions is their spatial dependence, which can be measured by GMI. GMI can not only reflect the spatial agglomeration characteristics of CO_2 emissions but it assists in the selection of the best (spatial or nonspatial) model. Table 4 provides the GMI results for CO_2 emissions in China, and all the GMI values from 1997 to 2017 are significantly positive at the 1% level, which means that the province-level CO_2 emissions present obvious positive spatial agglomeration.

Table 4

Global Moran's Index of CO_2 emissions.

Year	GMI of CO2 Emission	Year	GMI of CO2 Emission	Year	GMI of CO2 Emission
1997	0.195***	2004	0.238***	2011	0.297***
1998	0.197***	2005	0.251***	2012	0.282***
1999	0.225***	2006	0.260***	2013	0.215***
2000	0.213***	2007	0.272***	2014	0.218***
2001	0.224***	2008	0.287***	2015	0.197***
2002	0.205***	2009	0.288***	2016	0.225***
2003	0.211***	2010	0.273***	2017	0.231***

Notes: Computed with Stata 15. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

As a result, the CO_2 emissions present obvious spatial dependence characteristics, which means that provinces with high CO_2 emissions are likely to be distributed together, and low-emission regions are generally adjacent. These findings are very similar to those of Wang et al. (2017). Based on the results, we have to take spatial dependence into consideration to achieve a more scientific EKC.

4.2 Direct, indirect and total EKCs

Considering the significant spatial dependence of CO_2 emissions, a spatial panel model should be adopted to test the EKC hypothesis. These methods can not only measure the spatial interaction effects but can also be used to study the relationship between CO_2 emissions and economic growth

from both direct and indirect perspectives; subsequently, we can obtain the three types of EKCs, namely, direct, indirect and total effect EKCs.

4.2.1 Spatial econometric model selection

Based on the model selection process above, this study first compares and tests the models for the nonspatial model (OLS) and the spatial models for SLM and SEM. Subsequently, it compares SDM with SLM and SEM to obtain the optimal model. Finally, based on the optimal model, the specific effects, including the pooled, individual fixed, time-period fixed, and two-way fixed effects, should be compared.

Table 5 displays the test results of the LM and robust LM for the OLS, SLM and SEM. From the results of pooled effect and time-period fixed of OLS, both LM and robust LM tests for the SLM and SEM are all significant, so spatial models (SLM or SEM) are better than nonspatial model (OLS). From the results of the individual fixed effects of OLS, both LM and robust LM for SEM are significant, so SEM is better than OLS. While from the two-way fixed effect SLM is better. Consequently, the spatial models (SLM and/or SEM) are better than the nonspatial model (OLS).

Table 5

Test results of OLS, SLM and SEM.

Test	OLS			
	Pooled	Individual fixed	Time-period fixed	Two-way fixed
LM spatial lag	7.633***	0.001	16.546***	7.540***
LM spatial error	48.072***	3.744*	63.991***	0.605

Robust LM spatial lag	32.214***	1.325	79.064***	8.607***
Robust LM spatial error	72.653***	5.068**	126.510***	1.672

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 6 shows the test results of Wald and LR for SDM, SLM and SEM. From the results of all four specific effects of pooled, individual fixed, time-period fixed and two-way fixed, we find that both the Wald and LR test statistics are significant, which means that SDM is better than SLM and SEM. From the results of Table 5 and Table 6, we can confirm that SLM and/or SEM are better than OLS, while SDM is more suitable than SLM and SEM, so SDM is the best model.

Table 6

Test results of SDM, SLM and SEM.

Test	SDM			
	Pooled	Individual fixed	Time-period fixed	Two-way fixed
Wald spatial lag	173.668***	29.644***	255.709***	54.245***
LR spatial lag	161.600***	30.211***	183.483***	54.543***
Wald spatial error	128.409***	24.267***	174.179***	62.947***
LR spatial error	121.053***	26.188***	117.826***	64.435***

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Given that SDM is the best model, we should compare the four specific effects (pooled, individual fixed, time-period fixed and two-way fixed) of SDM to identify which is the best. Table

7 displays the total effects of independent variables for SDM with four different specific effects. In the SDM with a pooled effect, only the total effect of Ln(IND) is not significant. In the SDM with individual fixed effects, the 4 independent variables' total effects are not significant, while in the SDM with time-period and two-way fixed effects, the 3 independent variables' total effects are not significant. As a result, the SDM with the pooled effect is our best model, and the estimated results are shown in Table 8.

