Ecological Indicators 129 (2021) 108001

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Spatial heterogeneity and economic driving factors of SO_2 emissions in China: Evidence from an eigenvector based spatial filtering approach

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A R T I C L E I N F O

Keywords:
Environmental sustainability
Spatial dependence
Economic determinants
Non-spatially varying coefficients
Province-specific policies

A B S T R A C T

Sulfur dioxide (SO_2) emissions have been a great challenge in China over the last few decades due to their serious impact on the environment and human health. In this paper, a random effect eigenvector spatial filtering (RE-ESF) approach without and with non-spatially varying coefficients (SNVC) is identified to examine spatial heterogeneity and economic driving factors of SO_2 emissions in China from 2011 to 2017. Using the Moran eigenvectors to extract information on spatial dependence, the main findings of the RE-ESF approach are as follows: First, after comparing different approaches for dealing with spatial dependence, it is found that the RE-ESF approach demonstrates the best fit to the dataset. Second, the global investigation shows that SO_2 emissions are negatively determined by economic growth and government expenditure for environment protection, but are positively determined by road freight transport, coal consumption and oil consumption. Third, the local investigation indicates that the spatially varying coefficients of economic growth and coal consumption range from 0.1401 to 0.2732 with the median value of 0.2478 and from 0.2406 to 0.3611 with the median value of 0.3210, respectively, revealing significant spatial heterogeneity of SO_2 emissions driven by economic growth and coal consumption. These findings provide meaningful insights into centralized and province-specific policies for reducing SO_2 emissions.

1. Introduction

Over the last few decades, China's rapid economic growth has relied heavily on coal and oil consumption, which makes China one of the largest sulfur dioxide (SO_2) emitters (Ling et al., 2017). According to the report by Greenpeace Environment Trust (GET, 2019), China, as the third largest SO_2 emitter in 2018, contributed about 8% of global anthropogenic SO_2 emissions with 2,578 kilotonnes per year (kt/yr), following India (4,586 kt/yr) and Russia (3,683 kt/yr). The huge amount of SO_2 emissions in China causes not only severe environmental damages in terms of deforestation, soil and water acidification, corrosion on building materials and air pollution, but also serious health problems such as cardiovascular abnormalities, nose and throat irritation, and bronchoconstriction and dyspnea (Liu and Wang, 2013; Li et al., 2019; Liu et al., 2019). As a result, these SO_2 emissions have challenged environmental sustainability in China, reducing the possibility of providing abundant natural resources, clean air, and fresh water for future generations to live a life equal to current generations.

To improve environmental sustainability, the Chinese government has enforced more stringent SO_2 emission standards and implemented a series of emission control measures since 2005 (Ling et al., 2017). Nevertheless, the fact that China remains the third largest SO_2 emitter in the world requires further attention to SO_2 emission reduction (GET, 2019). An ever-deepening understanding of the role of economic activities in influencing SO_2 emissions attracts more researcher attention to identify economic driving factors of SO_2 emissions due to their profound policy implications. Previously, the Environmental Kuznets Curve (EKC) hypothesis (Kuznets, 1955) and the impacts of population, affluence and technology (IPAT) model (Ehrlich and Holdren, 1971) have been extensively applied to identify factors of pollution emissions. As suggested by the EKC hypothesis, economic growth plays a fundamental role in influencing pollution emissions, which leads to increased

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https://doi.org/10.1016/j.ecolind.2021.108001
Received 28 October 2020; Received in revised form 7 July 2021; Accepted 16 July 2021
Available online 26 July 2021

pollution in its early stages but leads to environmental improvement at high income levels. Two more fundamental factors (i.e., population and technology) and additional factors have also been identified, which will be discussed in Section 2.

Considering the diffusion and transport effects, SO_2 emissions in a region inevitably influence its neighbors' environmental quality. Although ecological and meteorological conditions (e.g., forest coverage, wind speed, atmospheric pressure) can influence this process, they are usually beyond policymakers' control in the short run, shifting policymakers' attention to the aforementioned economic driving factors of SO_2 emissions from a spatial perspective. To examine factors of air pollutant emissions across regions in China, a common way is to divide the whole provincial dataset into western China, eastern China and central China for a comparison purpose (Zhou and Liu, 2016; Wang et al., 2017; Ahmad et al., 2021a). However, this cannot investigate the global and local relationships between factors and emissions simultaneously. Moreover, previous studies mainly employed the number of registered vehicles to measure the vehicle population (Zhao et al., 2018; Zhang et al., 2019). It is widely recognized that vehicular exhaust emissions are more closely related to actual road transportation activities which can be measured by the road turnover rather than by the number of registered vehicles.

The above two gaps motivate us to re-examine spatial heterogeneity and economic driving factors of SO_2 emissions by employing the random effect eigenvector spatial filtering (RE-ESF) without and with non-spatially varying coefficients (SNVC) models due to their best goodness-of-fit performance. After filling these gaps, this paper can make contributions in the following two aspects. First, to better represent the actual road transportation activities, the road freight turnover and the road passenger turnover are chosen to replace the vehicle density, deepening the understanding of how road transport affects SO_2 emissions. Second, an empirical investigation of both the global and local relationships between economic driving factors and SO_2 emissions provides us with profound basis for developing appropriate centralized and province-specific policies for reducing SO_2 emissions in China.

The rest of this paper is organized as follows. Section 2 reviews economic driving factors of SO_2 emissions. Section 3 introduces the dataset and the empirical model addressing spatial dependence. Section 4 presents empirical results and discussions. Section 5 concludes this paper.

2. Literature review

A fundamental issue for developing appropriate SO_2 emission reduction policies is to identify economic driving factors of SO_2 emissions, which has been commonly addressed under the EKC and IPAT frameworks. Considering the potential spatial dependence of SO_2 emissions, a further step is to investigate how factors affect SO_2 emissions spatially.

