Energy consumption and economic development in Guangdong, China: Distribution, relationship and causes

Mengmeng Hu
Sun Yat-Sen University
Yafei Wang
Sun Yat-Sen University
Beicheng Xia (xiabch@mail.sysu.edu.cn)
Sun Yat-Sen University
Guohe Huang
University of Regina

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Energy consumption and economic development in Guangdong, China: Distribution, relationship and causes

Mengmeng Hu [a,b], Yafei Wang [a], Beicheng Xia [a,*], Guohe Huang [b,*]

[a] School of Environmental Science and Engineering, Sun Yat-sen University, Guangzhou 510275, PR China

[b] Faculty of Engineering and Applied Science, University of Regina, Regina, Saskatchewan S4S 0A2, Canada

*Corresponding author: Beicheng Xia: Tel.: +86-20-31145320; E-mail: xiabch@mail.sysu.edu.cn;

Guohe Huang: E-mail: huang@iseis.org.

Abstract

Analysing the relationship between energy consumption and economic growth is essential to achieve the goal of sustainable development. We employ hot spot analysis to discover the spatial agglomeration of GDP per capita and energy intensity in Guangdong, China, from 2005-2018. Furthermore, panel vector autoregression coupled with a system generalized method of moments is performed to examine the dynamic causal relationship between energy consumption and economic growth under the framework of the Cobb-Douglas production function. Using a multivariate model and grouped studies based on the differences in regional economic development, we show that the GDP per capita of the Pearl River Delta (PRD) is significantly higher than that of the peripheral municipalities. However, energy intensity shows an entirely different spatial distribution. The development of the regional economy depends on its own "assembling effect". GDP explains approximately 68.3% of the total variation in energy consumption in the PRD and only approximately 34.5% of that in the peripheral municipalities. We do not confirm Granger causality between energy consumption and economic development. Guangdong can decrease its energy consumption growth without substantially sacrificing its economic growth. The analysis framework of this paper has significant implications for regions in balancing economic development and energy consumption.

Keywords: Economic development; Energy consumption; PVAR model; Spatial statistics; Guangdong

Introduction

Energy is the foundation of the national economy and social development, and it plays a crucial role in resource allocation and economic growth (Bekhet et al., 2017). Simultaneously, economic growth will increase energy use (Shahbaz et al., 2013). The relationship between economic growth and energy consumption is essential as a scientific basis not only to support the management of energy systems but also to achieve sustainable development.

There have been several studies on the relationship between energy and the economy that use econometric analysis methods (Charfeddine and Kahia, 2019; Coondoo and Dinda, 2002; Hatfield-Dodds et al., 2015), and they can be classified into two categories. Those in the first category use a time series data model (Eren et al., 2019; Lu et al., 2016; Pinzón, 2018) and analyse data obtained from the continuous observation of the same object at different times; however, they might not be able to consider multiple objects. In contrast, those in the second category take a panel data approach, which has advantages in analysing various observations for each individual in the sample. For example, applying a panel vector autoregression (PVAR) model for 116 countries from 1990 to 2014, Acheampong (2018) argued that economic growth does not cause energy consumption. This finding is different from that of the study by Chen et al. (2019), who explored the effects of economic growth and energy consumption on CO_2 emissions for China over the 1995-2015 period. They found bi-directional causalities among these three factors in the long run. Furthermore, Ito (2017) found that renewable energy consumption contributes to economic growth, which is encouraging.

Using different frameworks to determine the link between energy consumption and economic growth is a relatively new field of research in energy economics. However, because of its importance to policymakers, numerous studies have been performed. As shown in Table 1, even under a comprehensive approach, the results in different studies are still contradictory due to the variety of methods and research backgrounds as well as data samples taken at different periods (Mirza and Kanwal, 2017; Ozturk, 2010).

Table 1. Overview of studies on the relationship between energy consumption and GDP.

Period	Country	Method	Relationship	Source
1960–2001	G11 countries	Granger non-causality testing	The results are mixed	(Lee, 2006)
1960-2006	G-7 countries	Bootstrap Granger non-causality tests	Energy consumption ≠ GDP	(Balcilar et al., 2010)
1970-1999	Korea	The vector error correction model	Energy consumption ↔ GDP	(Oh and Lee, 2004)
1970-2013	Countries along "the Belt and Road"	The vector error correction model, fully modified OLS and dynamic OLS approaches	Energy consumption ↔ GDP	(Liu and Hao, 2018)
1971-2002	Countries of the Gulf Cooperation Council	Developed panel cointegration and causality techniques	GDP → Energy consumption	(Al-Iriani, 2006)
1971-2002	11 selected oil exporting countries	Panel unit-root tests and panel cointegration analysis	GDP → Energy consumption	(Mehrara, 2007)
1971-2006	51 countries	The panel cointegration method	Energy consumption ↔ GDP	(Ozturk et al., 2010)
1972-2002	G7 countries	Panel cointegration, Granger causality and long-run structural estimation	Energy consumption→ GDP	(Narayan and Smyth, 2008)
1978-2014	U.S.A	Panel cointegration and panel causality tests	The results are mixed	(Mahalingam and Orman, 2018)
1980-2006	Albania, Bulgaria, Hungary and Romania	Autoregressive distributed lag bounds testing	Energy consumption ≠ GDP	(Ozturk and Acaravci, 2010)
1980-2006	93 countries	The panel fully modified ordinary least squares estimator	The results are mixed	(Narayan et al., 2010)
1980-2007	79 countries	Granger causality tests	The results are mixed	(Akkemik and Göksal, 2012)
1980-2012	Algeria	Granger causality tests	Renewable energy → GDP	(Amri, 2017)
1990-2014	Global	panel vector autoregression along with a system generalized method of moments	Energy consumption→ GDP	(Acheampong, 2018)
1992-2010	Croatia	Bivariate vector autoregression and Granger causality tests	Energy consumption→ GDP	(Borozan, 2013)
1995-2008	China	The vector error correction model and causal relationship testing	GDP → Energy consumption	(Zhang and Xu, 2012)

Note: ↔ means a bi-directional causal relationship, → means a uni-directional causal relationship, and ≠ means no causal relationship; GDP means gross domestic product.

Thus, these arguments have resulted in four major schools of thought on the causal relationship between economic growth and energy consumption: uni-directional causality from economic growth to energy consumption and vice versa, as well as no causality or bi-directional causality between economic growth and energy consumption. Lee (2005) conducted a detailed and extensive review of the causal relationship between energy and economic growth in developing countries and pointed out that there is no consensus on whether there is a short-term or long-term relationship between these two factors. Causality may exist in both directions (Belke et al., 2011; Belloumi, 2009). Notably, most studies reveal evidence of energy consumption. The link between economic activity and energy consumption has attracted considerable attention in developing economies at different levels. In such economies, the continuous development of the secondary industry has caused major environmental problems, and such development should be emphasized to determine effective methods of energy consumption. This overview shows that there is no consensus with regard to determining the adoption of different energy and environmental policies in small regions at the provincial level.