Table 7

Results of total effects of independent variables for SDM with four different specific effects.

Variable	Total effects of SDM			
	Pooled	Individual fixed	Time-period fixed	Two-way fixed
Ln(GDP)	-5.025***	-13.246***	-2.931	-9.260*
$(Ln(GDP))^2$	0.653***	1.578***	0.525	1.172**
$(Ln(GDP))^3$	-0.023***	-0.058***	-0.021	-0.045**
Ln(POP)	0.135***	-0.190	0.144***	-0.441
Ln(URB)	-0.218***	-0.055	-0.212***	-0.071
Ln(IND)	-0.027	-0.184	-0.150**	-0.686***
Ln(ENER)	1.300***	0.990***	1.354***	0.986***
Ln(TRAD)	0.039***	-0.018	-0.057**	-0.050

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 8

Estimated results of SDM with pooled effect.

Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Ln(GDP)	6.823*	Ln(TRAD)	-0.052***	WLn(ENER)	0.886***
$(Ln(GDP))^2$	-0.572	WLn(GDP)	-14.109***	WLn(TRAD)	0.108***
$(Ln(GDP))^3$	0.018	$W(Ln(GDP))^2$	1.519***	$WLn(CO_2)$	-0.450***
Ln(POP)	0.051***	$W(Ln(GDP))^3$	-0.051***	R^2	0.948
Ln(URB)	0.210***	WLn(POP)	0.145***	LH	334.977
Ln(IND)	0.180***	WLn(URB)	-0.532***	σ^2	0.02
Ln(ENER)	0.999***	WLn(IND)	-0.219**		

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

After obtaining the optimal model specification, the following analytical logic is used. First, based on the partial differential approach, we calculate the direct, indirect and total effects of all explanatory variables. Second, we perform a significance test for these three effects based on the variance-covariance matrices obtained from the ML results. Third, according to the direct, indirect and total effects of Ln(GDP), $(Ln(GDP))^2$ and $(Ln(GDP))^3$, we can develop the direct, indirect and total EKCs shown in Fig. 4.

4.2.2 Results of direct, indirect and total EKCs

First, we evaluated the direct EKC (Subfigure (a) & (d) in Fig. 4). The direct EKC forms a line due to the nonsignificant direct effect of $(Ln(GDP))^2$ and $(Ln(GDP))^3$. The linear characteristics suggest that the local CO_2 emissions increased rapidly during the sample period as the economy

grew in the same region. Similarly, Wang and Liu (2017) found that per capita CO_2 emissions have been increasing continuously since 1992 in Chinese cities. In addition, Shan et al. (2016) also stated that provincial aggregated CO_2 emissions increased from 3160 million tons in 2000 to 8583 million tons in 2012. These findings indicate that the extensive economic growth mode has not been completely transformed and that the share of energy-intensive industries was still larger during 1997-2017.

Table 9

Three types of effects of influential factors on CO_2 emissions.

Variable	Direct effect	Indirect effect	Total effect
Ln(GDP)	8.203**	-13.228***	-5.025***
$(Ln(GDP))^2$	-0.714	1.367***	0.653***
$(Ln(GDP))^3$	0.023	-0.045***	-0.023***
Ln(POP)	0.042***	0.093***	0.135***
Ln(URB)	0.254***	-0.473***	-0.218***
Ln(IND)	0.200***	-0.227***	-0.027
Ln(ENER)	0.968***	0.332***	1.300***
Ln(TRAD)	-0.062***	0.101***	0.039***

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Second, we evaluated the indirect EKC (Subfigure (b) & (e) in Fig. 4). The short-run EKC during 1997-2017 also exhibits a gentle rising stage within the long-run EKC; we can deeply

understand the relationship between CO_2 emissions and economic growth from the long-run curve (subfigure (b)), which looks like a lying-S shape. There are 3 obvious stages within the indirect EKC. The CO_2 emissions decrease at first, then have a steady transition stage at the second stage, and finally drop sharply. According to the long-run EKC (subfigure (b)), the CO_2 emissions in the local region decrease sharply with the economic growth of neighboring or related regions at an early stage and then enter a gentle rising stage; after the turning point, emissions will decrease rapidly.