2.1. Economic driving factors of SO_2 emissions

The EKC hypothesis has traditionally been employed to analyze the relationship between pollutants and economic growth. Inspired by Kuznets (1955) who suggested an inverted U-shaped relationship between income inequality and economic growth, Grossman and Krueger (1991); Grossman and Krueger (1995) found a similar relationship between a country's per capita income and its air and water pollution concentrations. A few studies have further supported the inverted U-shaped relation, including Roca et al. (2001); Stern (2004); Poon et al. (2006); Fodha and Zaghdoud (2010); Fosten et al. (2012); Wang et al. (2016); Sinha and Bhattacharya (2017); Yang et al. (2018). Nevertheless, evidence against the EKC hypothesis has also been provided. For example, a U-shaped relation between income and SO_2 concentrations was suggested by Kaufmann et al. (1998); Shen (2006); Ye et al. (2018). An N-shaped relationship between gross domestic product (GDP) per capita and SO_2 emissions was found by Llorca and Meunié (2009) and Huang (2018). In addition, Zhang et al. (2019) concluded that the relationship between SO_2 emissions and GDP per capita did not follow the EKC hypothesis.

Apart from economic growth, there is also a huge body of literature identifying additional emission factors with energy consumption being the most popular one in recent studies. For example, Irfan et al. (2019) found that CO_2 emissions could be reduced considerably by using the solar photovoltaic system to replace fossil fuels. Ahmad et al. (2020) supported a positive and unilateral causal impact of the intensity of energy use on CO_2 emissions in China. Findings of Li and Li (2020) indicated an emission promotion impact resulting from the energy-industry investment and Ahmad et al. (2021b) further suggested that the transformation of China's energy-industry structures should focus more on renewable energy technologies and more energy-efficient technological setup. Similar suggestions were provided by Alvarado et al. (2021) for alleviating global warming and Yang et al. (2021) for reducing $PM_{2.5}$ concentrations. Other factors mainly include population (Sinha and Bhattacharya, 2017), industrial structure (Llorca and Meunié, 2009), vehicle population (Zhang et al., 2019), trade activity (Harbaugh et al., 2002), race and education (Khanna and Plassmann, 2004), foreign direct investment (FDI; Llorca and Meunié, 2009), urbanization (Wang et al., 2016), environmental regulation (Yang et al., 2018), expenditure on environmental protection (Huang, 2018), and technology investment (Zhang et al., 2019).

On the other hand, the IPAT model together with its stochastic

Table 1
Previously identified economic driving factors of SO_2 emissions.

Determinants	Representative indicators and references
Economic growth or Affluence	per capita GDP (Grossman and Krueger, 1991; Grossman and Krueger, 1995; Wang et al. 2016)
Population	Population density (Selden and Song, 1994; Khanna and Plassmann, 2004; Sinha and Bhattacharya, 2017)
Technology	Number of university faculty and number of employees in the science and technology industry (He et al., 2017)
	Ratio of science and technology investment to the total investment (Zhang et al., 2019)
	Patent counts granted (Su and Yu, 2020)
Industrial structure	Share of the secondary industry sector (He et al., 2017; He and Lin, 2019)
	Tertiary industry GDP and secondary industry GDP (Zhao et al., 2018)
Urbanization	Ratio of non-agricultural population (He et al., 2017)
Energy consumption and energy structure	Electricity consumption (He et al., 2017)
	Energy intensity expressed as the ratio of total energy consumption to regional real GDP (He and Lin, 2019)
	Ratio of coal consumption to total energy consumption (Zhang et al., 2019)
	Combustion of petroleum products (Sinha and Bhattacharya, 2017)
Vehicle population	Proportion of the number of civilian vehicles to the total length of roads (Zhao et al., 2018; Zhang et al., 2019)
Trade and investment	FDI (Llorca and Meunié, 2009; Huang, 2018; Zhang et al., 2019)
	Trade intensity measured by the ratio of the sum of exports and imports to total GDP (Huang, 2018)
	Urban transportation investment (Yang et al., 2018)
Environmental expenditure	Governmental expenditure on environmental protection (Huang, 2018)
Environmental regulation and tax policy	Ratio of completed investments in waste gas control to total industrial SO_2 emissions (He and Lin, 2019)
	SO_2 tax (Xie et al., 2018)
	Sewage treatment (Yang et al., 2018)
Heat	Urban heated area (Zhao et al., 2018)
	Quantity of heat supplied (Huang, 2018)
Forest coverage	Forest coverage rate (Zhang et al., 2019)

Notes: Data were collected and summarized by authors.