Tremendous efforts have been made to study the relationship between economic growth and energy consumption on a country or regional scale using panel data (Costantini and Martini, 2010). However, there have been limited reports on the spatial relationship, causing the spatial autocorrelation among panel samples to be easily ignored. Moreover, from a Chinese perspective, there has been a crucial demand for a scientific basis to deal with economic development and energy consumption. This is especially true for Guangdong Province, which is located in southern China, is the province with the highest GDP, and dramatically relies on fossil energy to meet its domestic and industrial demands. Meanwhile, many studies have examined the relationship between energy consumption and economic growth at the country level. However, there is no report that analyses the relationship at the municipal level using panel data. There is a sizable gap in economic development between different municipalities in the same province. Samples involving different levels of economic development need to be analysed separately.

Therefore, as an extension of previous efforts, this study aims to fill these gaps by providing additional empirical evidence on the relationship between energy consumption and economic growth using multivariate methods and variables. In this case, we want to explore the following questions: (a) What are the spatial patterns of GDP per capita and energy intensity? Furthermore, is there spatial autocorrelation between these two variables? (b) What is the relationship between economic development and energy consumption, and which factors contribute to changes in this relationship ? Moreover, the analysis framework constructed by this research can be applied to other municipalities and regions to provide a policy basis for decision makers.

The rest of this paper is structured as follows: Section 2 shows the mathematical model and describes the data; Section 3 presents the empirical results; Section 4 provides the discussion of our work; and Section 5 draws our conclusions.

Materials and methods

Spatial statistical analysis

Spatial autocorrelation analysis can be used as a model to explore spatial data in depth to reveal the rules of the spatial distribution of GDP per capita and energy intensity. Moran's I index reflects the similarity of the attribute values of nearby locations in space (Anselin, 1996) and can be calculated as follows:

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

where I is $\text{Moran's}\, I$; x_i and x_j, which are the attribute values of features i and j, respectively; w_{ij} is the spatial weight between feature i and j; and n is the number of features in the dataset. In general, $\text{Moran's}\, I$ ranges from -1 to 1. If the values of *I* are equal to 0, the variable shows a random pattern. $\text{Moran's}\, I$ values less than 0 indicate negative spatial autocorrelation, and values higher than 0 indicate positive spatial autocorrelation.

$\text{Moran's}\, I$ measures spatial autocorrelation based on feature locations and attribute values. At the same time, hot spot analysis is used to reflect the neighbourhoods where high-value or low-value features are spatially clustered. Hot spot analysis calculates the Getis-Ord Gi* statistic (Anselin, 1995).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{x}\sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{x})^2}\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad \forall j \neq i \tag{2}$$

where $\forall j \neq i$ means that features i and j cannot be the same. The G_i^* statistic is a z-score. The larger the z-score is, the more intense the clustering of high values (hot spot).

PVAR model

The Cobb-Douglas (C-D) production function is used as the model framework (Cobb and Douglas, 1928). The production factors in the original form of the C-D production function include capital and labour. Subsequently, some studies have added energy factors (Zhang et al., 2019). This study uses the structure of the production function after adding energy factors.

$$\mathrm{Y} = A_0 e^{\lambda t} P^{\alpha} F^{\beta} E^{\gamma} \tag{3}$$

where Y is the output; P is the population input; F is an investment in fixed assets; E is the energy input; A_0 is a constant; e represents the technological level of the base period; λ is the rate of technological progress; t is the time series; and α, β, and γ are the elasticity coefficients of the population, investment, and energy inputs, respectively. Furthermore, we take the logarithm on both sides of Eq. (3), which can be further written as follows:

$$\ln Y = \ln A_0 + \alpha \ln P + \beta \ln F + \gamma \ln E + \lambda t \tag{4}$$

Based on the C-D production function, a PVAR modelpanel vector auto-regression (PVAR) is presented. PVAR was first proposed Holtz-Eakin et al. (1988) and has been continuously developed and improved by Binder et al. (2005) and Love and Zicchino (2006). This technique combines the vector autoregression (VAR) approach, which can effectively use panel data to solve the problem of individual heterogeneity, and it takes full account of time effects and individual effects. The form of the PVAR model is as follows:

$$Z_{it} = \Gamma_0 + \sum_{p=1}^{n} \Gamma_p Z_{it-p} + d_i + e_t + u_{it} \tag{5}$$

where $i = 1, 2, \ldots, \mathrm{N}$ (country) and $t = 1, 2, 3, \ldots, T$ (time); Z_{it} is a four-variable vector $\{y_{it}, p_{it}, f_{it}, e_{it}\}$; Γ_0 is the country-level fixed effects; Z_{it-p} represents the p-order lag term; Γ_p is the lag operator of the endogenous covariates; d_i represents the individual effect; e_t represents the time effect of a specific shock; and u_{it} represents the error term.

On the right side of Eq.(4), we derivative t on both sides of the formula, and we let $dt = 1$. Further conversion can be obtained as fallows:

$$\frac{\Delta Y}{Y} = \lambda + \alpha \frac{\Delta P}{P} + \beta \frac{\Delta F}{F} + \gamma \frac{\Delta E}{E} \tag{6}$$

Let $y = \Delta Y/Y, p = \Delta P/P, f = \Delta F/F, \mathrm{e} = \Delta E/E$:

$$\mathrm{y} = \lambda + \alpha p + \beta f + \gamma e \tag{7}$$

Eq. (5) and Eq. (7) are combined as the PVAR model of this study. y_{it}, p_{it}, f_{it}, and e_{it} represent the growth rates of GDP, population, investment, and energy consumption, respectively, of country i in period t.

First, the stability test is required before estimating a PVAR model. Second, the lag order of the PVAR model is determined by the following three criteria: the Akaike information criterion (AIC) (Sakamoto et al., 1986), Bayesian information criterion (BIC) (Vrieze, 2012), and Hannan and Quinn information criterion (HQIC) (Lopez and Weber, 2017). The basic idea of the above three criteria is a trade-off between the sum of squared residuals model and the number of parameters. Finally, the weighted sum of the two is used as the basis for judging the degree of model fit.

Because the PVAR model contains fixed effect Γ_0, it does not satisfy the strict exogenous assumption of explanatory variables in classical linear regression. The "forward mean difference" method (Helmert transform) is used to eliminate fixed effects in the model. In the process of estimating the PVAR model, system generalized method of moment (Sys-GMM) estimation is applied. The Monte Carlo simulation process is used to perform impulse response and variance decomposition and to analyse the relationship between energy consumption and economic growth. Furthermore, the Granger causality between the population input, investment in fixed assets, energy consumption and economic growth is examined.

An overview of the study area

The study area is Guangdong, which is a province in southern China with the highest GDP (Fig. 1) and covers approximately 179,800 km2. According to the Guangdong Statistical Yearbook (2019), the GDP of Guangdong reached approximately 9.73 trillion yuan (RMB) (USD 1.47 trillion, 2018), and its GDP per capita was 86,412 yuan (or USD 13,058). Guangdong is home to the Pearl River Delta (PRD), which is one of the most densely populated and industrialized areas in China and consists of 21 municipalities in different states of economic development (Hu and Xia, 2019).