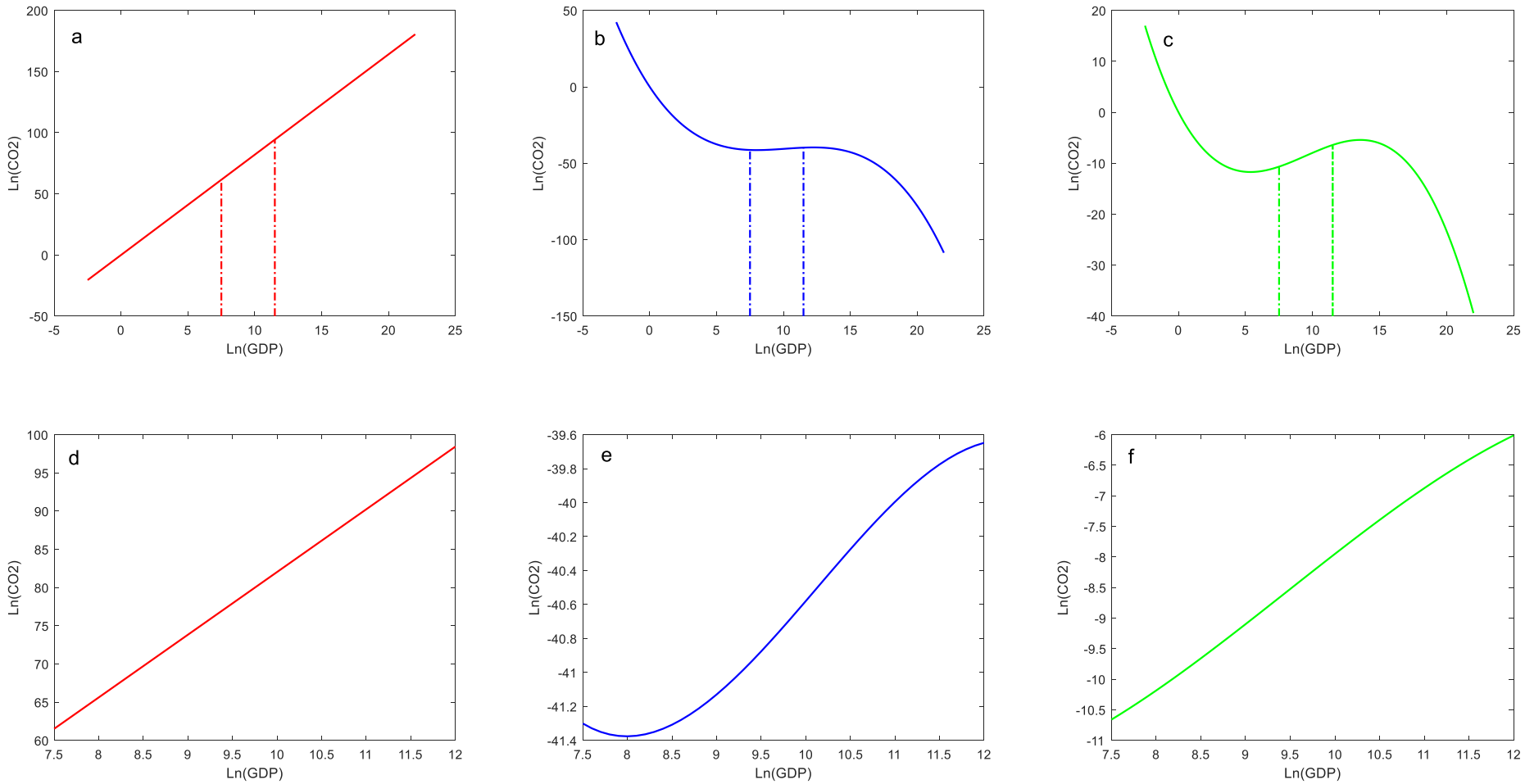

Fig. 4. Three types of EKC. (a) is long-run direct EKC, (b) is long-run indirect EKC, (c) is long-run total EKC, (d) is short-run direct EKC, (e) is short-run indirect EKC and (f) is short-run total

499 EKC.

Third, we evaluated the total EKC (Subfigure (c) & (f) in Fig. 4). At present, the short-run total EKC, which is marked with a dashed line in the long-run total EKC, is in a gentle upward phase. The long-run total EKC is also similar to a lying-S, which is similar to the long-run indirect EKC. From the long-run view, after a sharp reduction phase, the CO_2 emissions gently increase until reaching the turning point and then drop rapidly again with further economic growth in China. From the total EKC perspective, the shape of the EKC is a lying-S. There are some deviations from the conventional inverted-U shape shown in Fig. F1, which suggests that CO_2 emissions do not have to increase all the time in the early economic development stage; namely, considering the indirect (spillover) effects of economic development, emissions reduction may appear at some early time.