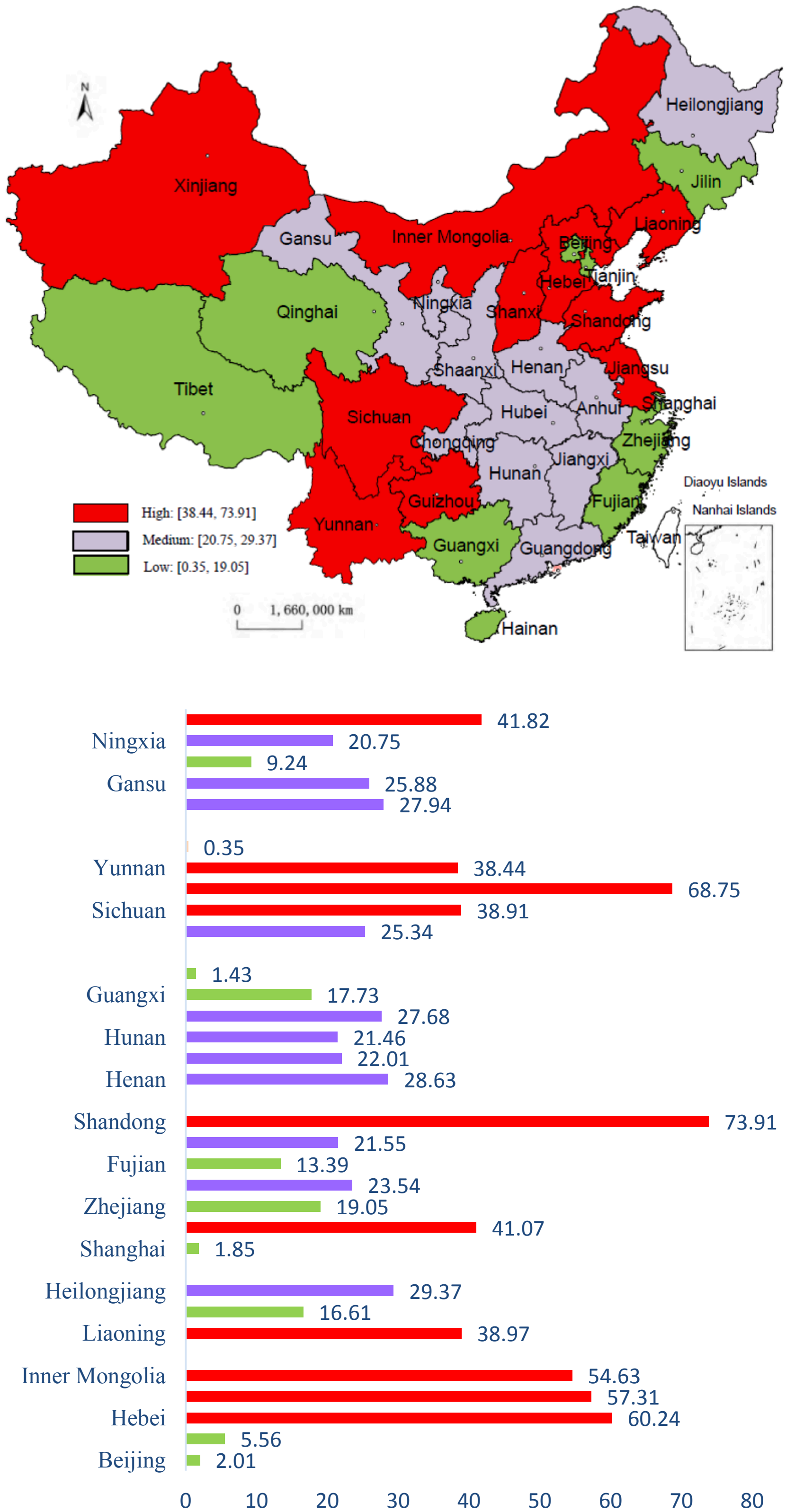

Fig. 1. Spatial distribution of provincial SO_2 emissions (10,000 tons) in China in 2017.

version (i.e., STIRPAT model) is also commonly used to reveal how a country's population size, affluence, and technology drive the environmental impact (Ehrlich and Holdren, 1971). However, previous studies have focused mainly on carbon dioxide (CO_2) and particulate matter (PM) emissions, paying insufficient attention to SO_2 emissions. For example, using a semi-parametric panel data analysis in the STIRPAT model, Wang et al. (2016) found evidence supporting an inverted U-shaped relation between economic growth and SO_2 emissions in China, but found no evidence supporting such relation between urbanization and SO_2 emissions. He et al. (2017) found that a higher urbanization level tended to increase SO_2 emissions and claimed that industrialization was a key driving factor of SO_2 emissions in China. As a result, the most frequently used economic driving factors of SO_2 emissions can be identified and reported in Table 1.

2.2. Approaches for dealing with spatial dependence

As noted earlier, the potential spatial dependence of SO_2 emissions create profound implications for province-specific policies for reducing SO_2 emissions. To capture potential spatial dependence adequately, extant studies have made tremendous efforts to identify the most appropriate spatial model. First, with the aim of identifying different sources of spatial dependence, the spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM) have been proposed and extensively applied (LeSage and Pace, 2009; Elhorst, 2014). More specifically, the SLM indicates that SO_2 emissions in a province depend not only on its own driving factors but also on its neighbors' SO_2 emissions. That is, the observed spatial dependence is from the spatially lagged SO_2 emissions. Compared with the SLM, the SEM has advantages in capturing different sources of spatial dependence which relate to shocks to a wider range of driving factors not just shocks to SO_2 emissions. As an extension of the SLM and SEM, the SDM identifies sources of spatial dependence of SO_2 emissions as the combination of the spatially lagged SO_2 emissions and the spatially lagged driving factors (Shi et al., 2020). Despite their advantages in identifying sources of spatial dependence, the SLM, SEM and SDM are essentially global models describing a spatial equilibrium state, making them disadvantageous in capturing the local relationships between SO_2 emissions and driving factors (Xu and Lee, 2019; Yu et al., 2020).

The second commonly used approach for dealing with spatial dependence is the geographically weighted regression (GWR) model. By viewing the dependent variable (i.e., SO_2 emissions) in each location (i.e., province) as a linear function of independent variables (i.e., driving factors), the GWR model generates spatially varying coefficients (SVC) and reveals the local relationships between SO_2 emissions and driving factors (Wu et al., 2014; Murakami et al., 2017). To capture temporal effects as well, the GWR model can be further extended to the geographically and temporally weighted regression (GTWR) model which deals with both spatial and temporal non-stationarity simultaneously in SO_2 emissions (Huang et al., 2010). However, the problems of multicollinearity and uniform smoothers make the GWR and GTWR models less attractive in empirical studies (Páez et al., 2011; Murakami et al., 2017).

Third, to overcome the above computational problems, the ESF model, especially the RE-ESF approach, has gained ever-increasing attention in the literature on dealing with spatial dependence. As proved by Murakami and Griffith (2015) and Murakami et al. (2017), the RE-ESF approach without and with SNVC demonstrated advantages in overcoming multicollinearity, improving computational efficiency, and increasing estimation accuracy. Moreover, both the global and local relationships between dependent variable and independent variables can be captured simultaneously, making it more popular in empirical studies (Yu et al., 2020). Then, the RE-ESF approach is identified in this paper to investigate spatial heterogeneity and economic driving factors of SO_2 emissions in China.

Table 2
Test for spatial dependence Moran's *I*.

Year	Moran's *I*	p-value
2011	0.136*	0.057
2012	0.131*	0.063
2013	0.127*	0.067
2014	0.122*	0.073
2015	0.132*	0.060
2016	0.100	0.105
2017	0.098	0.103

Note: * indicates statistical significance at 10% level.

