



# Estimating the provincial environmental Kuznets curve in China: a geographically weighted regression approach

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## Abstract

This study estimates the environmental Kuznets curve (EKC) relationship at the province level in China. We apply empirical methods to test three industrial pollutants—SO<sub>2</sub> emission, wastewater discharge, and solid waste production—in 29 Chinese provinces in 1994–2010. We use the geographically weighted regression (GWR) approach, wherein the model can be fitted at each spatial location in the data, weighting all observations by a function of distance from the regression point. Hence, considering spatial heterogeneity, the EKC relationship can be analyzed region-specifically through this approach, rather than describing the average relationship over the entire area examined. We also investigate the spatial stratified heterogeneity to verify and compare risk factors that affect regional pollution with statistical models. This study finds that the GWR model, aimed at considering spatial heterogeneity, outperforms the OLS model; it is more effective at explaining the relationships between environmental performance and economic growth in China. The results indicate a significant variation in the existence of the EKC relationship. Such spatial patterns suggest province-specific policymaking to achieve balanced growth in those provinces.

**Keywords** China · Economic growth · Environmental Kuznets curve · Environmental performance · Geographically weighted regression

## 1 Introduction

China has sustained remarkably rapid economic growth since the 1990s. Primarily, owing to the gradually implemented open market policies and subsequent expansion of the industrial sector, per capita gross domestic product

(GDP) increased from 381 yuan in 1978, when China first declared its economic reform, to 41,908 yuan in 2013.<sup>1</sup> However, such rapid industrialization has induced serious pollution problems. Therefore, the future of both economic and environmental performance is of great concern to China.

To address the relationship between Chinese economic growth and environment, numerous studies have investigated the existence of an environmental Kuznets curve (EKC) (e.g., De Groot et al. 2004; Shen 2006; Tao et al. 2008; Wang et al. 2012b; Song et al. 2013; He et al. 2014). Most of these have analyzed the EKC relationship, which exhibits an inverted-U shape, for various pollutants, such as SO<sub>2</sub> emissions and wastewater discharge from industrial sources. For example, Shen (2006) validated the EKC for SO<sub>2</sub> emissions and three water pollutants (arsenic, cadmium, and chemical oxygen demand). De Groot et al. (2004) found that EKC exists in industrial, gas, and solid

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<sup>1</sup> These values are in 2010 constant prices. The rate of exchange in 2010 was approximately US\$ 1 = 6.77 yuan. The index of GDP per capita for 2013 is 1,837.5 if using 1978 as the base year.

wastes at intermediate levels of economic development. More recently, Song et al. (2013) demonstrated that some areas, such as Beijing, Guizhou, Jilin, Shanghai, and Tibet, have already reached their inflection points on the EKC for industrial waste gas emissions, while Anhui, Fujian, Hainan, Liaoning, and Qinghai demonstrate no inflection points.

However, there is concern that the selection of pollutants and methods has a decisive effect on the results (Brajer et al. 2011; Paruolo et al. 2015). One major limitation of existing EKC studies is that most evaluate the average relationship between environmental quality and economic development in their respective study areas by using a global regression model. As this model might be particularly unrepresentative of a more diverse study area, the estimated average relationships may overlook or underestimate significant and important local interactions between the environment and economic growth. Thus, contrasting relationships in different parts of a country may tend to cancel each other out in the calculation of a global parameter estimate (Fotheringham et al. 2002).

Consequently, producing a set of local statistics by applying the locally weighted regression approach and mapping the estimated values would be substantially more informative and accurate than adopting a single global estimate. In environmental economics, the geographically weighted regression (GWR) model, one of the locally weighted regression models, adopts an economic approach that considers the possibilities of relationships among observations from various geographical spaces. Using it, we can match a regression model at individual data point. The GWR model has attracted increasing academic attention in several areas of study, including risk assessment and environmental management (Fotheringham et al. 2002; Cho et al. 2006; Fischer and Getis 2009; Helbich et al. 2013; Harris et al. 2014; Wang et al. 2017).

Geographic and environmental data often show a robust pattern of spatial dependency, making spatiality an important determinant for the accuracy of analysis results (Montello and Sutton 2012). By applying the GWR model to investigate the EKC relationship, we can identify local differences depending on geographical and socioeconomic local characteristics, as well as cultural, geographical, historical, and administrative features. Despite these advantages, in most previous studies, the EKC relationships have been hidden in global results. Only few studies have considered the spatial differences of EKC relationships with locally weighted models, including the GWR (Rupasingha et al. 2004; He et al. 2014; Li et al. 2014).

For large countries like China, uneven regional economic and environmental conditions are significant. For example, some preferential policies boost effective economic growth. This causes a regional economic gap and

polarization phenomena among Chinese provinces (Wang et al. 2014). However, there are few extant studies on the relationship between economic growth and environmental pollutants in China that apply spatial analysis with province level data. They are, however, limited regarding air pollutants due to data limitations (Chuai et al. 2012; Liu et al. 2014, 2016; Kim et al. 2017).

Considering that the spatial approach provides a more accurate EKC relationship, the primary objective of this study is to investigate the EKC relationship at province level in China using the GWR approach to account for spatial non-stationarity. Since different pollutants might exhibit different relationships, we select three environmental performance indicators from industrial sources: SO<sub>2</sub> emission, wastewater discharge, and solid waste production, while most previous studies on EKC focused on air pollutants or forest areas. Additionally, this study includes population density and geographical factors as control variables, thus reflecting local characteristics. These objectives are achieved by applying the GWR model to 29 provinces in China (Fig. 1) in 1994–2010.

The rest of this article is organized as follows. Section 2 discusses, in detail, the theoretical background, including history, challenges, and limitations of EKC. Section 3 describes the empirical models, and the data used for empirical estimations. Section 4 reports and interprets the estimated results for the three pollutants from the GWR and GeogDetector models. Section 5 summarizes our results, and provides several policy implications to achieve the EKC relationship for balanced growth in China.

## 2 Research background

The EKC hypothesis suggests an inverted-U relationship between economic performance and environmental degradation. In the early 1990s, Grossman and Krueger (1991) introduced this idea based on Kuznets (1955), who described inverted-U shape for time series patterns in income inequality and the level of income, spreading it through the World Development Report of the World Bank (1992). The EKC hypothesis illustrates that, environmental quality first increases with economic growth, then declines beyond a certain “turning point,” which indicates the maximum pollutant concentration.

This attractive assumption exists as an extension of the concept of economic sustainable development, which was initially introduced in Brundtland and Khalid (1987), showing the possibility that economic growth can be achieved along with the improvement of environmental quality if a country reaches a certain level of economic development. Ever since the EKC was proposed, and considering its concerns, numerous scholars have tried to