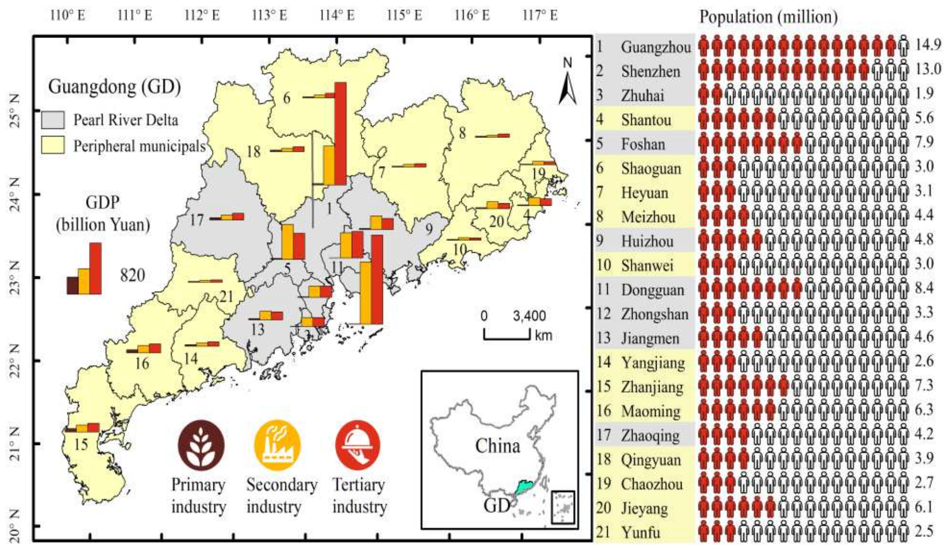

Fig. 1. The location, population and industrial structure of the study area.

Furthermore, the data are from the official website of the Guangdong Statistics Bureau and the 2006-2019 Guangdong Statistical Yearbook. The summary statistics are used to explain the basic characteristics of Guangdong (Table 2). They also show the imbalanced development of municipalities in Guangdong. Both the economic development and the total energy consumption of the PRD are larger than those of peripheral municipalities.

Table 2. Summary statistics of the variables.

	Pearl River Delta					Peripheral municipalities				
	Mean	Standard deviation	25^{th} percentile	50^{th} percentile	75^{th} percentile	Mean	Standard deviation	25^{th} percentile	50^{th} percentile	75^{th} percentile
GDP	525.96	550.61	158.76	290.76	693.71	99.92	64.21	52.78	84.07	124.02

(billion ¥)										
Population (million)	6.05	3.45	3.75	4.65	8.29	4.06	1.57	2.75	3.34	5.62
Investment (billion ¥)	161.02	136.53	71	123.96	194.34	52.5	42.59	20.42	43.58	66.78
Energy (Mt)	27.4	22.63	10.26	18.02	37.76	7.97	4.35	4.75	7.15	10.5

Results

Spatial panel data analysis of GDP per capita and energy intensity

Spatio-temporal characteristics

The spatio-temporal changes in Guangdong's GDP per capita and energy intensity are shown in Fig. 2. GDP per capita exhibited an increasing trend from 2005-2018. Take Shenzhen as an example; its GDP per capita increased from 60,837 yuan per capita in 2005 to 185,942 yuan per capita in 2018, which is the highest GDP per capita in China. Furthermore, there is a significant gap between the PRD and the peripheral municipalities. From the perspective of GDP per capita, the GDP per capita of the PRD is much higher than that of the peripheral municipalities. There is an unbalanced development of the regional economy in Guangdong.

The energy intensity in Guangdong had a significant downward trend from 2005 to 2018; that is, the energy consumption per unit of GDP output (ten thousand yuan) decreased. The energy intensity of developed municipalities such as Guangzhou and Shenzhen dropped significantly with the increase in GDP. In 2018, the tertiary industry in Guangzhou and Shenzhen accounted for a sizable proportion (more than 70%), resulting in extremely low energy intensity (<0.4 tons of coal equivalent (tce)/ten thousand yuan) in these regions. Currently, in the PRD, only Huizhou has an energy intensity higher than 0.6 tce/ten thousand yuan. From 2005-2018, Huizhou has the smallest (9.1%) and Foshan has the largest (57.7%) reduction in energy intensity. The energy intensity of the PRD is lower than that of the peripheral municipalities, and this result is strongly related to the industrial structure. The eastern region of the peripheral municipalities typically develops industries with a high energy consumption intensity but low GDP added.