3. Data and methodology

3.1. Economic driving factors and data sources

As previously discussed, the IPAT and STIRPAT models can be formulated as Eqs. (1) and (2), respectively (Ehrlich and Holdren, 1971; Dietz and Rosa, 1997).

$$I = P \cdot A \cdot T \tag{1}$$

$$I_t = a_0 P_t^{a_1} A_t^{a_2} T_t^{a_3} e_t \tag{2}$$

where I indicates the environmental impact and it depends on a country's population size (P), affluence (A), and technology (T). t denotes the time, a_0, a_1, a_2, a_3 indicate parameters, and e is the error term.

Referring to the STIRPAT framework and previous studies, three fundamental factors and seven additional economic driving factors of SO_2 emissions are identified in this paper. Fig. 1 displays the spatial distribution of the total annual volume of SO_2 emissions in China in 2017. Three fundamental factors (i.e., affluence, population and technology) are represented by per capita gross regional product (*pgrp*), population density (*pd*) measured by the number of people per square kilometer, and the number of patent counts granted (*tech*), respectively. Seven additional factors are industrial structure (*is*), urbanization (*urb*), road freight turnover (*rft*), road passenger turnover (*rpt*), coal and coke consumption (*coal*), oil consumption (*oil*), and governmental expenditure for environmental protection (*eep*).

Notably, *pgrp* is calculated by dividing the gross regional product by the population size, *is* is measured by the share of the secondary industry in GDP, *pd* is measured by the number of people per square kilometer, and *urb* is expressed as the ratio of urban population to the total population. *rft* (*rpt*) refers to the sum of the product of the volume of transported cargo (passengers) multiplied by the transport distance. For further empirical analysis, a balanced panel dataset of 29 Chinese provinces, autonomous regions, and municipalities from 2011 to 2017 was collected from the China Statistical Yearbook (2012–2018)[1], yielding 203 observations. In addition, to eliminate the impact of inflation, the consumer price index, with the year 2011 being the base year, was used to convert *pgrp* and *eep* from nominal values to real values. To further examine spatial heterogeneity of SO_2 emissions, the collected data will be processed as follows: 1) Using Moran's I to preliminarily test the presence of spatial dependence of SO_2 emissions; 2) Estimating a pooled panel data model without consideration of spatial dependence as a benchmark for comparison; 3) Identifying the most appropriate spatial model by comparing their goodness-of-fit; 4) Investigating the global and local relationship between different economic driving factors and SO2 emissions.

3.2. Moran's I

Prior to presenting the empirical spatial model, a preliminary step is to test the presence of spatial dependence of SO_2 emissions in China over 2011–2017, which can be achieved by calculating Moran's *I* (Moran, 1950).

$$I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(SO_{2,i} - \overline{SO_2})(SO_{2,j} - \overline{SO_2})}{\sum_{i=1}^{N}(SO_{2,i} - \overline{SO_2})^2} \tag{3}$$

where N is the number of provinces. $SO_{2,i}$ and $SO_{2,j}$ are the SO_2 emissions in provinces i and j, respectively. $\overline{SO_2}$ denotes the mean of SO_2, and w_{ij} is

[1] http://www.stats.gov.cn/tjsj/ndsj/; Tibet and Hainan were excluded due to their poor data availability.

the row i^{th}-column j^{th} element of the spatial weight matrix W which quantifies the spatial relation among provinces. Due to the diffusion and transport effects of SO_2 emissions, it is more likely to observe that contiguous provinces affect each other. As a result, the binary contiguity weights with the Queen rule are used to construct W (Anselin and Griffith, 1988).

As shown in Eq. (3), Moran's I lies within the range [-1, 1]. A positive value indicates that provinces with high or low SO_2 emissions tend to spatially cluster, while a negative value implies that provinces with high and low SO_2 emissions tend to spatially disperse. Table 2 reports the results of Moran's I. As observed, the calculated Moran's I for SO_2 emissions were positive and exhibited an overall downward trend over 2011–2017. Moreover, at the 10% level, significant spatial dependence was found in five out of seven years, indicating that provincial SO_2 emissions might be positively spatially autocorrelated. This provides preliminary evidence supporting the consideration of spatial dependence.

3.3. Empirical spatial model addressing spatial dependence

By taking the logarithmic transformation, Eq. (2) can be expressed as:

$$lnI_t = lna_0 + a_1 lnP_t + a_2 lnA_t + a_3 lnT_t + lne_t \tag{4}$$

where I_t represents provincial SO_2 emissions in year t. Three fundamental factors (i.e., P_t, A_t, T_t) are represented by pd_t, $pgrp_t$ and $tech_t$, respectively. As a result, Eq. (4) is rewritten as Eq. (5) for panel data analysis.

$$lnSO_{2,it} = lna_0 + a_1 lnpd_{it} + a_2 lnpgrp_{it} + a_3 lntech_{it} + lne_{it} \tag{5}$$

To examine impacts of additional factors on SO_2 emissions, Eq. (5) is extended as:

$$lnSO_{2,it} = b_0 + b_1 lnpd_{it} + b_2 lnpgrp_{it} + b_3 lntech_{it} + c_1 lnis_{it} + c_2 lnurb_{it} + c_3 lnrft_{it}$$

$$+ c_4 lnrpt_{it} + c_5 lncoal_{it} + c_6 lnoil_{it} + c_7 lneep_{it} + \varepsilon_{it} \tag{6}$$

where $b_k (k = 0, 1, 2, 3)$ and $c_q (q = 1, \cdots, 7)$ are the estimated parameters of factors, and ε_{it} are error terms.