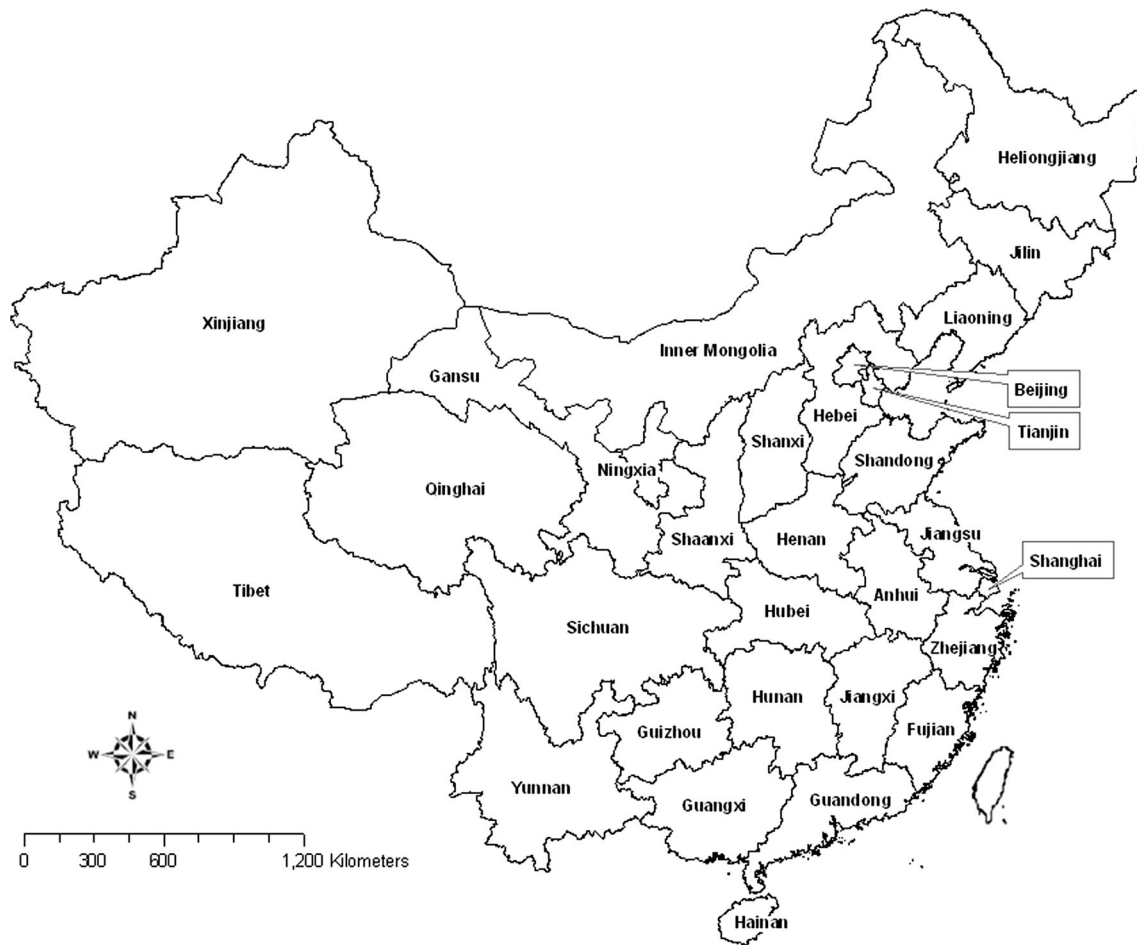


Fig. 1 Provinces and major cities in China

find empirical evidence to support its relationship. As such, many previous studies conduct empirical analysis with quadratic equations using data on economic performance from, for example, income or GDP per capita and environmental quality.

However, although this stylized hypothesis has received attention from scholars, many still have reservations, and criticize EKC due to its lack of theoretical foundation and empirical consistency (Stern et al. 1996; Ekins 1997; Stern 1998, 2004; Dasgupta et al. 2002). The empirical evidence remains mixed, varying among targets and methods of analysis. Some studies identified EKC relationships, and calculated the turning points from their data (Lopez 1994; Selden and Song 1994; Stern and Common 2001), while other recent studies failed to identify the EKC existence (Gangadharan and Valenzuela 2001; Azomahou et al. 2006; Aslanidis and Iranzo 2009). Therefore, scholars endeavor to obtain more accurate results of the relationship between economic growth and environmental quality by improving data and the econometric methods used (Stern 2004). For instance, Dasgupta et al. (2002) introduced the “new toxics,” a revised EKC, and the race to bottom

scenarios, while insisting on the need to break the monotonic frame of EKC.<sup>2</sup> Stern (2004) also pointed out the lack of consensus on EKC results, and provided alternative approaches.

Moreover, it is difficult to generalize the results obtained from previous studies. Existing literature, including Grossman and Krueger (1991), adopted air pollutants, as well as SO<sub>2</sub>, NO<sub>x</sub>, and CO, as proxies of environmental quality due to data limitation (e.g., Selden and Song 1994; Stern and Common 2001; Bravo and Marelli 2007). Besides, as Stern et al. (1996) pointed out that “notoriously patchy in coverage and/or poor in quality” data on environmental quality is one of the problems that affects the estimation and analysis of EKCs. Most previous literature, including both cross-country and country-specific EKC

<sup>2</sup> The “new toxics” scenario argues that new pollutants, for example, CO<sub>2</sub>, may not show the inverted U-shape curve. The revised EKC scenario claims that technological change may accelerate to achieve the turning point; thus, the EKC graph shifting downward and left. The race to bottom scenario insist the greatest increase of environmental regulations and policies happen from low to middle economic levels (Dasgupta et al. 2002).

estimations, studied developed countries, since it is easier to secure environmental data over adequate research periods. However, selection of pollutants and methods can affect the estimation results of the EKC (Brajer et al. 2011).

More recently, scholars have been trying to estimate EKC relationships in developing countries, thus raising questions on whether these exist and whether their trends are similar to developed countries. Specifically, scholars focus on China, which has witnessed both remarkable economic growth and serious environmental degradation for decades (e.g., De Groot et al. 2004; Shen 2006; Tao et al. 2008; Song et al. 2013). However, despite large economic gaps and polarization phenomena among Chinese provinces, there are some previous studies on the relationship between economic growth and environmental pollutants that apply spatial analysis. Furthermore, most studies are at province level and limited to air pollutants (Chuai et al. 2012). Therefore, a necessity arises to carefully investigate the various relationships between economic performance and environmental quality in China among various pollutants, while considering difference in regional characteristics.

### 3 Model

#### 3.1 Geographically weighted regression

The GWR model produces a set of local estimates to identify spatial differences in the study area. It is an extension of the traditional ordinary least squares (OLS) model that considers spatial differences with local parameters to be estimated in an equation as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i, \quad (1)$$

where  $y$  and  $x$  represent the dependent and the independent variables, respectively;  $\beta_0$  and  $\beta_i$  are the parameters to be estimated;  $k$  is the number of independent variables;  $i$  is the data point; and  $\varepsilon$  denotes the error term.  $\beta_0(u_i, v_i)$  and  $\beta_k(u_i, v_i)$  denote the local estimated parameter for independent variables,  $x_{ik}$ . GWR is calibrated through weights based on the distance between the observed data and point,  $i$ , assuming that observed data closer to point,  $i$ , have more impact on local estimations of  $\beta_k(u_j, v_j)$  than the ones located farther from point,  $i$ . Through this approach, GWR can recognize and measure possible spatial variations in the relationships between independent and dependent variables (Fotheringham et al. 2002; Fischer and Getis 2009).

To define spatial weights, we use kernel functions, which are weighting functions used in non-parametric estimation techniques. As the uneven distribution in some regression points causes issues like large standard errors or

estimation failure, the adaptive kernel function can adjust the bandwidths between regression and data points according to data density, while the fixed kernel function sets the fixed bandwidth, ignoring the density of the data points.<sup>3</sup>

To calculate spatial weights,  $w_{ij}$ , we apply the adaptive bi-square function for the kernel type.<sup>4</sup> This approach can control the spatial size variation among provinces; it is useful because the spatial weighting function specifies weights as a continuous function until distance,  $b$ , from the analyzed point, while the data point has zero weight if the distance between  $i$  and  $j$  is equal to or greater than the bandwidth:

$$w_{ij} = \begin{cases} \left[1 - (d_{ij}/b)^2\right]^2 & \text{if } d_{ij} < b, \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

where  $b$  is a certain bandwidth and  $d_{ij}$  is the distance between  $i$  and  $j$ . In this function, if a locally weighted regression parameter is similar to a global OLS model,  $w_{ij}$  would be close to 1 regardless of  $d_{ij}$  (Fotheringham et al. 2002; Fischer and Getis 2009).

We derive the bandwidth using the Akaike information criterion (AIC) to calibrate the spatial weighting function.<sup>5</sup> A numerical analyst for function minimization with a correction for small sample size, AIC provides more accurate results in small-sample applications (Cavanaugh 1997). According to Fotheringham et al. (2002), deriving the bandwidth that offers equilibrium between the goodness-of-fit and degrees of freedom is equivalent to minimizing the corrected AIC (AICc). They define AICc for GWR based on Hurvich et al. (1998) and Fischer and Getis (2009) as follows:

<sup>3</sup> Bandwidth defines how each data point is weighted by the distance from the regression point. This is determined by a spatial weighting function that affects the distance between regression and data points (Fotheringham et al. 2002). Therefore, in the adaptive spatial kernels, we can observe larger bandwidths of kernels, where data are scarce, and smaller bandwidths, where data are dense, while all regression points have the same bandwidth in the fixed kernel function.