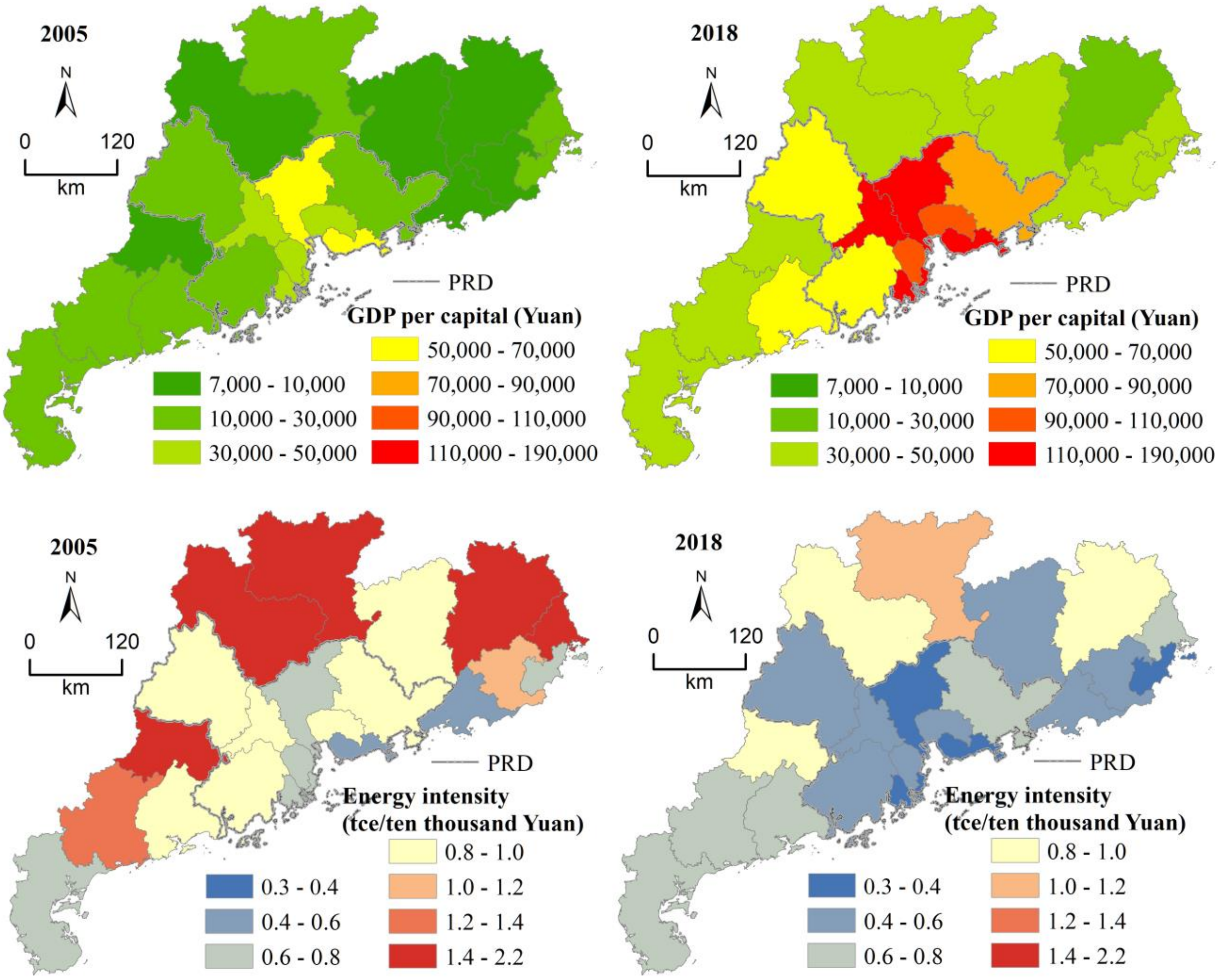

Fig. 2. Spatial-temperal changes in Guangdong's GDP per capita and energy intensity. tce means ton of coal equivalent.

Spatial correlation effects

The spatial pattern of GDP per capita in Guangdong is high in the central part of the PRD and low in the eastern and western regions. However, the inverse is true for energy intensity (Fig. 2). To search for sufficient evidence, ArcGIS is used to perform global spatial autocorrelation analysis on the GDP per capita and energy intensity in Guangdong (Table 3). The resulting *z*-score represents a multiple of the standard deviation. Furthermore, Fig. 3 (b) shows the relationship between the *z*-score and *p*-value, as well as the cluster effect represented. Both the *z*-score and *p*-value are associated with a standard normal distribution. When the result obtains a small *p*-value and a very high (or low) z-score, the observed spatial pattern is unlikely to reflect the theoretical random patterns represented by the null hypothesis.

Table 3 shows that the values of Moran's *I* of GDP per capita are all larger than 0.7 from 2005-2018, showing significant positive spatial correlation (p<0.001). Given the z-score greater than 5.9, there is less than a 1% likelihood that these clustered patterns could be the result of random chance. Specifically, the geographical distribution of Guangdong's economic development shows spatial clustering. Radiation effects by regional central cities primarily drive the characteristics of spatial correlation. Furthermore, the dynamic range of Moran's *I* of energy intensity is (0.1,0.3), showing positive but not significant spatial correlation (p >0.05). The p-values of energy intensity in different years are different. From 2005-2018, the Moran’s *I* of energy intensity showed a fluctuating trend, and overall, it showed an upward trend; the result of linear curve fitting is $I = 0.0018t + 0.209, \mathrm{R}^2 = 0.0703$. This result indicates that similar values, either high or low, are more likely to spatially cluster.

Table 3. Moran’s *I* of GDP per capita and energy intensity from 2005 to 2018.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GDP per capita														
Moran's *I*	0.7489	0.7618	0.7766	0.7838	0.7912	0.7560	0.7514	0.7351	0.7132	0.7010	0.7095	0.7202	0.7198	0.7358
z-score	6.2374	6.3211	6.4094	6.4558	6.5013	6.2565	6.2363	6.1399	5.9920	5.9084	5.9528	6.0352	6.0289	6.1497
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Energy intensity														
Moran's *I*	0.2463	0.2188	0.2082	0.2201	0.2252	0.2365	0.1877	0.1875	0.1923	0.2005	0.2022	0.2645	0.2776	0.2510
z-score	2.3834	2.1491	2.0325	2.1239	2.1573	2.2550	1.8358	1.8393	1.8755	1.9324	1.9428	2.4161	2.5290	2.3147
p-value	0.0172	0.0316	0.0421	0.0337	0.0310	0.0241	0.0664	0.0659	0.0607	0.0533	0.0520	0.0157	0.0114	0.0206

Spatial hot spot detection

In addition, spatial hot spot analysis is used to describe the correlation of the attribute value between an area and its neighbouring area (Fig. 3). Thus, the hot spots and cold spots are obtained. From the perspective of GDP per capita, the hot spots and cold spots did not considerably change from 2005 to 2018. In 2018, the hot spots (99% confidence) were mainly clustered in the central part of the PRD (Guangzhou, Shenzhen, Zhuhai, Dongguan), which has better location conditions and developed economies. The “low-low” clustering (low values surrounded by low values) were mostly located in the northwest region (peripheral municipalities). The economic development of peripheral municipalities lagged far behind that of the PRD.

The spatial clustering of energy intensity changed significantly from 2005 to 2018. The cold spots of energy intensity were mainly located in the PRD. Interestingly, combined with the cluster map of GDP per capita, the results show that the hot spots of GDP per capita and the cold spots of energy intensity had high levels of coincidence. In Guangzhou, no cold spots of energy intensity appeared, mainly due to the influence of neighbouring areas. The energy intensity of Qingyuan and Shaoguan, next to Guangzhou, was very high. The cold spots of GDP per capita did not overlap with the hot spots of energy intensity; both were located in peripheral municipalities. The hot spots of energy intensity were Qingyuan and Shaoguan; such municipalities develop industries with low value-added products and high energy intensity, and they trade higher energy consumption in exchange for GDP growth. Heyuan, Shanwei, and other municipalities with a relatively low energy intensity were located in the “low-low” cluster (cold spot) of GDP per capita.