The further issue is to address the potential spatial dependence of SO_2 emissions by using an appropriate spatial model. To this end, this paper estimates the most frequently used spatial models (i.e., SDM, GTWR, RE-ESF, RE-ESF-SNVC), compares their goodness-of-fit performance, and eventually identifies the RE-ESF approach as the most appropriate model. According to Tiefelsdorf and Griffith (2007), the ESF approach can be written as:

$$\begin{gathered} lnSO_{2,i} = \sum_{k=1}^{10} x_{ik}\beta_k + f_{MC}(s_i) + \varepsilon_i \\ \varepsilon_i \sim N(0, \sigma^2) \end{gathered} \tag{7}$$

where x_{ik} is the k-th economic driving factor of SO_2 emissions and β_k is the corresponding parameter to be estimated. As shown in Eq. (6), to capture the potential spatial dependence in ε_{it}, $f_{MC}(s_i)$ is used which is fixed and step-wisely selected based on the Moran eigenvectors (Moran, 1950). As noted, the Moran coefficient (MC) of SO_2 emissions, expressed in Eq. (3), can be eigen-decomposed as Eq. (8) to obtain $f_{MC}(s_i)$ in Eq. (7).

$$MC(SO_2) = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} = \frac{N}{1'W1}\frac{SO_2' MWMSO_2}{SO_2' WSO_2} \tag{8}$$

where **1** is an N by 1 vector of ones and 'denotes the matrix transposition operation. Other notations are the same as above. Using the eigenvector-based spatial filtering, MWM is decomposed as $E\Lambda E'$ with E being the eigenvector matrix and Λ being the diagonal matrix taking the corresponding eigenvalues. The MC for the i^{th} eigenvector is expressed as:

Table 3
Estimation results of the pooled panel date regression model.

	lnSO$_2$
Intercept	−1.886*
	(0.079)
lnpgrp	−0.211*
	(0.082)
lnpd	0.019
	(0.560)
lntech	−0.189***
	(0.000)
lnis	0.668***
	(0.000)
lnurb	−0.326
	(0.308)
lnrft	−0.249***
	(0.000)
lnrpt	0.399***
	(0.000)
lncoal	0.737***
	(0.000)
lnoil	0.095*
	(0.055)
lneep	0.070
	(0.373)
F-statistic	93.149***
	(0.000)
Adjusted R^2	0.820
LM (lag)	22.668***
	(0.000)
Robust LM (lag)	36.718***
	(0.000)
LM (error)	58.685***
	(0.000)
Robust LM (error)	0.700
	(0.402)

Notes: LM indicates Lagrange multiplier test. P-values are in the parentheses. *** and * indicate statistical significance at the 1% and 10% level, respectively.

$$MC(e_i) = \frac{N}{1'W1}\frac{e_i' MWMe_i}{e_i' We_i} = \frac{N}{1'W1}\frac{e_i' E\Lambda E' e_i}{e_i' e_i} = (\frac{N}{1'W1'})\lambda_i \tag{9}$$

Then, eigenvectors corresponding to large positive eigenvalues capture higher spatial dependence, which should be selected first (Griffith, 2003; Griffith, 2009). Consequently, spatial dependence observed in Eq. (6) is removed by using the Moran eigenvectors to extract information on spatial dependence, generating normal distributed residuals in Eq. (7).

Due to more stable and higher estimation performance, regression coefficients of Moran eigenvectors in Eq. (7) are usually extended to a Gaussian process whose variance depends on the scale of the spatial dependence and the Moran eigenvalues, which is the RE-ESF model (Murakami and Griffith, 2015; Murakami et al., 2017). To further investigate the local relationships between economic driving factors and SO_2 emissions, Eq. (7) can be extended to the RE-ESF-SNVC model for panel data analysis (Murakami and Griffith, 2020a; Murakami and Griffith, 2020b; Yu et al., 2020).

$$\begin{gathered} lnSO_{2,i} = \sum_{k=1}^{10} x_{ik}\beta_{ik} + f_{MC}(g_{I(0)}) + \sum_{h=1}^{H} \eta(g_{I(h)}) + \varepsilon_i \\ \beta_{ik} = b_k + f_{MC,k}(g_{i(0)}) + f_{x_i,k}(g_{i(0)}) \\ \varepsilon_i \sim N(0, \sigma^2) \end{gathered} \tag{10}$$

where $g_{I(h)} (h = 0, 1, \cdots, H)$ is the group variable consisting of province I and year H in this paper. $f_{MC}(g_{I(0)})$ indicates spatially dependent group effects and $\eta(g_{I(h)})$ indicates spatially independent h-th group effects. β_{ik} represents the regression coefficient and consists of the constant mean b_k, the spatially varying component $f_{MC,k}(g_{i(0)})$, and the non-spatially

Table 4
Estimation results of different spatial econometric models.

	SDM	GTWR-Global	RE-ESF
Intercept	−3.237**	−1.886*	−0.715
	(0.026)	(0.079)	(0.545)
lnpgrp	−0.174**	−0.211*	−0.144**
	(0.018)	(0.082)	(0.025)
lnpd	−0.061	0.019	−0.111*
	(0.256)	(0.560)	(0.076)
lntech	−0.062	−0.189***	−0.027
	(0.311)	(0.000)	(0.605)
lnis	0.772***	0.668***	0.221
	(0.000)	(0.000)	(0.222)
lnurb	−0.026	−0.326	−0.083*
	(0.943)	(0.308)	(0.076)
lnrft	0.047	−0.249***	0.131**
	(0.510)	(0.000)	(0.035)
lnrpt	0.127*	0.399***	0.074
	(0.097)	(0.000)	(0.271)
lncoal	0.411***	0.737***	0.474***
	(0.000)	(0.000)	(0.000)
lnoil	0.170**	0.096*	0.184***
	(0.034)	(0.055)	(0.005)
lneep	−0.128*	0.070	−0.175***
	(0.064)	(0.373)	(0.001)
$w \times lntech$	0.222***		
	(0.005)		
$w \times lnis$	0.430*		
	(0.051)		
$w \times lnrpt$	−0.170*		
	(0.061)		
$w \times lnoil$	−0.549***		
	(0.000)		
ρ	0.684***		
	(0.000)		
Adjusted R^2	0.741	0.820	0.969

Notes: The Hausman statistics is −12.93, indicating the appropriateness of the SDM with random effects. p-values are in the parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

varying component $f_{x_i,k}(g_{i(0)})$. Other variables are the same as before. The above three spatial models are estimated in R.