<sup>4</sup> In this function, if a locally weighted regression parameter is similar to a global OLS model,  $w_{ij}$  would be close to 1 regardless of  $d_{ij}$ . In other words, a value of  $w_{ij}$  close to 0 indicates that the estimated parameter would vary across space. This function allows us to use the bandwidth with the same number of data points with non-zero weights (Fotheringham et al. 2002; Fischer and Getis 2009).

<sup>5</sup> AIC is a model selection technique based on information theory, providing the information loss of models between the goodness-of-fit and degrees of freedom. In this analysis, AIC evaluates an optimal bandwidth between the global OLS and GWR models. The bandwidth with minimized AIC value is utilized in the GWR estimation (Zhen et al. 2013).

$$AIC_c = 2n \log_e(\hat{\sigma}) + n \log_e(2\pi) + n \left\{ \frac{n + \text{tr}(\mathbf{S})}{n - 2 - \text{tr}(\mathbf{S})} \right\}, \quad (3)$$

where  $n$  is the number of observations,  $\hat{\sigma}$  represents the estimated standard deviation of the error term, and  $\text{tr}(\mathbf{S})$  is the trace of the hat matrix that is a function of the bandwidth. The AICc can be used to estimate a better fit between a global OLS and a local GWR because it considers the different degrees of freedom for the two models. Further details about the GWR model can be found in Fotheringham et al. (2002), Fischer and Getis (2009), and Wheeler (2014).

Since the GWR model estimates local regression coefficients by considering spatial differences, we can measure the spatially varying relationships between environmental performance and their determinants in each province. Thus, spatially varying parameters are displayed in spatial maps using the Geographic Information System (GIS). The results section demonstrates the synergy effect of the GWR model and GIS in detail.

### 3.2 Model specification and data

The models to investigate the EKC relationship of each Chinese province mainly focus on the relationship between regional economic performance and pollution. To measure the economic performance of each province, gross regional product (GRP), income level, or per capita gross city product could be considered for the analysis. In the spatial analysis, we use provincial GRP per capita to represent the regional economic performance well (de Groot et al. 2004; Managi and Kaneko 2009; Wu 2010). The coefficients and the signs of the GRP and GRP squared variables indicate the relationship between the economy and pollutants. This study uses data on three pollutants from industrial sources ( $\text{SO}_2$  emission, wastewater discharge, and solid waste production) from 29 Chinese provinces.<sup>6</sup>

For the control variables, population density and dummy variables for coastal regions, and time are included. The effect of population density on pollution remains controversial. As many previous studies mentioned, they are closely related. Some insist that more densely populated areas are likely to have more pollutants because more pollutants are generated in populated areas by vigorous human activity, such as complicated transportation and industry. However, others insist that a highly-populated area is likely to be more developed, have high income, and

thus, could put more effort into reduce emissions (Selden and Song 1994; Shen 2006; Brajer et al. 2008, 2011).

Previous studies also demonstrate that it is crucial to consider geographical characteristics that affect the GRP growth rate. Particularly, there are significant differences in economic performance between coastal and land-locked regions. The share of GDP per capita for coastal regions accounts for more than 60% of total GDP, and coastal regions' growth rate is higher than that of land-locked regions' as well (de Groot et al. 2004). On the other hand, previous studies asserted that cities located on the coastline have better air quality, although they are expected to have more developed economies and higher population density (Brajer et al. 2011). In this context, this study includes a dummy variable for coastal regions to determine the difference between the EKC relationships among different pollutants for both coastal and land-locked regions. Moreover, a time dummy needs to be included because there are several changes in the criteria of collecting statistical data by the State Statistical Bureau (1995–2013) corresponding to certain periods.

Accordingly, we estimate Eq. (1) in the previous subsection by using the following specification:

$$Y_{it} = \beta_0 + \beta_1 \text{GRPP}_{it} + \beta_2 \text{GRPPSQ}_{it} + \beta_3 \text{POPDENSE}_{it} + \beta_4 \text{D\_COAST}_{it} + \beta_5 \text{D\_TIME}_{it} + \varepsilon_{it}, \quad (4)$$

where  $Y_{it}$  is per capita volume of pollutants, that is,  $\text{SO}_2$  emission per capita, wastewater discharge per capita, or solid waste production per capita from the industrial sector in province,  $i$ , at year,  $t$ . GRPP and GRPPSQ denote GRP per capita and its squared term, respectively. Provincial GRP is adjusted by consumer price index (CPI) (1993 = 100); POPDENSE is the population density (in person/ $\text{m}^2$ ); D\_COAST a dummy variable for coastal regions<sup>7</sup>; and D\_TIME a dummy variable that indicates time period after the year 2003. Finally,  $\beta$ s are the parameters to be estimated. The variables used for estimating Eq. (4) are obtained from the China Statistical Yearbook (State Statistical Bureau 1995–2013).<sup>8</sup> The descriptive statistics of the analyzed variables are presented in Table 1.

We test the spatial stratified heterogeneity to verify and compare relevant risk factors that affect regional pollution by using the GeogDetector (Wang et al. 2010, 2016). This tool provides four types of results—risk, factor, ecological, and interaction detectors—which indicate information on

<sup>6</sup> Tibet is not included in our analysis, because of data limitations from statistical data sources. Chongqing is also not included, because it was split from Sichuan during the estimation period (in 1997). To maintain data consistency, we merge Chongqing and Sichuan data, and treat them as a single province in this study.

<sup>7</sup> Coastal provinces refer to Beijing, Fujian, Guangdong, Guangxi, Hainan, Hebei, Jiangsu, Liaoning, Shanghai, Shandong, Tianjin, and Zhejiang.

<sup>8</sup> GRP per capita and statistics of three pollutants in 2012 are used to identify the trend of sustainable development after 2010 in Table 7.



**Table 1** Descriptive statistics

Variable	Definition	Original data	Unit	Mean	SD	Min.	Max.
INDSO2P	SO <sub>2</sub> emissions per capita	Volume of SO <sub>2</sub> emission by industry	tons	149.537	94.658	22.734	579.470
INDWWP	Wastewater discharged per capita	Total volume of wasted water discharged	10,000 tons	17.170	10.530	3.083	87.114
INDSWP	Industrial solid waste produced per capita	Volume of industrial solid wastes produced	10,000 tons	1.004	0.850	0.091	6.875
GRPP	GRP per capita	GRP adjusted by CPI (1993 = 100)	100 million yuan	0.442	0.257	0.139	1.388
GRPPSQ	Square of GRP per capita	–	100 million yuan	0.261	0.369	0.019	1.928
POPDENS	Population density	Population by urban and rural residence and region	10,000 person/m <sup>2</sup>	0.038	0.048	0.001	0.354
COAST	Dummy variable for coastal regions	–	–	0.414	0.493	0.000	1.000
TIME	Dummy variable for year after 2003	–	–	0.471	0.500	0.000	1.000

All data except the dummy variables are from China Statistical Yearbook (State Statistical Bureau 1995–2013)

each risk factor, the impact of each factor, the impact of different levels of significance on factors, and the impact of combinations of different factors, respectively (Wang et al. 2010; Todorova et al. 2016). With the result thereof, we can detect the consistency of spatial distribution of each pollutant with those of the risk factors. We consider the status of economic development, population density, and coastal regions as the environmental and socioeconomic risk factors in the perspective of the EKC hypothesis.<sup>9</sup> More details on the GeogDetector can be found on its official website (<http://www.geodetector.org/>) and previous studies like Wang et al. (2010), Li et al. (2013), and Fei et al. (2016).

## 4 Results

The distribution of the GRP per capita, and each pollutant in 1994 and 2010, shows spatial heterogeneity among the provinces (“Appendix”). We conduct the spatial methods with the GWR 4 software assuming that the spatial approach provides a more accurate EKC relationship at province level in China. The estimated coefficients for SO<sub>2</sub>, wastewater, and solid waste models are presented in Tables 2, 3, and 4, respectively. The tables indicate that local GWR models outperform global OLS models for all three pollutants in terms of Adjusted  $R^2$ , AIC, and AICc. Specifically, model fit is significantly improved by estimating variables locally rather than globally because

models with higher  $R^2$  and smaller AIC or AICc offer a better fit.