Based on the results of direct, indirect and total EKCs, we can obtain three interesting conclusions as follows.

First, the economic growth of neighboring regions plays a very different role in influencing the local CO_2 emissions compared to that of the local region. Local economic growth stimulates emissions all the time, while economic growth from neighboring regions may be restricted, subsequently stimulated gently, and finally strongly restrict the enhancement of CO_2 emissions after the turning point. Therefore, the different roles of economic growth in native and neighboring regions should be considered when we promulgate some carbon emission reduction policies.

Second, the shape of the total EKC is determined by that of the indirect EKC, which indicates that the impacts of the neighboring economy on local CO_2 emissions are much stronger than those from the local region. However, it is worth noting that the range of neighbors is closely determined by the adopted spatial weighting matrix, and this study takes the economic and geographic comprehensive matrix as our spatial weight matrix. Therefore, the neighboring regions refer to all

other regions, while the nearer the distance and the higher the similarity of the economy, the larger the spatial weight. Suppose that the economy of the neighboring areas grows while that of the local area does not change significantly, and the energy-related CO_2 emissions may be decreased or increase gently in the local region. For example, compared with the developed eastern coastal area, the CO_2 emissions in some less-developed provinces, such as Hainan and Qinghai provinces, remain much lower than those in other provinces. These important and interesting findings suggest that, first, the indirect impacts of economic development and indirect EKCs are important, and we should pay attention to them; second, CO_2 emissions are a larger-scale regional matter, we should take multiregional effective measures, rather than restricting efforts to one region, to achieve CO_2 reduction targets.

Finally, the relationship between economic growth and CO_2 emissions has a lying-S (similar to inverted-N) shape but not a regular inverted-U shape. This is slightly different from the results of the conventional EKC shown in Fig. F1, which has a regular inverted-U shape. Similarly, Li, J. et al. (2019) confirmed that the relationship between the carbon intensity of human wellbeing (CIWB) and economic growth has an inverted-N shape in China. Another example came from Ana et al. (2014), who also reported that an inverted-N curve was estimated for the relationship between CO_2 emissions and GDP per capita with EU-27 panel data. It should be noted that the lying-S shape is not a denial of the EKC hypothesis but a useful supplement to it. The lying-S shaped curve, which indicates that the CO_2 emissions do not have to increase constantly during the early stage, contains more information than the conventional EKC hypothesis.

In summary, this study takes the spatial dependence of CO_2 emissions and economic growth into the analysis framework and investigates the relationship between CO_2 emissions and economic

growth from direct, indirect and total effects perspectives. Furthermore, the direct, indirect and total EKCs can provide more information than the conventional EKC. Compared with the conventional EKC (Fig. F1), the turning point of the total EKC (subfigure (c) in Fig. 4) will occur much earlier due to the existence of an indirect EKC, and this finding was confirmed by Balado-Naves et al. (2018). However, note that we do not encourage the use of long-run accurate predictions, such as the turning point of the EKC, with these models. The value of these kinds of EKC analyses is the revelation of the developed trend of the relationship between CO_2 emissions and economic growth and the different effects of income, scale, composition and technology during different economic growth phases, as opposed to predicting the accurate value of dependent variables (CO_2 emissions) (Sarkodie and Strezov, 2018).

4.3 The impacts of other control variables on CO_2 emissions

Based on the partial derivative approach, we can achieve the impacts of control variables, Ln(POP), Ln(URB), Ln(IND), Ln(ENER) and Ln(TRAD), from direct, indirect and total perspectives (shown in Table 9). Considering the difference between the direction of direct and indirect effects, we take these variables into two types as follows.