4. Empirical results and discussions

4.1. Estimation results without consideration of spatial dependence

To provide a benchmark for comparison, we start by estimating a pooled panel data model without consideration of spatial dependence and report the estimation results in Table 3. As seen, *lnis*, *lnrpt*, *lncoal*, and *lnoil* significantly increase SO_2 emissions, whereas *lnpgrp*, *lntech*, and *lnrft* tend to decrease SO_2 emissions. There is no evidence supporting the roles of *lnpd*, *lnurb*, and *lneep* in influencing SO_2 emissions. To further examine the potential positive spatial dependence of SO_2 emissions, previously detected by Moran's *I*, the Lagrange multiplier (LM) test and robust LM test for both spatial lag and spatial error effects are reported in Table 3 (LeSage and Pace, 2009). As observed, all tests except the robust LM test for spatial error effect are significant at the 1% level, indicating that spatial dependence should not be ignored. The presence of spatial dependence of air emissions has also been observed in previous studies, including Wang and Fang (2016) for analyzing the spatio-temporal distribution and determinants of $PM_{2.5}$ concentrations, Ye et al. (2018) for examining spatiotemporal patterns and spatial clustering characteristics of six air pollutants, Li et al. (2019) for illustrating the spatiotemporal variation and key factors of SO_2 concentrations, and Wang and Zhou (2021) for demonstrating spatial agglomeration and driving factors of SO_2 emissions and solid waste.

Table 5
Summary of the varying coefficients of the GTWR model.

	Minimum	Q_1	Median	Q_3	Maximum
Intercept	−8.401	−2.374	−1.425	−0.693	1.908
lnpgrp	−1.273	−0.401	−0.271	−0.157	1.605
lnpd	−0.466	−0.072	0.008	0.065	0.184
lntech	−0.552	−0.257	−0.173	−0.104	0.357
lnis	−0.673	0.299	0.695	0.962	1.730
lnurb	−4.690	−0.512	−0.207	0.187	2.382
lnrft	−0.448	−0.321	−0.280	−0.215	0.114
lnrpt	−0.164	0.263	0.391	0.461	0.836
lncoal	0.347	0.714	0.781	0.826	0.958
lnoil	−0.272	0.063	0.134	0.176	0.390
lneep	−0.436	−0.062	0.103	0.201	0.606
Adjusted R^2	0.848				

Notes: Q_1 indicates the first quartile and Q_3 indicates the third quartile.

Table 6
Summary of the spatially varying coefficients of the RE-ESF-SNVC model.

	Minimum	Q_1	Median	Q_3	Maximum
Intercept	−0.972	−0.908	−0.841	−0.811	−0.777
lnpgrp	0.140	0.247	0.255	0.259	0.273
lnpd	0.010	0.010	0.010	0.010	0.010
lntech	−0.110	−0.110	−0.110	−0.110	−0.110
lnis	0.105	0.105	0.105	0.105	0.105
lnurb	−0.483	−0.483	−0.483	−0.483	−0.483
lnrft	−0.023	−0.023	−0.023	−0.023	−0.023
lnrpt	0.172	0.172	0.172	0.172	0.172
lncoal	0.240	0.319	0.321	0.328	0.361
lnoil	0.154	0.154	0.154	0.154	0.154
lneep	−0.090	−0.090	−0.090	−0.090	−0.090
Adjusted R^2	0.978				

Notes: Q_1 indicates the first quartile and Q_3 indicates the third quartile.

4.2. Estimation results with consideration of spatial dependence

We take spatial dependence into account and estimate different spatial econometric models including the SDM, the global and varying coefficients of the GTWR models, and RE-ESF without and with SNVC models. Tables 4, 5 and 6 present the estimation results and diagnostics tests. Compared with the non-spatial panel data regression model, the SDM performs worse due to its lower adjusted R-squared value of 0.741, while the global and the varying coefficients of the GTWR models achieve the adjusted R-squared values of 0.820 and 0.848, respectively. Notably, the RE-ESF without and with SNVC models have increased the adjusted R-squared value from 0.820 to 0.969 and 0.978, respectively, implying a better fit to the collected dataset. That is, using the RE-ESF approach, over 95% of variation in the transformed SO_2 emissions can be explained by the identified factors together with the extracted spatial filters. As a result, the RE-ESF without and with SNVC models are identified as the most appropriate spatial model dealing with spatial dependence of SO_2 emissions in China over the sample period. The superiority of the RE-ESF model has also been previously supported by Tan et al. (2020) for capturing $PM_{2.5}$ concentration distribution characteristics, Yu et al. (2020) for investigating the impact of high-speed rail construction on economic growth, Yang et al. (2021) for examining the role of financial deepening in driving spatial heterogeneity of $PM_{2.5}$ concentrations, and Sun et al. (2021) for estimating electricity energy consumption with consideration of demographic, remote sensing, and social sensing data. This finding provides methodological implications for other emissions such as CO_2, nitrogen oxides (NO_X), PM, and methane (CH_4) by examining the global and local impacts of economic driving factors on these emissions.

Table 7
Median values of the spatially varying coefficients for each province.

Province	Intercept	*lnpgrp*	*lncoal*	Province	Intercept	*lnpgrp*	*lncoal*
Anhui	−0.925	0.260	0.324	Jiangxi	−0.910	0.260	0.319
Beijing	−0.833	0.199	0.254	Jilin	−0.907	0.247	0.319
Chongqing	−0.779	0.248	0.315	Liaoning	−0.889	0.247	0.329
Fujian	−0.939	0.247	0.319	Ningxia	−0.801	0.255	0.319
Gansu	−0.836	0.256	0.318	Qinghai	−0.859	0.259	0.242
Guangdong	−0.867	0.247	0.324	Shaanxi	−0.792	0.250	0.326
Guangxi	−0.807	0.261	0.319	Shandong	−0.880	0.248	0.359
Guizhou	−0.777	0.259	0.321	Shanghai	−0.973	0.213	0.310
Hebei	−0.831	0.257	0.352	Shanxi	−0.811	0.261	0.353
Heilongjiang	−0.909	0.258	0.321	Sichuan	−0.783	0.261	0.320
Henan	−0.842	0.260	0.337	Tianjin	−0.842	0.182	0.313
Hubei	−0.833	0.249	0.320	Xinjiang	−0.924	0.259	0.324
Hunan	−0.831	0.257	0.320	Yunnan	−0.793	0.257	0.319
Inner Mongolia	−0.841	0.249	0.352	Zhejiang	−0.971	0.247	0.321
Jiangsu	−0.944	0.238	0.343				