The parameter estimates for the seven independent variables vary widely over space. Table 5, which shows the results of the spatial variability test for the GWR coefficients, demonstrates significant spatial variability in terms of model selection criteria. All variables have negative values of the diff-criterion.<sup>10</sup> This provides strong evidence that the EKC relationships are not constant among provinces. In other words, it is difficult to capture the reasonable average relationship by global OLS in these three models because global OLS estimates can only produce the average relationship among all provinces.

The results regarding spatial stratified heterogeneity are in line with the results from the statistical models above. Considering the uneven distribution of regional risk factors that cause spatial heterogeneity, we used the GeogDetector to investigate the risk factors’ impact as per the EKC hypothesis. Table 6 presents the power determination values, which show the effect of a risk factor on each pollutant with values between 0 and 1 (Wang et al. 2010; Li et al. 2013; Fei et al. 2016). The results indicate that population density is the strongest risk factor in all three pollutants. The economic situation, which is measured by the GRP per capita, is also an important risk factor. Coastal region and time factors are also more important factors for both SO<sub>2</sub> emissions and industrial solid waste production, while time factor is not significant for the results of industrial wastewater discharge.

<sup>9</sup> To conduct GeogDetector, the numerical dependent variables—GRP per capita and population density—were transformed to the categorical variables based on the ranking among the provinces, since the precondition for this program is “Y is numerical and X MUST be categorical” (Wang et al. 2010).

<sup>10</sup> A positive value of the diff-criterion (AICc, AIC, Bayesian inference criterion/minimum description length, or coefficient of variation) suggests no spatial variability in terms of model selection criteria.

**Table 2** Model estimates: industrial SO<sub>2</sub> emissions

Variable	OLS		GWR				
	Coeff.	SE	Min	LQ	Med	UQ	Max
Intercept	97.321***	20.936	– 60.569	34.535	77.577	187.183	410.212
GRPP	154.925*	82.120	– 1879.372	– 509.581	140.218	592.800	1405.910
GRPPSQ	– 67.329	59.962	– 826.218	– 341.635	– 56.517	480.571	3489.591
POPDENS	6.313	167.550	– 4142.977	– 1714.141	– 358.989	101.443	4634.437
COAST	– 39.504***	12.106	– 286.922	– 50.614	– 2.316	23.963	55.189
TIME	37.007***	8.519	– 5.104	14.861	33.799	46.812	89.160
N	493		493				
Adjusted R <sup>2</sup>	0.062		0.638				
AIC	5860.842		5403.448				
AICc	5861.073		5406.252				

\*\*\*, \*\*, \* indicate 1, 5, and 10% significance levels, respectively

**Table 3** Model estimates: industrial wastewater discharge

Variable	OLS		GWR				
	Coeff.	SE	Min	LQ	Med	UQ	Max
Intercept	6.480***	1.942	– 19.071	– 7.909	– 5.230	– 1.696	16.049
GRPP	21.105***	7.616	0.581	56.551	77.974	86.473	163.440
GRPPSQ	– 12.531**	5.561	– 227.178	– 59.501	– 51.448	– 29.914	38.218
POPDENS	81.070***	15.539	– 246.838	– 70.621	30.220	112.089	622.395
COAST	4.862***	1.123	– 11.319	– 0.569	1.736	9.856	15.174
TIME	– 0.985	0.790	– 4.402	– 2.853	– 1.901	0.035	3.041
N	493		493				
Adjusted R <sup>2</sup>	0.350		0.688				
AIC	3516.205		3164.880				
AICc	3516.436		3167.684				

\*\*\*, \*\*, \* indicate 1, 5, and 10% significance levels, respectively

As previously indicated, one of the advantages of the GWR model is that the estimated results are spatially displayed based on the resolution of data used in the study. Spatial variations of estimated results using GWR are displayed in terms of sign of the parameter and significance. Since this study conducts province-level local regressions, all results can be displayed using provincial data and GIS software, such as QGIS. Through this process, Figs. 2, 3, and 4 illustrate the spatial variations in the EKC relationships for SO<sub>2</sub>, wastewater, and solid waste from industrial sources in China. This study revealed that spatial variations of the EKC relationships between the three pollutants are considerably distinct.

Figure 2 indicates that 12 out of 29 provinces are demonstrated to have EKC relationships for SO<sub>2</sub> emissions. This is remarkably different from OLS estimates in Table 3, where the EKC relationship for SO<sub>2</sub> is absent for the national average. Our results indicate that 12 provinces

located in northern China (Beijing, Gansu, Hebei, Henan, Inner Mongolia, Liaoning, Ningxia, Shaanxi, Shandong, Shanxi, Tianjin, and Xinjiang) achieve SO<sub>2</sub> emission reduction with GRP growth, although economic growth does not seem to mitigate SO<sub>2</sub> emissions in the other 17 southern and northwestern provinces.

Some southern provinces, such as Guangdong, were concerned about regional air pollution in their rapidly developing areas. For example, the Guangdong and Hong Kong governments established The Pearl River Delta Regional Air Quality Monitoring Network in November 2005. This is the first joint regional air pollution monitoring network in China (Zhong et al. 2013). However, although there are efforts on improving air quality in these provinces, more active environmental policies (e.g., environmental standards and environmental management enhancements) would be needed to induce air quality improvement.

**Table 4** Model estimates: industrial solid waste production

Variable	OLS		GWR				
	Coeff.	SE	Min	LQ	Med	UQ	Max
Intercept	0.231	0.173	− 2.047	0.080	0.773	1.244	2.444
GRPP	2.236***	0.677	− 13.978	− 2.595	0.777	5.633	14.632
GRPPSQ	− 1.036**	0.495	− 9.027	− 3.066	− 0.362	2.059	29.046
POPDENS	− 2.514*	1.382	− 32.527	− 16.735	− 11.115	− 2.816	17.543
COAST	− 0.372***	0.100	− 0.546	− 0.307	− 0.232	0.063	0.849
TIME	0.649***	0.070	0.211	0.511	0.565	0.787	1.221
N	493		493				
Adjusted R <sup>2</sup>	0.210		0.631				
AIC	1130.339		766.224				
AICc	1130.570		769.028				

\*\*\*, \*\*, \* indicate 1, 5, and 10% significance levels, respectively

**Table 5** Test for spatial variability of GWR coefficients

Variable	SO <sub>2</sub> emission		Industrial wastewater discharge		Industrial solid waste production	
	F	Diff of criterion	F	Diff of criterion	F	Diff of criterion
Intercept	40.726	− 103.642	19.589	− 49.613	17.660	− 44.374
GRPP	60.740	− 150.795	16.747	− 42.165	24.762	− 63.825
GRPPSQ	45.262	− 103.798	16.152	− 36.220	17.944	− 40.659
POPDENS	29.635	− 48.787	40.183	− 66.279	47.786	− 78.513
COAST	22.955	− 37.995	5.781	− 6.897	16.125	− 25.861
TIME	8.542	− 27.293	7.155	− 21.527	10.824	− 36.638

Positive value of diff-criterion (AICc, AIC, BIC/MDL, or CV) suggests no spatial variability in terms of model selection criteria

**Table 6** Power determination of risk factors affecting regional pollution

Pollutant	Risk factors		
	SO <sub>2</sub> emission	Industrial wastewater discharge	Industrial solid waste production
GRPP	0.172***	0.477***	0.165***
POP DENCE	0.529***	0.603***	0.454***
COAST	0.007*	0.243***	0.011**
TIME	0.050***	0.000	0.175***