The first type includes the variables Ln(POP) and Ln(ENER), which have the same directions of direct and indirect impacts. The direct and indirect effects of Ln(POP) are 0.042 and 0.093, respectively, and they are significant at the 1% level, which indicates that an average 1% rise in the local population will lead to a 0.042% increase in CO_2 emissions in the local region, and a 1% growth in the population of neighboring regions will also result in a 0.093% increase in the local region. Thus, due to the significantly positive direct and indirect effects, the total effect is 0.135, which is greater than that of the direct and indirect effects. For the variable Ln(ENER), the direct

and indirect effects are 0.968 and 0.332, which means that a 1% increase in energy intensity in local/neighboring regions can lead to 0.968%/0.332% emission growth in the local region, and these results in a total effect of Ln(ENER) of 1.300, which indicates that an average 1% decline in energy intensity can lead to a decrease in CO_2 emissions by 1.3%.

The second type contains Ln(URB), Ln(IND) and Ln(TRAD), which have different directions of direct and indirect impact. The direct and indirect effects of Ln(URB) are 0.254 and -0.473, respectively, and they are significant at the 1% level, which indicates that a 1% rise in the local urbanization rate will lead to a 0.254% increase in CO_2 emissions in the local region, and a 1% growth in neighboring regions' urbanization rate will result in a 0.473% reduction in the local region. Thus, due to the significantly positive direct and negative indirect effects, the total effect is -0.218, which reflects that its direction is the same as that of the indirect effect, while its magnitude is less. For the variable Ln(IND), the significant values of the direct and indirect effects are 0.200 and -0.227, respectively, which means that each 1% increase in the proportion of secondary industry in GDP from local/neighboring regions can lead to a 0.200% and -0.227% growth in the local region. However, the total effect of Ln(IND) is nonsignificant due to the opposite direction and minor difference in magnitude of direct and indirect effects. Similarly, the values of the direct and indirect effects of Ln(TRAD) are -0.062 and 0.101, respectively, and they pass the significance test at the 1% level. These results indicate that each 1% rise in the openness of local regions can lead to a 0.062% reduction in emissions, while a 1% growth in neighboring regions can result in a 0.101% increase. Although its total effect is significantly positive, the magnitude is less than that of the indirect effect.

In summary, the analyses of direct and indirect effects can explore the impacts of explanatory

variables on CO_2 emissions from direct (local) and indirect (neighboring) perspectives. The total effect will be reinforced with the same direction of direct and indirect effects, while it will be mitigated or even nonsignificant with different directions. Specifically, the growth of the population in both local and neighboring regions may stimulate carbon emissions. For instance, nearly half of the population in China is concentrated in the BTH region, the Pearl River Delta and Yangtze River delta, and the CO_2 emissions in these regions accounted for 61.15% in 2017. The improvement of industrial technology (energy intensity, Ln(ENER)) of local and neighboring regions can lead to a reduction in carbon emissions. Overall, an increase in the urbanization rate is beneficial to carbon emissions reduction, while this may stimulate emissions in the local region. The increase in the proportion of secondary industry in the GDP can result in the rise of CO_2 emissions in the local region, while it can be beneficial to its neighboring regions. However, the comprehensive effect is not significant, which indicates that industrialization is the essential process for economic development. Consequently, considering the development of the whole country in the long run, we should improve the industrial level in the appropriate region, although these may be harmful for the local region in the short run. From the total effect of Ln(TRAD), trade openness may stimulate an increase in emissions, which indicates that we may export more energy-intensive products (e.g., steel and iron) and import more nonenergy-intensive products (e.g., integrated circuit products).

5 Conclusion

The EKC hypothesis for CO_2 emissions has always been the studied focus due to its importance in examining the relationship between income and the environment, but little research has separated direct and indirect effects from the total effect. Therefore, this paper first studied the spatiotemporal evolutionary process of CO_2 emissions in China based SDE-GC model, and the spatial

characteristics with GMI method, and then investigated the relationship between economic growth and CO_2 emissions from the three perspectives of direct, indirect and total effects with SDM. According to the empirical results above, the following major conclusions can be drawn.

First, China's CO_2 emissions have obvious spatiotemporal evolutionary features. The gravity center of per capita CO_2 emissions has shifted toward the west mainly due to energy-intensive industrial transfer. Additionally, the high CO_2 emissions were mainly concentrated in the BTH region, Yangtze River delta and Pearl River delta, which are the most developed regions in China, and carbon emissions presented significant spatial dependence. Second, the greatest contribution to the existing literature is that we obtained three types of relationship curves between CO_2 emissions and economic growth: direct EKC, indirect EKC and total EKC. Compared with the conventional EKC, these three types of EKCs can provide more comprehensive information. Finally, local economic indicators may have the same directional impacts as neighboring indicators, such as population and energy consumption per GDP, which will lead to the total impacts on carbon emissions being enhanced. However, the different directions of the impacts of economic indicators between local and neighboring regions can reduce the impacts on emissions, such as urbanization rate, proportion of secondary industry and trade openness.