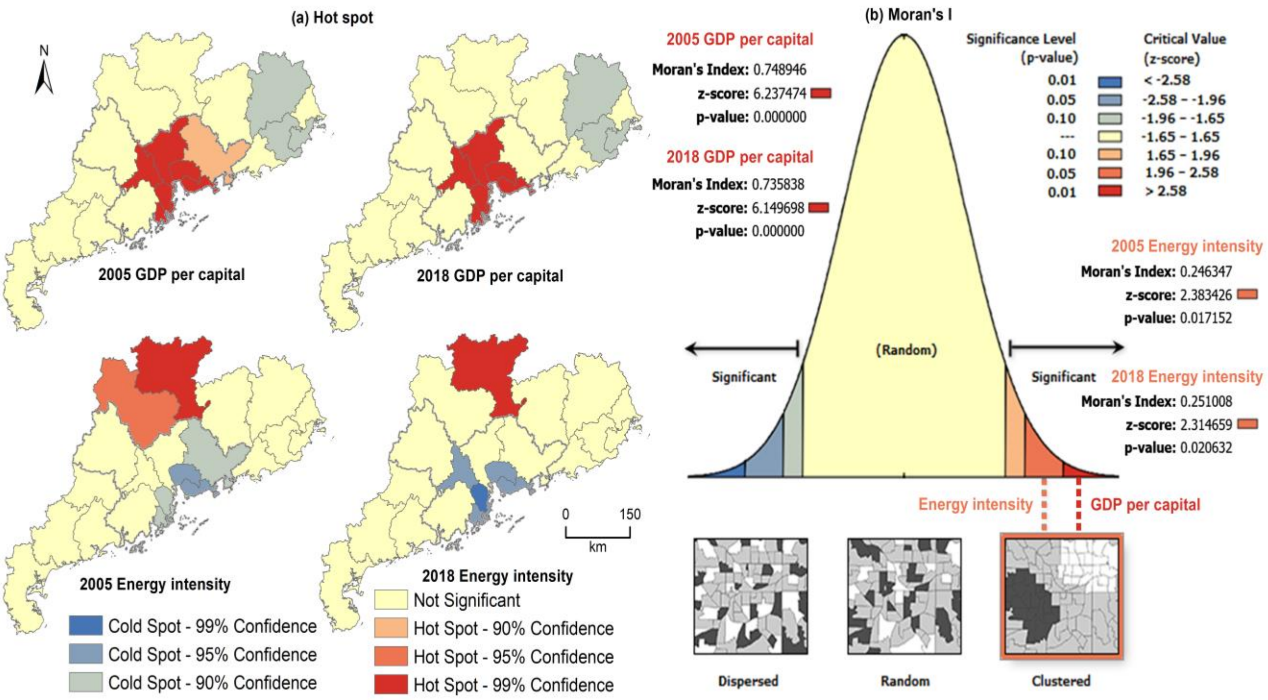

Fig. 3. Hot spot map of GDP per capita and energy intensity.

PVAR analysis of GDP and energy consumption

Stability test of the panel

Spatial panel data analysis, on the one hand, reflects the spatial autocorrelation of energy intensity and GDP per capita; on the other hand, it demonstrates imbalanced development in Guangdong Province. In the next step, a PVAR methodology is presented. It is necessary to perform a stability test of the PVAR model. The reciprocals of the four characteristic roots of the constructed PVAR model are all located in the unit circle, indicating that the established models are stable (Fig. 4).

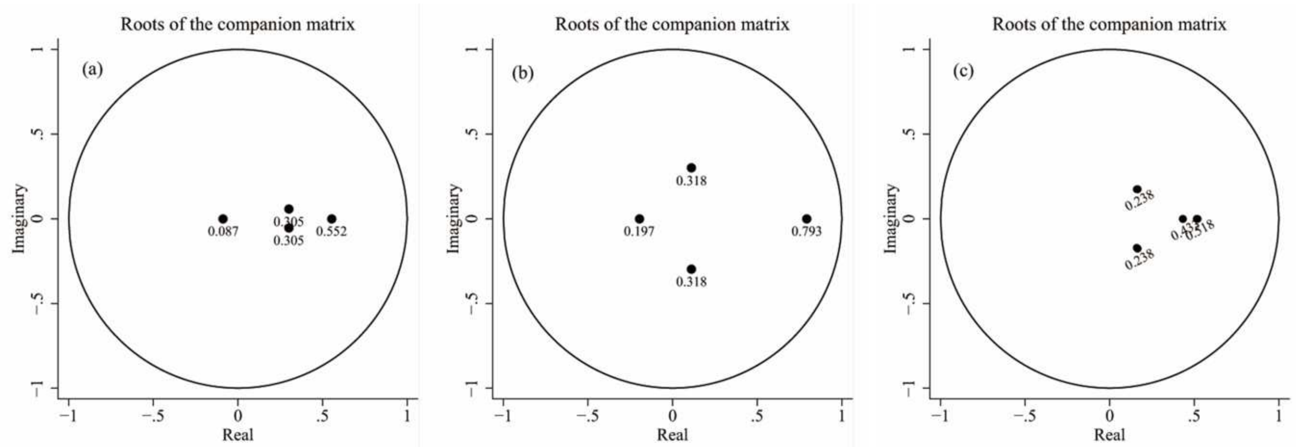

Fig. 4. Stability test of the PVAR model. Panel data in (a) Guangdong (all); (b) Pearl River Delta; and (c) peripheral municipalities.

Additionally, the choice of the lag order has an important impact on the PVAR model. If the lag order is too long, the degrees of freedom will be reduced, or conversely, the test result will be unreliable. This study uses the AIC, BIC, and HQIC to determine the lag order of the model (Table 4). According to the principle of selecting the minimum value and achieving comparable results, first-order lag models can obtain an established result for this study.

Table 4. Selection order criteria for PVAR.

	All samples			Pearl River Delta			Peripheral municipalities		
lag	AIC	BIC	HQIC	AIC	BIC	HQIC	AIC	BIC	HQIC
1	-10.7461	-9.2559*	-10.1451	-12.4158	-11.0527*	-11.8643	-12.1895	-10.7918*	-11.6215*

2	-11.0278*	-9.1789	-10.2804*	-12.7423*	-10.8536	-11.9807*	-12.2649*	-10.4066	-11.5102
3	-10.9802	-8.7161	-10.0629	-12.5256	-10.0425	-11.5293	-12.1683	-9.7841	-11.2016
4	-10.8631	-8.1110	-9.7462	-11.5755	-8.4135	-10.3167	-12.0949	-9.1032	-10.8856

Note: "*" indicates that the optimal lag order is selected according to the AIC, BIC, and HQIC.

System-GMM estimation

The estimated results of the PVAR model between GDP, population, investment, and energy using the system-GMM estimation method are obtained (Table 5). From panel A, the first-order lag of the GDP growth rate and investment growth rate has a significantly positive correlation with the GDP growth rate ($p<0.01$), reflecting that an increase in fixed-asset investment has a significant role in promoting economic growth. Furthermore, the first-order lag of the energy consumption growth rate has no significant impact on the growth rate of GDP, population and investment. The importance of energy consumption to other factors is not shown in panel A. An increase in energy consumption is positively related to the first-order lag of energy consumption ($p<0.05$), investment ($p<0.01$), and the growth rate of GDP ($p<0.1$). This result suggests that a 1% increase in GDP will cause a 0.159% increase in energy consumption. Moreover, due to the inertia of energy consumption, the previous changes in energy consumption will continue in the current period; thus, a change in energy consumption will be related to its previous value.

Panel B of Table 5 shows an increase in economic growth caused by investment, and the relationship is positive ($p<0.05$). Interestingly, the first-order lag of the growth rate of the population has a significantly negative correlation with the energy consumption growth rate ($p<0.05$). An increase in population does not lead to an increase but, rather, a decrease in energy consumption. In the PRD, the proportion of the tertiary industry increased from 2005 to 2018, and the population engaged in the tertiary industry increased, resulting in a reverse change in energy consumption.

However, regarding energy consumption, the results of the samples in the peripheral municipalities are different from those in the PRD. The coefficient of the lagged investment growth rate on the level of GDP is twice as large in the “high development” (PRD) sample compared to in the “low development” (peripheral municipalities) sample (i.e., 0.245 compared to 0.120), and this difference is statistically significant. From panel C, the growth rate of energy consumption is significantly affected by the lagged growth rate of population, investment, and energy consumption. Population growth and investment increases have contributed to energy consumption in the peripheral municipalities. Combined with Fig. 3, the results show that these municipalities have relatively high energy intensity. One possible reason is that those regions mostly adopt an "extensive" industrial structure and excessively develop heavy industry and manufacturing industry, which are characterized by high energy consumption, low technology, and low value added. For the peripheral municipalities, more attention should be devoted to reducing energy intensity by promoting techniques to use energy.