4.2.1. Global investigation using the RE-ESF model

By modifying the *spmoran* package in R, four eigenvectors corresponding to the largest four positive eigenvalues can be extracted among the 29 potential eigenvectors, which are further used as spatial filters for explaining spatial dependence of SO_2 emissions. As an averaging process of multiple local relationships, the global investigation helps us to better understand the overall relationship between driving factors and SO_2 emissions (Murakami and Griffith, 2019). According to the global estimation results of the RE-ESF model with two-way random effects in Table 4, the coefficients of *lnpgrp* (p-value = 0.025), *lnpd* (p-value = 0.076), *lnurb* (p-value = 0.076) and *lneep* (p-value = 0.001) are −0.144, −0.111, −0.083 and −0.175, respectively, which are statistically significant at the 10% level. This indicates that, given other factors and spatial filters, every 1% increase in *pgrp*, *pd*, *urb* and *eep* could result in approximately 0.144%, 0.111%, 0.083% and 0.175% decrease in SO_2 emissions, respectively. It reveals that higher population density and urbanization level will likely promote the development of tertiary industry and reduce the economy's reliance on secondary industry, leading to declined SO_2 emissions. According to China Statistical Yearbook (2018), the proportion of tertiary industry in GDP has increased from 44.2% in 2011, to 47.8% in 2014, and 51.6% in 2017, which confirms the above finding. Meanwhile, the roles of economic growth and governmental expenditure for environment protection in reducing SO_2 emissions can be explained by China's energy consumption structure (Huang, 2018; Li et al., 2019). In recent years, China has gradually used more clean energy to replace fossil fuels. Specifically, the consumption of natural gas, primary electricity and other energy accounted for about 13% of the total energy consumption in 2011, and this share rose up to 17% in 2014, and 20.8% in 2017 (China Statistical Yearbook, 2018). In addition, the ever-increasing environmental awareness has promoted the application of SO_2 abatement technologies by increasing governmental expenditures for environment protection (Huang, 2018).

On the other hand, *lnrft* (p-value = 0.035), *lncoal* (p-value = 0.000) and *lnoil* (p-value = 0.005) show significant and positive relationships with SO_2 emissions, enjoying elasticities of 0.131, 0.474 and 0.184, respectively. Since SO_2 emissions are largely from coal and oil burning, higher coal and oil consumptions are expected to cause more emissions and deteriorate air quality (Cherniwchan, 2012; He et al., 2017). Not surprisingly, a higher road freight turnover is associated with more transport activities, which likely increases SO_2 emissions.

As indicated by the above global results, appropriate policies should be implemented to promote economic growth, population density, urbanization, and government expenditure for environment protection and to reduce economy's reliance on road freight transportation and consumptions of coal and oil. For example, by deepening household registration reform, labor mobility can be enhanced, which likely increases population density and urbanization. The focus of energy policy should be shifted from coal and oil to clean energy to promote economic growth in a more sustainable manner. Government expenditure for environment protection can be better utilized by developing appropriate incentive policies for reducing SO_2 emissions, such as financial subsidies towards using energy conservation and emission reduction products, tax relief and concession on clean energy investment, preferential bank loans and diverse financing channels for energy conservation and emission reduction projects. In addition, the promotion and development of intermodal transport not only reduces the economy's reliance on road freight transport but also contributes to energy savings and SO_2 emission reduction.

4.2.2. Local investigation using the RE-ESF-SNVC model

After providing an overall picture of the global relationship between different factors and SO_2 emissions, we further investigate the local relationship which depends on the geographical location. For this reason, the RE-ESF-SNVC model is estimated and summarized in Table 6.

First, as indicated by the adjusted R-squared values of the RE-ESF (0.969) and RE-ESF-SNVC (0.978) models, the inclusion of local relationships can fit the collected dataset better and explain approximate 97.8% variations in the transformed SO_2 emissions. Second, it is found that *lnpd*, *lntech*, *lnis*, *lnurb*, *lnrft*, *lnrpt*, *lnoil* and *lneep* display non-spatially varying impacts on SO_2 emissions, reflected by constant coefficients of 0.010, −0.110, 0.105, −0.483, −0.023, 0.172, 0.154, and −0.090, respectively. Interestingly, *intercept*, *lnpgrp* and *lncoal* demonstrate spatially varying characteristics, achieving the median values of −0.841, 0.255, and 0.321, respectively. Third, to identify the underlying spatial patterns, the median values of provincial spatially varying coefficients of *lnpgrp* and *lncoal* are presented in Table 7 and Fig. 2. As observed, local impacts of economic growth on SO_2 emissions are strongest in Guangxi (0.261), Shanxi (0.261), and Sichuan (0.261), which, however, are much weaker in Beijing (0.199) and Tianjin (0.182). As for coal consumption, Shandong (0.359), Shanxi (0.353), Hebei (0.352), and Inner Mongolia (0.352) exhibit much stronger local impacts on SO_2 emissions, while Beijing (0.254) and Qinghai (0.242) demonstrate weaker local impacts.

Results of the local investigation support spatially varying characteristics of economic growth and coal consumption, suggesting the differentiation between centralized and decentralized policies for reducing SO_2 emissions. That is, the centralized policymaking process is expected to develop national emission reduction policies for driving factors with non-spatially varying coefficients, which aims to control their overall impacts on SO_2 emissions. For economic growth and coal consumption, the decentralized policymaking process is encouraged to develop province-specific emission reduction policies by considering their spatial heterogeneity. For example, greater efforts are required for provinces (e.g., Guangxi, Shanxi, Sichuan) with larger spatially varying coefficients of economic growth to increase their respective per capita