Additionally, our findings provide new evidence that local CO_2 emissions are closely related to not only local economic conditions but also the economic growth of neighboring areas; furthermore, the influence of neighboring regions may be much stronger. Therefore, according to the empirical results regarding direct, indirect and total effect EKCs, this paper provides more sufficient information for carbon market regulars and policy makers to develop scientific CO_2 emissions reduction strategies in the following four ways. First, policy makers should pay close

attention to local economic growth and neighboring economic conditions due to the strong spillover effects of the economy. Second, the total population needs to be controlled to an appropriate level due to its local and neighboring negative effects on carbon emissions, while urbanization related to population structure can be improved because of its total reduction effects, although it is not beneficial to local emissions. Third, the industrialization proxy for the share of secondary industry seems to be nonsignificant for emissions as a whole, which is similar to the assertions by Balado-Naves et al. (2018) that the degree of service sector is almost nonsignificant for carbon emissions. Fourth, technology related to energy intensity has to be improved for the impacts on emissions in both local and neighboring regions, and the technology impacts are the largest in these control variables.

It should be noted that there is also some further work needed on this topic of this paper. For instance, under the direct, indirect and total effect EKCs studied framework, it is meaningful to investigate the spatial heterogeneity of the three types of EKCs. In addition, it is another useful work to explore whether there are some differences in the three types of EKCs among countries with different income levels.

Acknowledgments

The paper is supported by Guizhou Key Laboratory of Big Data Statistical Analysis (No: BDSA20200109), Talent introduction fund of Guizhou University of Finance and Economics (No: 2018YJ68), Research project of Humanities and Social Sciences in Colleges and universities of Hebei Province (No: BJ2017089), National Social Science Foundation of China (No: 17BJY076).

Declarations

Author statement

Manuscript title:

I have made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; AND

I have drafted the work or revised it critically for important intellectual content; AND I have approved the final version to be published; AND

I agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

All persons who have made substantial contributions to the work reported in the manuscript, including those who provided editing and writing assistance but who are not authors, are named in the Acknowledgments section of the manuscript and have given their written permission to be named. lf the manuscript does not include Acknowledgments, it is because the authors have not received substantial contributions from nonauthors.

Credit Author Statement(Author Contributions):

Langang Feng: Conceptualization, Methodology, Software,Writing – original draft,Funding acquisition. **Xiangyun Gao:** Data curation, Writing – review & editing. **Sufang An:** Visualization, Formal analysis. **Xiaodan Han:** Supervision. **Shu Shang:** Software, Validation.

Declaration of interests

☒ 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.

☒The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

None

Ethics approval and consent to participate

The studies involving human participants were reviewed and approved by the Academic Committee of Guizhou University of Finance and Economics. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Consent for publication

All authors have read and approved the manuscript being submitted，and agree to its submitted to this journal for publication.

The statement of availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request. Meanwhile, all origional data generated or analysed during this study are included in the supplementary information files.

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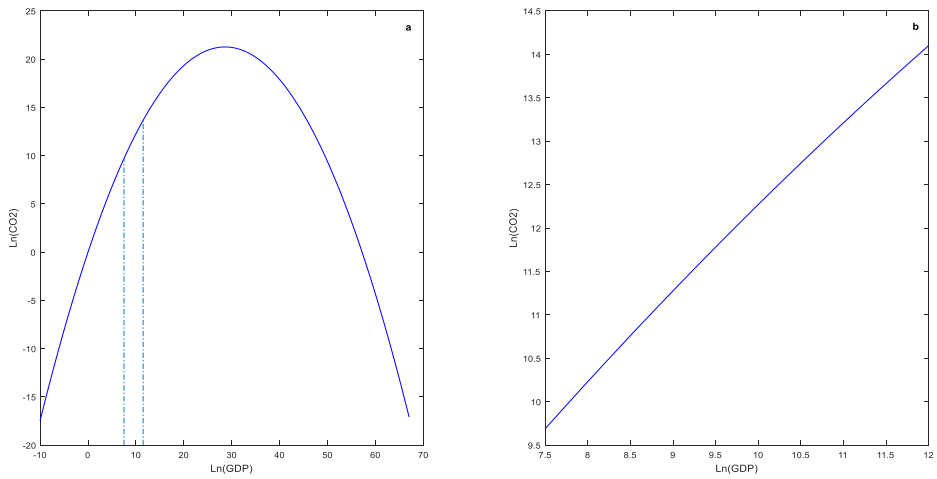

Fig. F1. EKC based on common panel model. (a) is the long-run EKC, (b) is the short-run EKC.