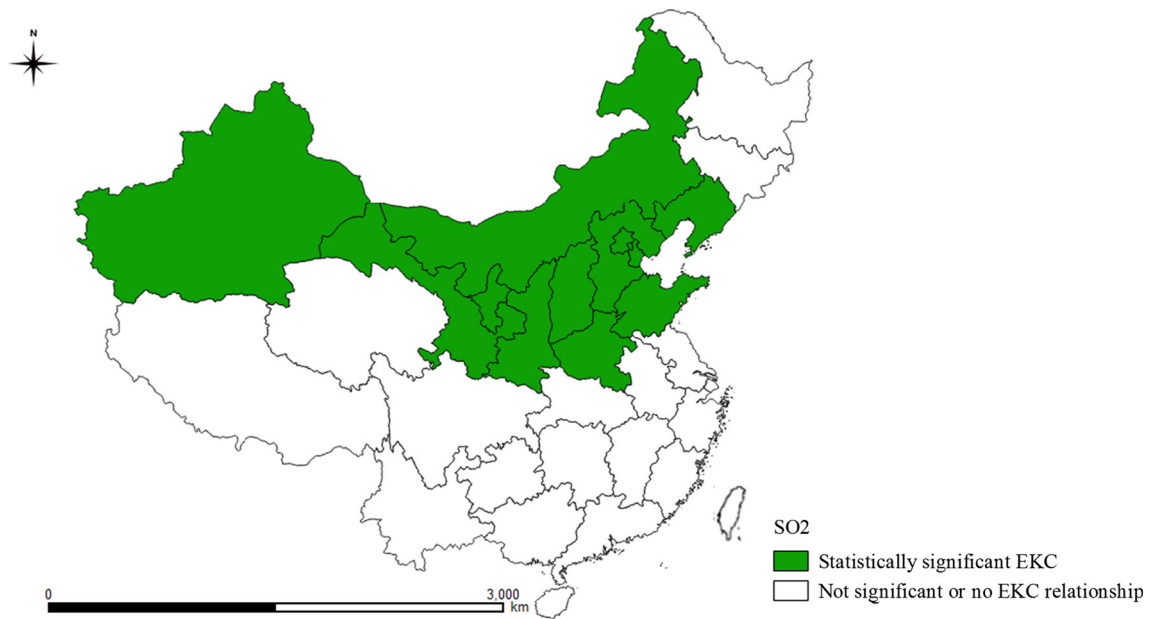
All power determination values are significant except time in industrial wastewater discharge

\*\*\*, \*\*, \* indicate 1, 5, and 10% significance levels, respectively

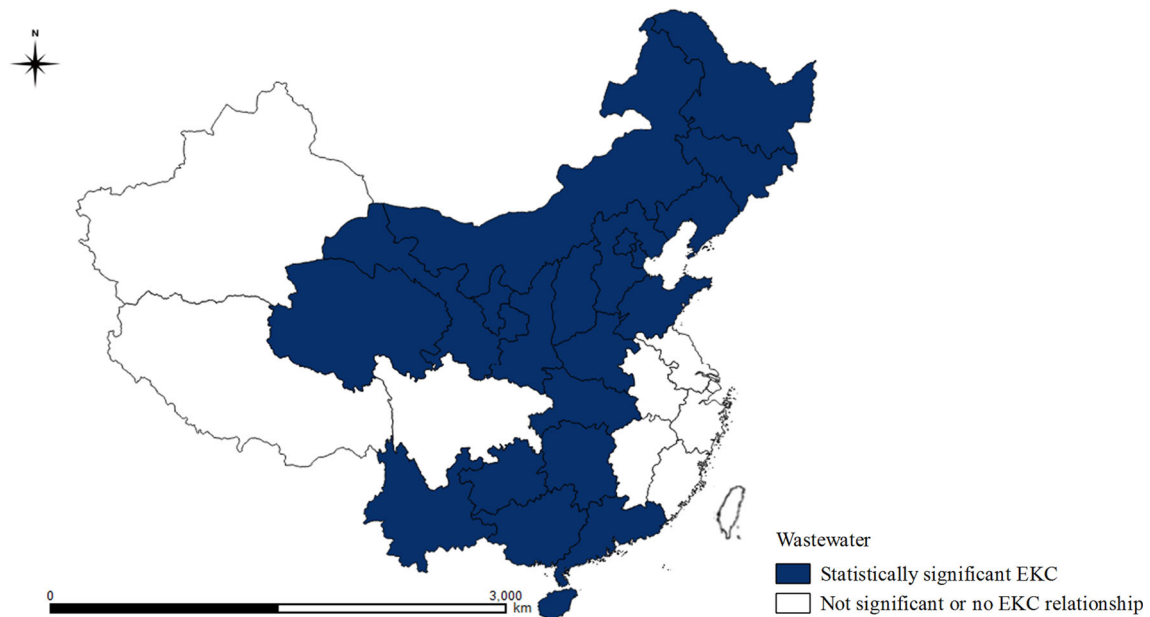
Figure 3 indicates the EKC relationship for wastewater discharge, predicting significant EKC relationships between GRP growth and industrial wastewater discharge in 21 out of 29 provinces. This suggests that, ultimately, there would be reduced discharge of wastewater in these 21 provinces along with economic growth. However, the results show that eight provinces, namely Anhui, Fujian, Jiangsu, Jiangxi, Shanghai, Sichuan, Xinjiang, and Zhejiang, do not exhibit an EKC relationship for wastewater discharge.

Regarding industrial solid waste production, the EKC relationship holds in 10 northern-central provinces, namely Beijing, Gansu, Hebei, Henan, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Shanxi, and Tianjin, except for coastal regions (Fig. 4). This result demonstrates a positive tendency for solid waste to decrease in these 10 provinces as China's economy grows. However, economic growth is not likely to reduce solid waste in most western, southern, and coastal provinces, but rather, a shortage of sites for waste disposal facilities tends to occur in some provinces, such as





**Fig. 2** Spatial variations in SO<sub>2</sub> EKC relationship. *Note:* The green colored provinces represent the areas that have a significant EKC relationship [i.e.,  $\beta_1 > 0$  and  $\beta_2 < 0$  in Eq. (4)]

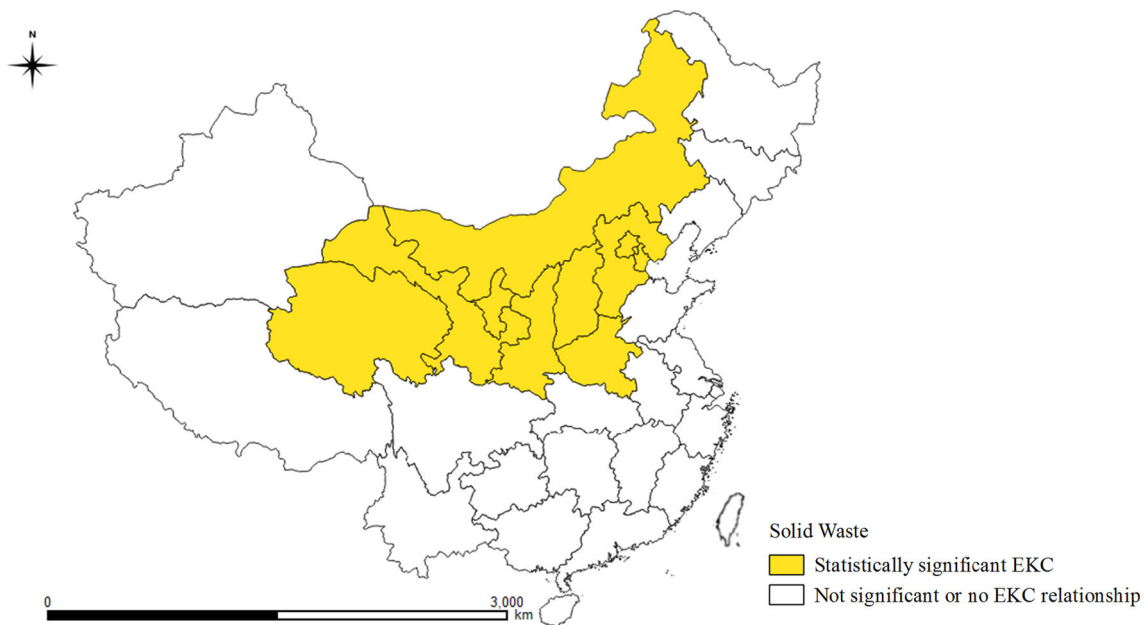


**Fig. 3** Spatial variations in wastewater EKC relationship. *Note:* The blue colored provinces represent the areas that have a significant EKC relationship [i.e.,  $\beta_1 > 0$  and  $\beta_2 < 0$  in Eq. (4)]

Guangzhou. This might be due to the lack of solid waste disposal facilities in this region, mainly caused by poor waste management, a low-quality institutional system, and local governments' financial burdens (Chung and Poon 2001; Chung and Lo 2012). Although relevant laws and

policies are increasing, a more effective and sustainable management system would be needed in these regions.