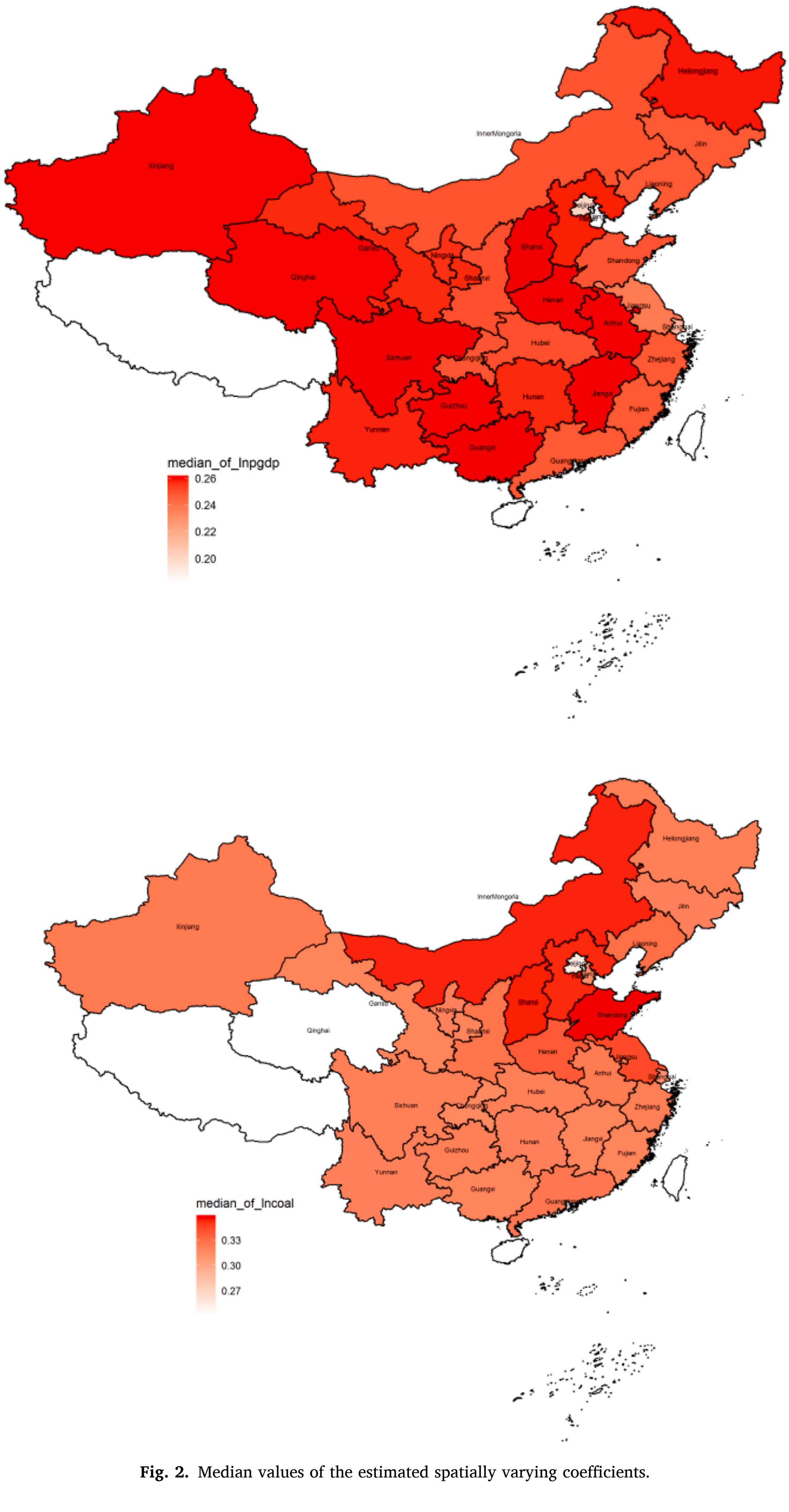

Fig. 2. Median values of the estimated spatially varying coefficients.

gross regional product rapidly, which can be achieved by efficiently redistributing incomes to individuals and providing direct financial subsidies. For provinces and municipalities (e.g., Jiangsu, Shanghai, Beijing, Tianjin) with smaller spatially varying coefficients of economic growth, it is suggested that, given a certain rate of economic growth, more attention can be paid to promote economic equality among individuals by implementing various income redistribution policies. On the other hand, compared with provinces and municipalities (e.g., Beijing, Qinghai) with smaller spatially varying coefficients of coal consumption, Shandong, Shanxi, Hebei, and Inner Mongolia should implement more stricter restrictions on coal consumption, encourage the use of clean energies, and promotes emission reduction technologies to reduce SO_2 emissions significantly.

5. Conclusions

Using a Chinese provincial panel dataset from 2011 to 2017, this paper finds that the RE-ESF and RE-ESF-SNVC models are the most appropriate models due to the highest goodness-of-fit, which confirms the hypothesis about the presence of spatial heterogeneity of SO_2 emissions in China. The main findings are as follows. First, the higher adjusted R-squared values of the RE-ESF and RE-ESF-SNVC models suggest that they can investigate how driving factors spatially affect SO_2 emissions. Second, as indicated by the global results, appropriate policies should be implemented to promote economic growth, population density, urbanization, and government expenditure for environment protection but to reduce economy's reliance on road freight transportation and consumptions of coal and oil. Third, results of the local investigation support spatially varying characteristics of economic growth and coal consumption, suggesting the differentiation between centralized and decentralized policies for reducing SO_2 emissions.

The results provide both methodological and managerial implications for policymakers to develop emission reduction policies from a spatial perspective. As suggested, more efforts should be made to increase population density and urbanization by deepening household registration reform, promote economic growth by shifting energy policy from coal and oil to clean energy, better use government expenditure for environment protection by offering various financial incentives, and promote intermodal transport. Particularly, the decentralized policy-making process is encouraged to develop province-specific emission reduction policies for economic growth and coal consumption due to their spatial heterogeneity.

Despite these profound implications, this paper can still be extended in different aspects. One extension is to use a city-level dataset when it is available in the future. In so doing, more details regarding spatial disparities can be revealed, which may validate the findings in this paper. Another extension is to focus on economic performance of different emission reduction approaches, allowing us to identify the most cost-efficient approach.

CRediT authorship contribution statement

Wenming Shi: Conceptualization, Methodology, Software, Writing – original draft. **Yuquan Du:** Writing - review & editing. **Chia-Hsun Chang:** Visualization, Investigation. **Son Nguyen:** Writing - review & editing. **Jun Wu:** Conceptualization, Methodology, Writing - review & editing.

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.

Acknowledgement

We appreciate the financial support by the Major Program of the National Social Science Foundation of China, Grant No. 21ZDA094.

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