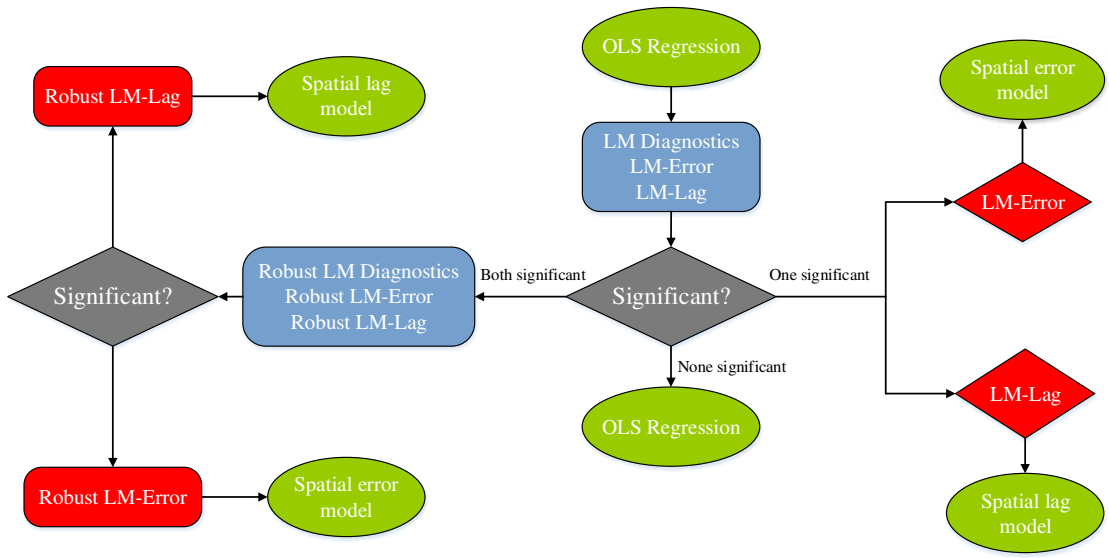

Fig. F2. Test of OLS, SLM and SEM

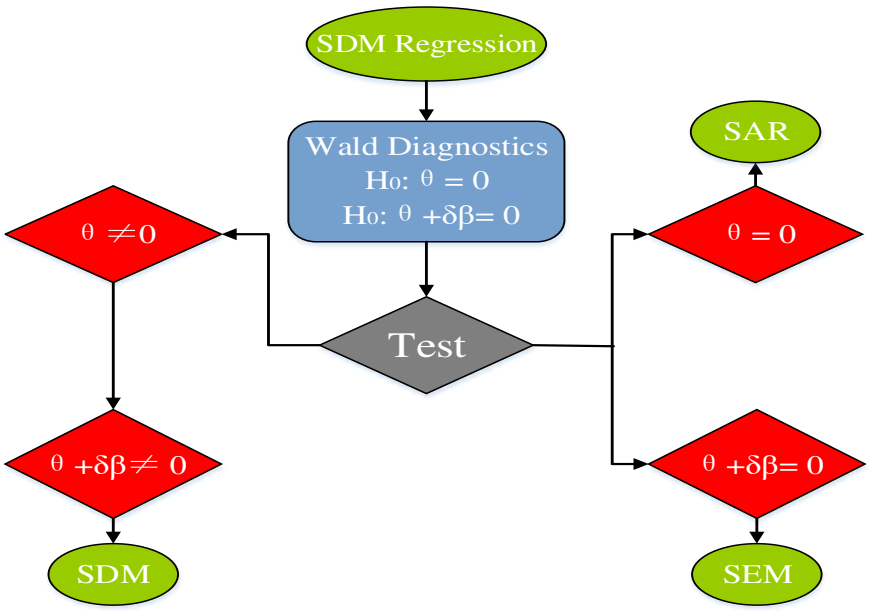

Fig. F3. Test of SDM, SLM and SEM

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