Considering these graphical results, we can better understand the geographical distribution of EKC for each pollutant. The development stage of the local economy and regional industrial structure, and characteristics of



**Fig. 4** Spatial variations in solid waste EKC relationship. *Note:* The yellow colored provinces represent the areas that have a significant EKC relationship [i.e.,  $\beta_1 > 0$  and  $\beta_2 < 0$  in Eq. (4)]

pollutants can be considered the reasons for the different patterns. Regarding the relationship between economic development and pollutant characteristics, previous studies indicated several types of pollutants, and some of these studies categorized them based on the countries' social and economic characteristics (Matsuoka 2004; Matsuoka et al. 1998).

The empirical results show that regions that have significant EKC relationships for  $\text{SO}_2$  and solid waste are concentrated in northern China, while regions with significant EKC relationship for wastewater are broadly distributed across the country. Therefore, establishing environmental policies according to regional differences and the characteristics of pollutants is needed to enhance their effectiveness.

Finally, Table 7 presents the ratio of actual GRP per capita to calculate the turning point (i.e., the inflection point of EKC) based on the analytical results of the EKC relationships in each province for 2012. From these estimates, it is possible to identify the trend of sustainable development after the analysis period, although this calculation assumes a trend of provincial economic growth similar to the current pattern. Specifically, a ratio over 1.00 indicates that GRP per capita has reached the calculated turning point. As the pollutants start to decrease after this point along with economic growth, it is possible to identify their status on the EKC of each province.

For  $\text{SO}_2$ , while 12 provinces have a valid EKC relationship between GRP and  $\text{SO}_2$  emissions, only Beijing and Liaoning passed the inflection points on the EKC.

Regarding industrial solid waste production, only Beijing reached the calculated turning point with a ratio of 1.341. Beijing and Liaoning are representative of developed provinces in China that hold the first and third ranks of the actual 2012 GRP per capita, respectively.<sup>11</sup> These results may imply that environmental institutions (e.g., local governments and environmental NGOs) could be established in developed provinces that have a better capacity for reducing such pollutants compared to other regions.

As per the central column of Table 7, numerous provinces have passed through the turning points in EKC for wastewater. Specifically, eight of 21 provinces, which show the EKC relationship, have a ratio over 1.00—Beijing, Guangdong, Guangxi, Hainan, Hunan, Liaoning, Tianjin, and Yunnan. This demonstrates a unique geographical distribution. Beijing, Liaoning, and Tianjin, located in the eastern coastal region, hold the first, third, and fifth rank of GRP per capita in 2012, respectively. Thus, similar to  $\text{SO}_2$  and solid waste EKC, developed provinces with high GRP per capita are likely to control industrial wastewater discharge more effectively than other provinces. The other five provinces, Guangdong, Guangxi,

<sup>11</sup> Adjusted GRP per capita by CPI (1993 = 100) of each province in 2012 is as follows: Beijing (1.223), Shanghai (1.112), Liaoning (0.794), Tianjin (0.759), Jiangsu (0.708), Zhejiang (0.706), Guangdong (0.609), Xinjiang (0.566), Shandong (0.553), Heilongjiang (0.543), Fujian (0.530), Inner Mongolia (0.530), Hainan (0.513), Jilin (0.512), Ningxia (0.489), Shaanxi (0.482), Shanxi (0.475), Qinghai (0.457), Hebei (0.457), Hubei (0.443), Hunan (0.439), Sichuan (0.399), Henan (0.385), Yunnan (0.343), Guangxi (0.343), Jiangxi (0.338), Gansu (0.324), Anhui (0.324), and Guizhou (0.298).

**Table 7** Ratio of actual GRP per capita to calculated turning point

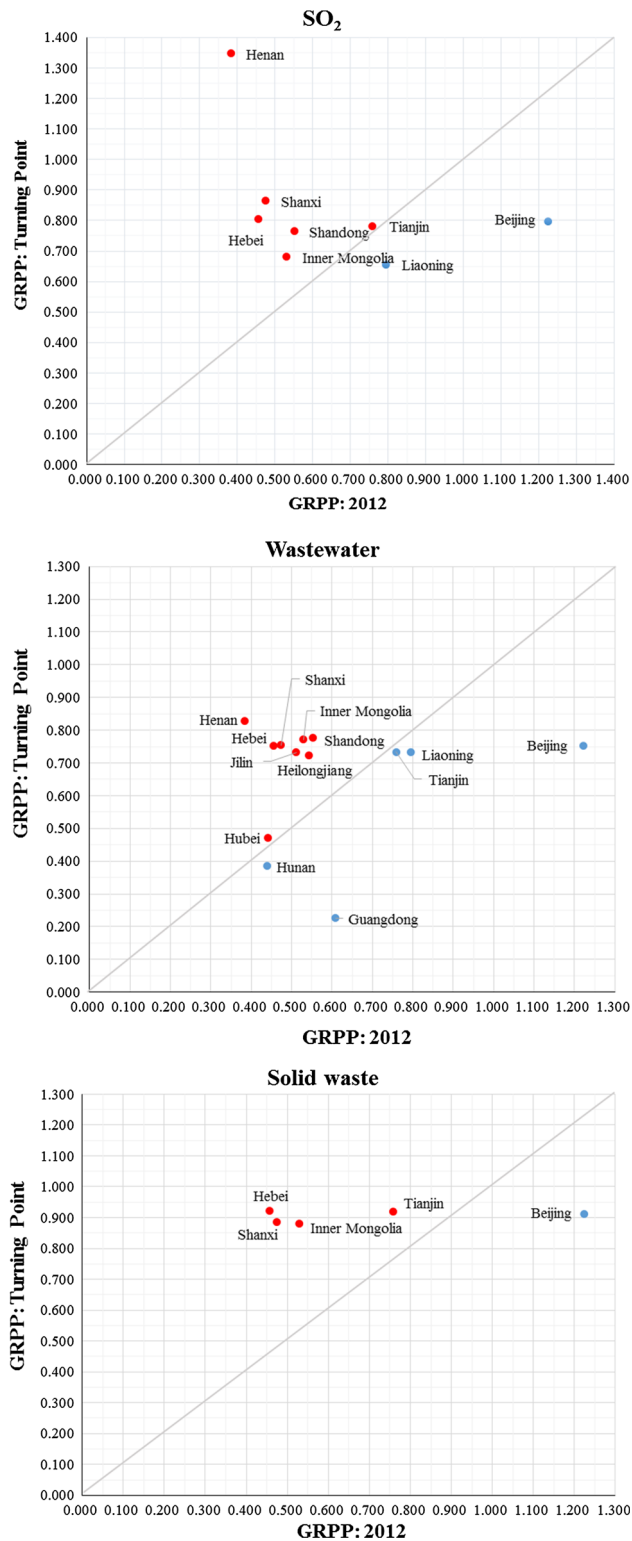
Province or city name	2012 GRP per capita	SO <sub>2</sub>		Wastewater		Solid waste	
		Turning point	Ratio	Turning point	Ratio	Turning point	Ratio
Beijing	1.223	0.798	1.531	0.753	1.625	0.911	1.341
Tianjin	0.759	0.781	0.973	0.734	1.034	0.918	0.827
Hebei	0.457	0.803	0.569	0.752	0.608	0.922	0.496
Shanxi	0.475	0.863	0.551	0.755	0.630	0.884	0.537
Inner Mongolia	0.530	0.680	0.780	0.770	0.688	0.880	0.602
Liaoning	0.794	0.655	1.211	0.733	1.083	–	–
Jilin	0.512	–	–	0.732	0.699	–	–
Heilongjiang	0.543	–	–	0.723	0.751	–	–
Shanghai	1.112	–	–	–	–	–	–
Jiangsu	0.708	–	–	–	–	–	–
Zhejiang	0.706	–	–	–	–	–	–
Anhui	0.324	–	–	–	–	–	–
Fujian	0.530	–	–	–	–	–	–
Jiangxi	0.338	–	–	–	–	–	–
Shandong	0.553	0.764	0.724	0.776	0.713	–	–
Henan	0.385	1.347	0.286	0.828	0.465	1.670	0.230
Hubei	0.443	–	–	0.471	0.940	–	–
Hunan	0.439	–	–	0.385	1.140	–	–
Guangdong	0.609	–	–	0.226	2.695	–	–
Guangxi	0.343	–	–	0.297	1.155	–	–
Hainan	0.513	–	–	0.261	1.971	–	–
Sichuan	0.399	–	–	–	–	–	–
Guizhou	0.298	–	–	0.338	0.881	–	–
Yunnan	0.343	–	–	0.339	1.012	–	–
Shaanxi	0.482	0.891	0.541	0.783	0.617	0.811	0.595
Gansu	0.324	0.797	0.407	0.755	0.429	0.809	0.400
Qinghai	0.457	–	–	0.661	0.692	0.643	0.711
Ningxia	0.489	0.851	0.574	0.787	0.621	0.803	0.609
Xinjiang	0.566	0.614	0.922	–	–	–	–