Table 5. Main results of the system-GMM estimation.

	Panel A: All samples	Panel B: Pearl River Delta	Panel C: Peripheral municipalities
GDP (*t*)			
GDP (*t*-1)	0.534*** (8.08)	0.339* (1.93)	0.575*** (8.12)
Population (*t*-1)	0.110* (1.80)	0.074 (1.04)	0.268 (0.77)
Investment (*t*-1)	0.138*** (4.86)	0.245** (2.52)	0.120*** (4.21)
Energy (*t*-1)	0.057 (0.92)	0.21 (1.03)	0.02 (0.42)
Population (*t*)			
GDP (*t*-1)	0.025 (0.52)	-0.061 (-0.36)	0.049*** (4.07)
Population (*t*-1)	-0.109 (-1.17)	-0.07 (-0.65)	-0.023 (-0.30)
Investment (*t*-1)	0.027 (1.58)	0.237** (2.35)	-0.012* (-1.84)
Energy (*t*-1)	-0.042 (-0.92)	-0.144 (-0.68)	0.019* (1.77)
Investment (*t*)			
GDP (*t*-1)	0.759** (2.57)	0.241 (0.72)	0.840** (2.05)
Population (*t*-1)	-0.002 (-0.01)	-0.398** (-2.45)	3.435** (2.12)
Investment (*t*-1)	0.344*** (4.75)	0.164 (0.91)	0.373*** (5.32)
Energy (*t*-1)	-0.396 (-1.27)	0.371 (0.68)	-0.632** (-2.00)
Energy (*t*)			
GDP (*t*-1)	0.159* (1.79)	0.097 (0.48)	0.121 (1.12)
Population (*t*-1)	-0.081 (-0.77)	-0.240** (-2.33)	1.272** (2.38)
Investment (*t*-1)	0.103*** (2.75)	0.137 (1.14)	0.095** (2.57)
Energy (*t*-1)	0.192** (2.04)	0.332 (1.30)	0.170* (1.96)
N	231	99	132
AIC	-10.746	-11.446	-11.644
BIC	-9.256	-8.825	-9.46
HQIC	-10.145	-10.385	-10.757

t statistics in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Impulse response functions

Impulse response analysis can obtain the impact of a standard deviation from the random disturbance term on the variables in the VAR system over a period of time, which can better reflect the dynamic relationship between the variables. In this study, 1000 Monte Carlo simulations are used to generate confidence intervals. The confidence interval is 95% (the middle red line is the estimated value of the impulse response function (IRF), and the two outer sides are the upper and lower boundaries of the 95% confidence interval). Fig. 5 shows the simulation results of the IRF with four variables estimated for all samples, and Fig. 6 and Fig. 7 report the results with the samples in the PRD and the samples in the peripheral municipalities, respectively, to compare the impulse responses for the model with different (high and low) levels of economic development.

In Fig. 5, the population, investment, and energy show a positive response to a shock to GDP. However, this response has a larger impact on early shocks. Energy consumption increases in response to a shock to GDP (a higher GDP implies more energy), and subsequently, it decreases and stabilizes in the long run. Furthermore, the response of the growth rate of GDP, population, and investment to energy consumption is positive in the estimated confidence and impulse responses. A positive shock to energy consumption growth initially increases GDP, and subsequently, it stabilizes in the long run.

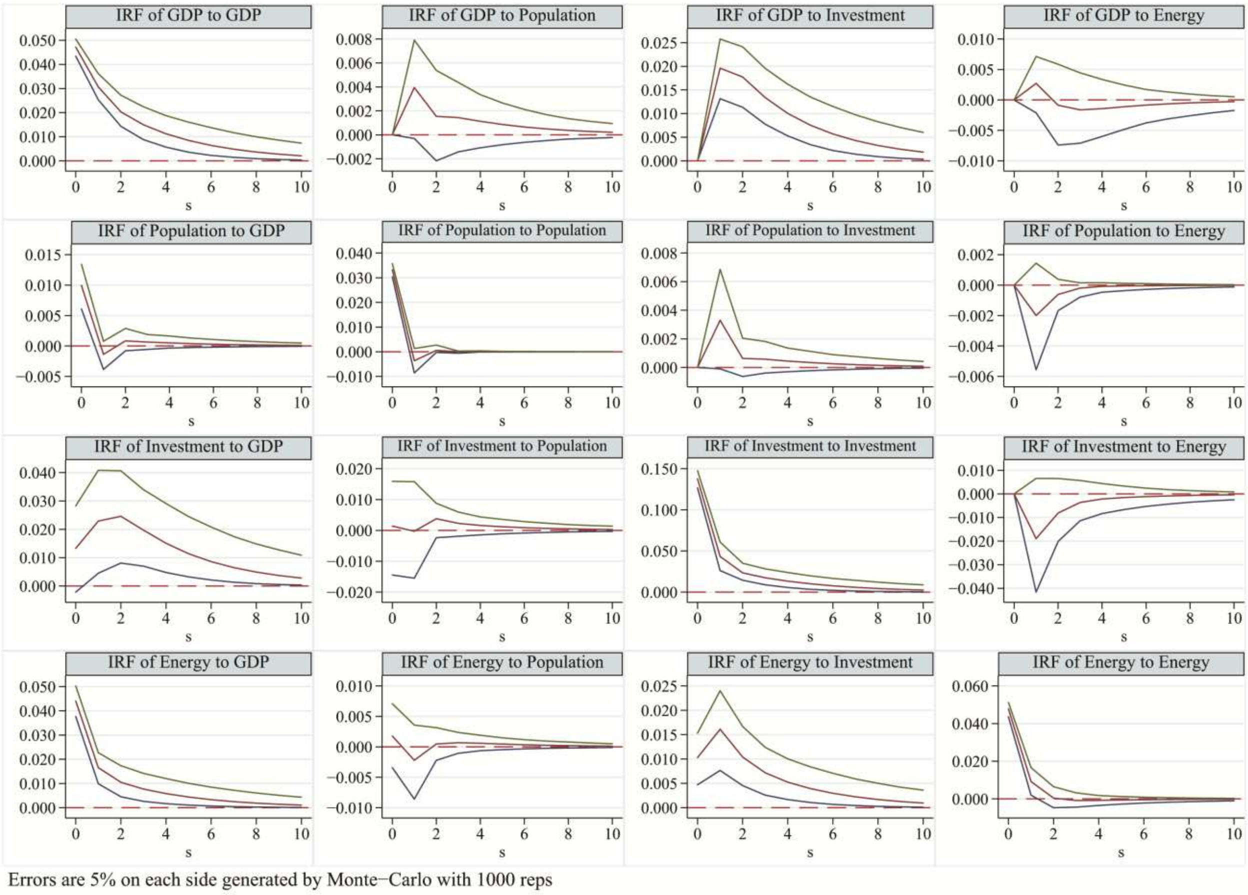

Fig. 5. Impulse responses for all samples (Guangdong).