The turning point of each province or city indicates the calculated inflection points of EKC from the analysis in this study. The equation to calculate the ratio of actual GRP per capita to the turning point is  $1 + (\text{GRPP}_{2012} - \text{GRPP\_OPT})/\text{GRPP\_OPT}$ . Thus, ratio 1.00 indicates that the current GRP per capita in 2012 reached the calculated turning point. Only provinces or cities that have significant EKC relationship are calculated

Hainan, Hunan, and Yunnan, are all located in southern China, where the manufacturing industry has been historically developed. For example, Guangdong, which has the highest ratio of 2.695, contains one of the leading economic regions of China, known as the Golden Delta of Guangdong. Since this region is in contiguity with Hong Kong, there are substantial movements of labors, goods, or services. With abundant freshwater resources and high population density, Southern China is known as the Pearl River Delta, and has achieved rapid development over the past 20 years (Ediger and Hwang 2009). Therefore, the awareness of provincial environmental protection has been increasing here historically more than in other provinces. In

this context, the preceding growing concern of wastewater pollution problems in response to the early development of manufacturing in these five provinces might result in significant EKC and ratio values above 1.00.

Based on the expected turning point estimations of the GRP per capita results and actual 2012 GRP per capita, Fig. 5 shows the graphs of each pollutant, which presents the relationships of the expected calculated turning point and the actual GRP per capita in 2012 based on the GWR analysis results in each province. We show the EKC with the calculated expected turning point of EKC in each province. A 45 degrees reference line with different colors (marking the color into red and blue to present provinces



**Fig. 5** The graphs of the expected turning points of SO<sub>2</sub> emission, wastewater, and solid waste that present the calculated turning point and the actual GRP per capita (100 million yuan) in 2012 on the GWR analysis results in each province

before and after the expected point of inflection) is used in each graph to compare provinces before and after the point of inflection effectively. Through Table 7 and Fig. 5, we can easily compare different turning point scenarios in a single time axis for 2012.

Overall, only Beijing successfully passed through the EKC inflection points of all three pollutants, and simultaneously entered a phase of improving environmental and economic performance. Here, SO<sub>2</sub>, wastewater, and solid waste diminish with increasing GRP. One potential reason for this could be that Beijing has been undertaking stringent measures and enforcing environmental policies, part of the Green Olympic Movement, ever since the city received Olympic sponsorship in 1998 (Berkowitz et al. 2007). Another reason could be policies or political strategies and type of region related to industrial development that this study did not consider. Numerous manufacturing industries are established in provinces near Beijing, such as Tianjin, and thus, environmental quality in Beijing is relatively better compared to other neighboring provinces. Moreover, principles related to environmental policy implementation may affect the shape of the EKC relationship (Wang et al. 2012b).

The EKC status of Beijing also presents the implications for cities with similar industrial structure. Wang et al. (2012a) showed the remarkable improvement of Beijing development, and emphasized that similar cities are likely to show analogical tendency in their development paths.<sup>12</sup> We can assume similar effects on environmental quality in each province. Therefore, policymakers should consider city type and regional industrial policies and structures.

Other provinces, such as Hebei and Shanxi, exhibit EKC relationships, but need more time to reach a stage of reducing pollutants along with economic development. Moreover, EKC relationships for all pollutants are not significant in seven provinces located in southeastern China, thus indicating that it is currently difficult to define the relationship between economic growth and environmental pollutants in these provinces. It is possible that their EKC graphs have different shapes from the typical inverted-U shape, such as a linear relationship or cubic function. A longer term analysis may capture the shapes of the relationships between economic growth and environmental pollutants in those provinces. Moreover, further analysis would be needed to reveal the determinants of different EKC patterns.

<sup>12</sup> In their analyses, the city type of Beijing shows significant improvement between 1990 and 2000, but is categorized with other cities (Wang et al. 2012a).

## 5 Conclusions and discussion

This study estimated the EKC relationship at province level in China using the GWR approach, where the model can be fitted at each spatial location in the data, weighting all observations by a function of distance from the regression point. Hence, considering spatial heterogeneity, the EKC relationship can be analyzed by region through this approach rather than describing the average relationship over the entire study area. We applied this approach to three industrial pollutants—SO<sub>2</sub> emission, wastewater discharge, and solid waste production—in 29 provinces of China during 1994–2010.

The results have significant implications for prospective environmental and industrial policymaking by the Chinese government. This study produced a set of local statistics by applying the GWR models, and mapped the differences in the EKC relationship among regions and pollutants. Therefore, the results could describe the state of the EKC relationship of each province, thus enabling us to provide more detailed suggestions by province, while most previous studies evaluated a country-level average EKC.

The empirical results from our three GWR models indicate three types of relationships between economic performance and environmental quality: achieving an EKC relationship and passing the turning point, achieving an EKC relationship before passing the turning point, and no EKC relationship exists. If a province has achieved the EKC relationship, we can consider it has adopted a sustainable trend regardless if this was before or after the turning point. However, regions with no EKC relationship indicate they have lost the balance between economy and environmental quality, and forecast a grim future for sustainable development.

This study provides policy implications from different EKC relationship types in the framework of policymaking. The results by region show that the relationships between economic and environmental performance largely differ among provinces. Since the results indicate a significant variation of the existence of EKC relationships among provinces, we could raise implication based on empirical evidence—necessity of a critical attitude toward the monotonous hypothesis of the relationship between environmental degradation and economic development, and the importance of province-specific policymaking for achieving province balanced growth.

We did not observe any EKC relationship for any pollutant in seven provinces, namely Anhui, Fujian, Jiangsu, Jiangxi, Shanghai, Sichuan, and Zhejiang. In this respect, it is difficult to determine an equilibrium point, which is the turning point on the EKC graph in this study, between economic and environmental performance. In other words,

these provinces lack the balance of economy and environment. It should be corrected in terms of new normal policies. Considering the gap between growth rate and urbanization (Wang et al. 2012a), stricter regulations and laws may be required in provinces that achieve the EKC relationship before the turning point as opposed to other provinces, since more pollution would be expected to be generated by an increasing economic performance. In such provinces, environmental policies and laws should be implemented for the relationship between regional economies and environmental performance to move in a sustainable direction. The “Coal Consumption Cap plans,” enacted in China, which depend on each province’s unique situation, aims to provide effective “red-line restrictions” for natural resources. This scheme is a good beginning for sustainable development (China Coal Cap Project 2015).