In the PRD, GDP and investment have a positive impact on energy consumption growth (Fig. 6). Compared with the impact of other types of factors, GDP has a larger impact on energy consumption, which will cause the region's economic growth to further increase the pressure on energy consumption even though the impact of this pressure will be reduced. Additionally, energy consumption and GDP positively interact with each other. The magnitude of the impact of energy consumption on GDP is larger than that of GDP on energy consumption.

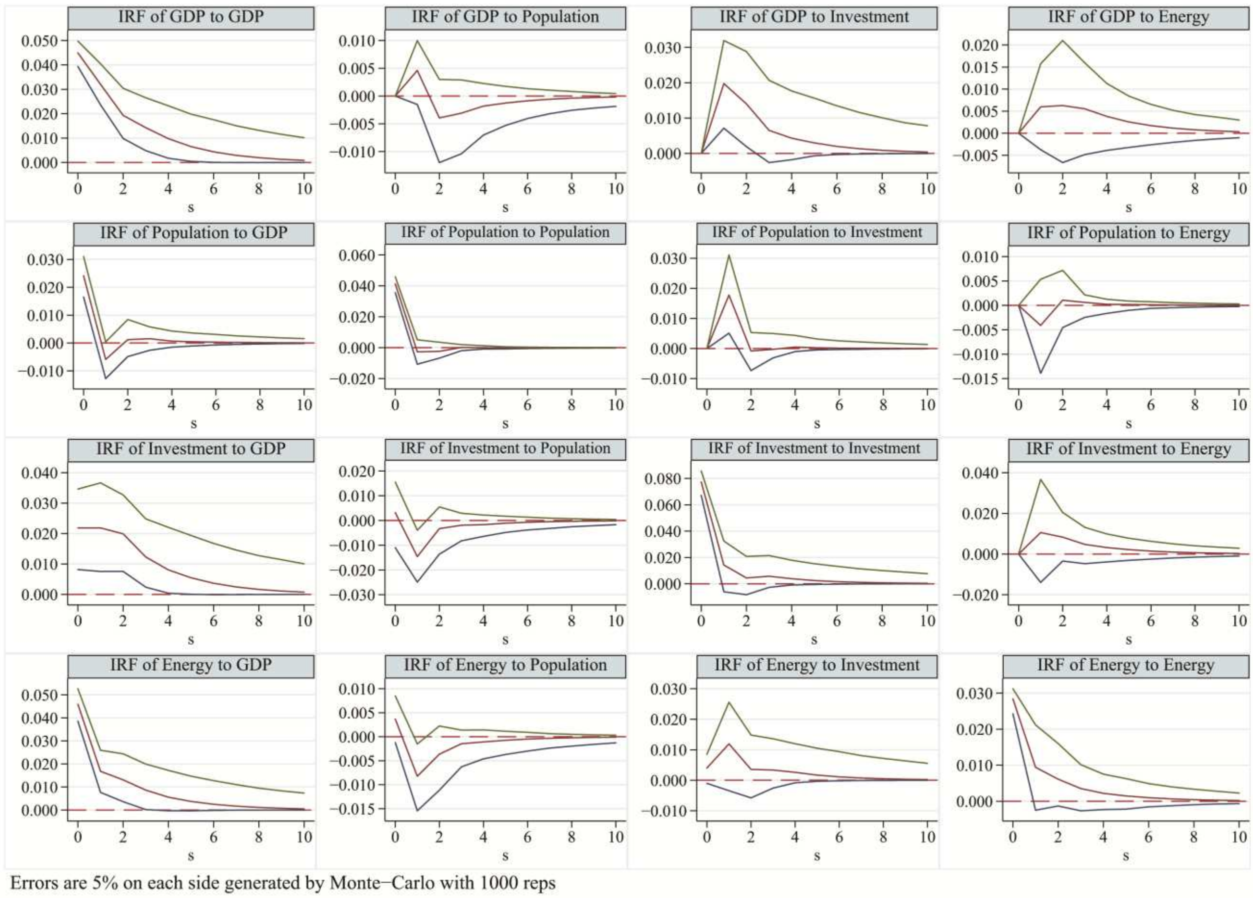

Fig. 6. Impulse responses for the high economic development samples (Pearl River Delta).

Fig. 7 shows the IRF results for the peripheral municipalities. GDP increases in response to growth in population, investment, and consumption. A positive shock to economic growth in the peripheral municipalities initially increases energy consumption, and then it obviously decreases. This result is expected, as an increase in GDP will reduce heavy industry with low value added and high pollution, leading to a reduction in energy intensity. Furthermore, investment has a significant negative effect on energy consumption.