Particularly, a more careful and efficient approach will be required in regions with no EKC relationship and high economic performance because they are expected to witness intensified pollution due to their active industrial development. For example, the results of Shanghai deserve attention. While Shanghai’s adjusted GRP per capita in 2012 ranks second, following Beijing (refer to footnote 11), the empirical results on the EKC relationship show the opposite pattern. As previously mentioned, Beijing shows an exemplary pattern of EKC relationship, while no significant pattern is found in Shanghai during the same period. Existing EKC consideration in China tend to focus on the national framework and overlook spatial heterogeneity. However, the empirical results provide a strong implication that policymakers need to carefully consider the EKC relationship in each province, and be aware of the importance of further efficient environmental policies in regions with lively economic activity, but no EKC relation.

Some provinces, including Hebei, Shanxi, and Tianjin are found to exhibit EKC relationships, but they are still away from the turning point. This implies that greater environmental deterioration would be observed, although they follow a path of sustainable growth. Specifically, discharges of pollutants are still increasing along with economic development, although the existence of EKC indicates that its economic development is moving in a direction where economic and environmental performance can be improved simultaneously. Further, the results indicated that many provinces have passed the turning point of wastewater EKC, whereas only one and two provinces have successfully passed the turning points of solid waste and SO<sub>2</sub> emissions, respectively. From these results, diligent efforts to manage those types of pollutants are necessary for promoting more balanced development policies for each province. Therefore, active and effective



environmental policies and laws to shorten the time to the turning point are required. Additionally, in the case of provinces achieving an EKC relationship after the EKC turning point, the role of policies for maintenance, control, and monitoring would be increasingly important for further sustainable development in the long term.

There is a growing perception that China's economy has been entering a so-called "new normal" stage. This represents a significantly lower growth rate than the previous three decades'. China's annual growth rate is expected to be less than 7% from 2016 to 2020, implying a new phase of the Chinese economy in comparison with the past high economic growth rates. The Chinese government officially accepts this new stage, and has been shifting its primary economic focus from a development-oriented structure to growth-balancing economic activities and environmental protection (Zhang et al. 2016).

The Chinese government has also been under global pressure to consider the quality of living, including environmental protection. Although stronger environmental regulations aimed at reducing pollution and improving environmental quality have been established after the reform and opening up of the economy, the effectiveness of the Chinese government's environmental policies has been questioned owing to increasing pollution. In this regard, one of Chinese government's first and most important tasks upon entering the new normal is to harmonize economic growth and environmental quality.

According to this study, it is clear that policymakers should establish different types of environmental policies to address current states of environmental problems and the economy. In other words, they should pay attention to whether the state of pollution in each region is balanced from the sustainable development perspective. Particularly, for large countries like China, regional and specialized approaches are more effective than universal policies, since regional development levels, characteristics, history, and industrial structure vary among provinces. Empirical evidence on the existence of the EKC relationships is one key indicator that allows policymakers to ascertain whether economic and sustainable developments are simultaneous. Therefore, this study contributes valuable implications for environmental policymakers who focus on China's sustainable development.

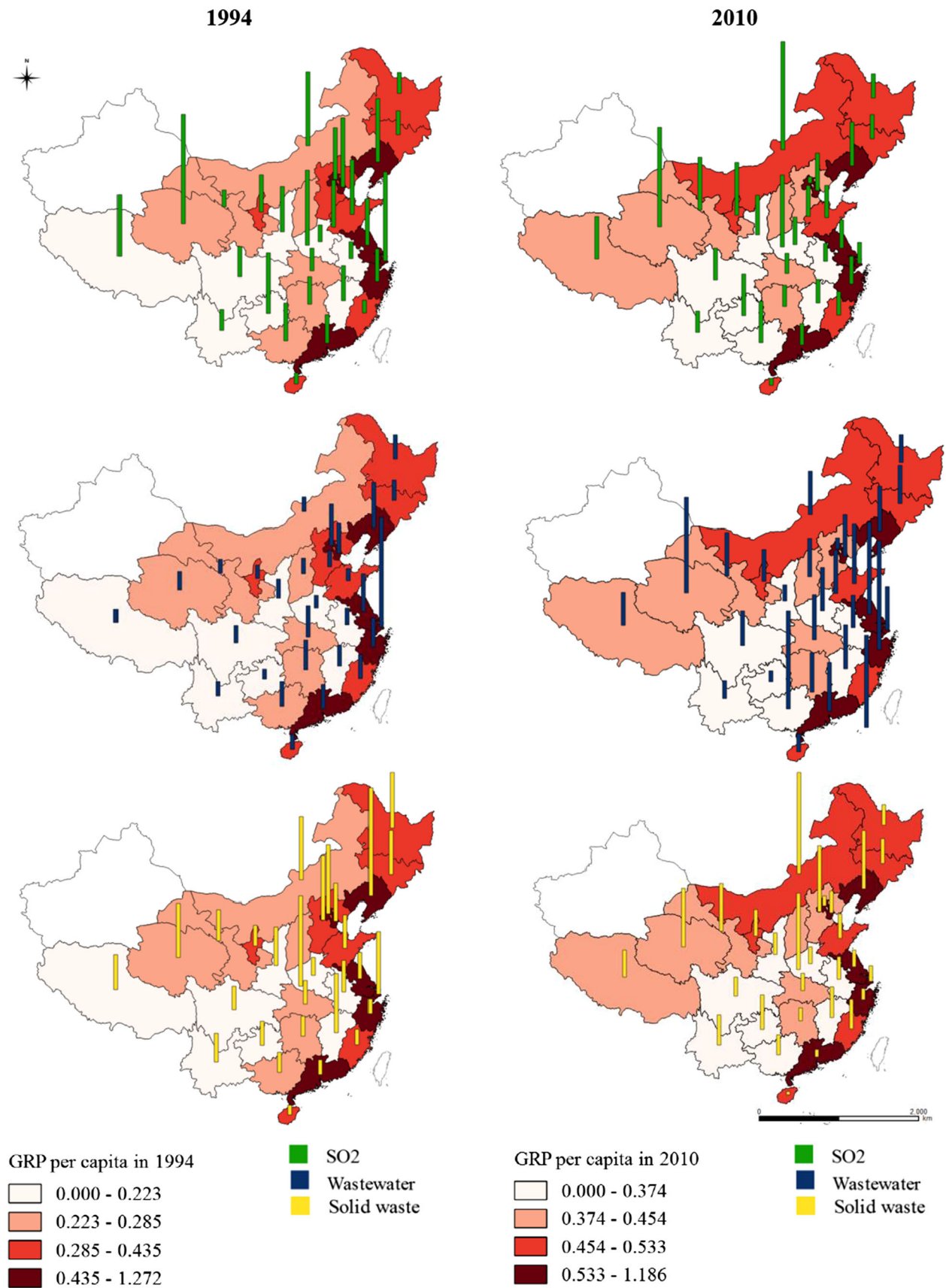
Before closing this study, several limitations need to be pointed out. First, our models are limited in terms of variables, since the analyses are conducted focusing on the

EKC hypothesis. This study could not consider various factors mainly because of multicollinearity and data limitations, while previous literature suggests that socioeconomic factors, such as industrial structure, capital intensity, and environmental management capacities, are major driving forces. For example, considering type and development path of cities is very important for investigating the EKC (Wang et al. 2012a; Arsanjani et al. 2013)—especially, city type based on industrial structure should be considered. Moreover, all major pollution sources should be fully accommodated to address balanced growth in China. Vehicles and households are also major pollution sources, especially for air. As such, more detailed analysis would be required to include such exhaustive data. The city type and its development path can be verified based on various characteristics for more accurate inference of the EKC, thereby leading to more effective policy implications for balanced economic growth in China.

Finally, although we report significant and interesting results on the relationship between economic growth and environmental quality from province-level data, the unit of analysis could be improved by using data on smaller units. Due to data limitation, this study used province-level data to provide a sufficiently long period for investigating the relationship between Chinese economic growth and environment. The process to obtain consistency and specific data on various regional environmental quality factors for China was very delicate and difficult. Further studies should overcome this limitation by developing data for small geographic units, such as miscellaneous cities, and methods focusing on particular pollutants, including those affecting the quality of the air.

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## Appendix: Distributions of the GRP per capita and the pollutants in 1994 and 2010



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