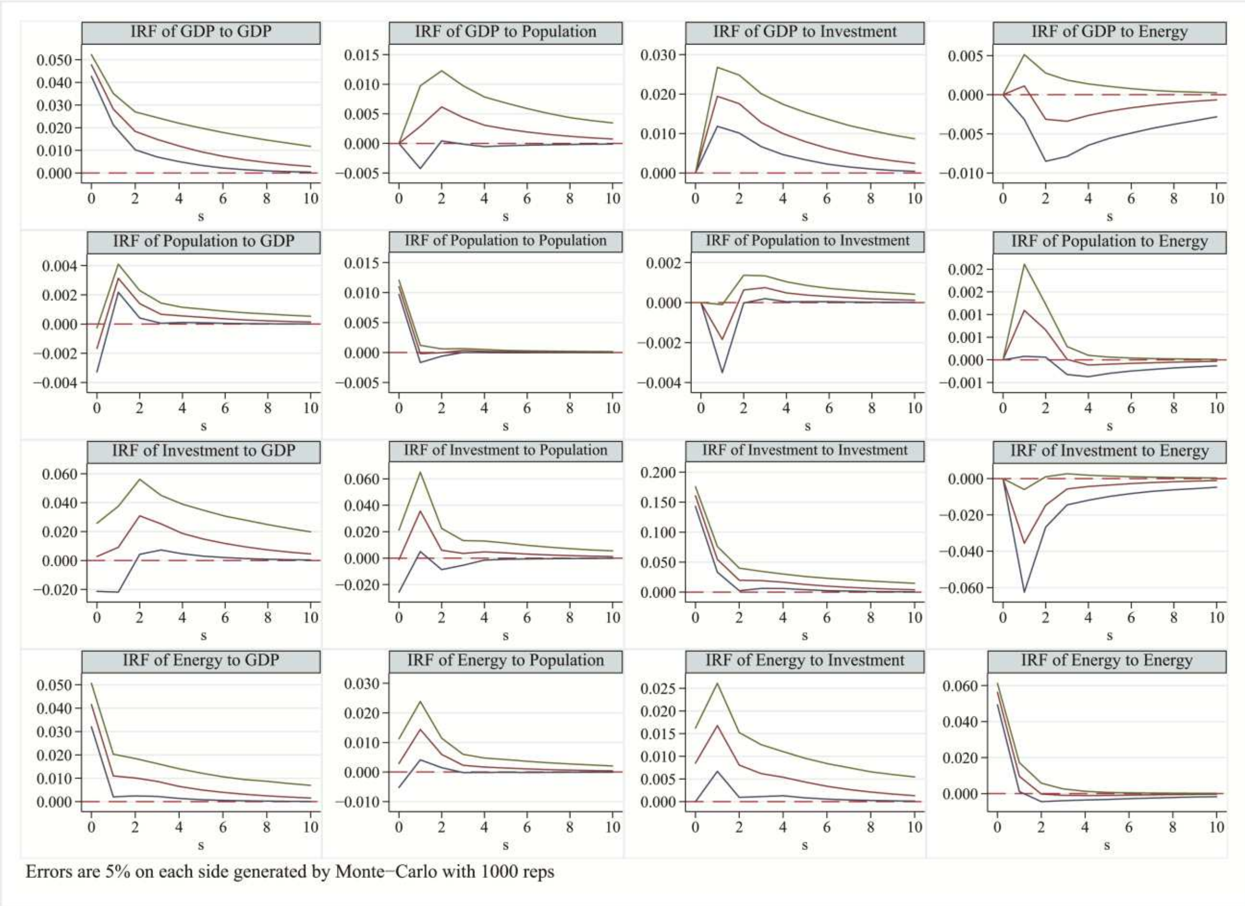

Fig. 7. Impulse responses for the low economic development samples (peripheral municipalities).

Variance decomposition analysis

Table 6 presents the variance decompositions for the different samples. According to the variance decomposition of energy consumption in Guangdong (all samples), GDP explains a large percentage (45.3%) of the total variation in energy consumption 10 periods ahead. As the number of periods increases, the contribution of GDP to energy consumption gradually increases, and the increase in GDP will lead to more energy consumption. The variance analysis of GDP shows that the contribution of energy consumption is 0.3%.

In particular, GDP explains approximately 68.3% of the variation in energy consumption in the PRD and approximately 34.5% of that in the peripheral municipalities 10 periods ahead. In the PRD, as shown by the variance decomposition, the contribution of energy consumption to GDP explains only approximately 2.7% of the variation 5 periods ahead and approximately 2.8% of that 10 periods ahead. In the peripheral municipalities, the prediction error of each factor is mainly explained by itself.

Table 6. Variance decompositions.

Periods	5				10			
	GDP	Population	Investment	Energy	GDP	Population	Investment	Energy
Panel A: All samples								
GDP	0.795	0.004	0.198	0.003	0.781	0.004	0.211	0.003
Population	0.083	0.904	0.010	0.004	0.083	0.904	0.010	0.004
Invest	0.079	0.001	0.901	0.018	0.089	0.001	0.892	0.018
Energy	0.451	0.002	0.103	0.444	0.453	0.002	0.108	0.438
Panel B: Pearl River Delta								
GDP	0.820	0.011	0.143	0.027	0.817	0.011	0.143	0.028
Population	0.232	0.643	0.118	0.007	0.232	0.642	0.118	0.007
Invest	0.190	0.029	0.756	0.026	0.194	0.029	0.750	0.026
Energy	0.683	0.025	0.048	0.243	0.683	0.025	0.049	0.242
Panel C: Peripheral municipalities								
GDP	0.782	0.016	0.196	0.006	0.764	0.017	0.211	0.008
Population	0.107	0.849	0.032	0.011	0.110	0.844	0.034	0.012
Invest	0.059	0.039	0.859	0.044	0.072	0.038	0.846	0.044
Energy	0.341	0.043	0.080	0.536	0.345	0.043	0.086	0.527

Percentage of variance in the row variable explained by the column variable.

Robustness check

Because of the limitation regarding general correlations, the causal relationship between different variables needs more comprehensive analysis. Therefore, the panel Granger causality test is used to check the robustness of the causal results obtained by the system-GMM-based PVAR analysis (Table 7).

Under the 95% confidence level, investment and all factors Granger cause GDP in the three panels. This finding suggests that all panels prove the applicability of the C-D production function. Under the 90% confidence interval, the combination of all factors Granger causes energy consumption. Furthermore, there is evidence that there does not exist a Granger causal relationship between GDP and energy consumption in these three panels. The Granger causality test results of different panels are different. There is a bi-directional causal relationship between investment and GDP that is significant at the 10% level in panel A (Guangdong). In the peripheral municipalities, bi-directional causality exists between investment and energy consumption. In the PRD, there is uni-directional Granger causality running from population to energy consumption that is significant at the 5%level (a change in population will lead to a change in energy consumption, but not vice versa).

Table 7. Granger causality tests of the PVAR analysis.

	Panel A: All samples		Panel B: Pearl River Delta		Panel C: Peripheral municipalities	
	chi^2	Prob.> chi^2	chi^2	Prob.> chi^2	chi^2	Prob.> chi^2
Population does not Granger cause GDP	3.224	0.073	1.083	0.298	0.592	0.442
Investment does not Granger cause GDP	23.580	0.000	6.329	0.012	17.721	0.000
Energy does not Granger cause GDP	0.854	0.355	1.064	0.302	0.175	0.675
All do not Granger cause GDP	36.817	0.000	12.046	0.007	24.017	0.000
GDP does not Granger cause population	0. 25	0.600	0.131	0.717	16.548	0.000
Investment does not Granger cause population	2.511	0.113	5.511	0.019	3.394	0.065
Energy does not Granger cause population	0.854	0.355	0.457	0.499	3.142	0.076
All do not Granger cause population	2.736	0.434	11.169	0.011	43.795	0.000
GDP does not Granger cause investment	6.630	0.010	0.513	0.474	4.189	0.041
Population does not Granger cause investment	0.000	0.994	5.992	0.014	4.478	0.034
Energy does not Granger cause investment	1.613	0.204	0.459	0.498	3.996	0.046
All do not Granger cause investment	7.374	0.061	12.910	0.005	10.375	0.016
GDP does not Granger cause energy	3.192	0.074	0.226	0.635	1.247	0.264
Population does not Granger cause energy	0.590	0.442	5.434	0.020	5.648	0.017
Investment does not Granger cause energy	7.554	0.006	1.293	0.255	6.597	0.010
All do not Granger cause energy	9.374	0.025	7.558	0.056	11.257	0.010

Discussions

To summarize, these results indicate that there is unbalanced development in Guangdong's economy. The GDP per capita in the PRD is significantly higher than that in the peripheral municipalities, and the exploratory spatial data analysis shows the same pattern, in which the hot spots are mainly clustered in the PRD. However, energy intensity shows an entirely different spatial distribution and low energy intensity in places with high economic development. These results are not surprising because there are apparent differences in the industrial structure. The PRD's tertiary industry (with high value added) accounts for 57.3% of GDP.

The most crucial result reveals that there is no confirmation of Granger causality between energy consumption and GDP in Guangdong for either the high economic development samples or the low economic development samples. In Guangdong Province, economic growth does not significantly lead to an increase in energy consumption. Guangdong is undergoing rapid change to its industrial structure (Tian et al., 2014; Wing-Hung Lo and Tang, 2006). In particular, the growth of the heavy chemical industry has slowed down, and the rapid development of the tertiary industry has driven the decline in energy consumption growth.

One of the contributions of this study is the breakdown of the analysis of the relationship between economic development and energy consumption on a city scale, and there is no research to directly contrast to our work. However, the aggregate findings of this research compare well with those in the existing literature. Wang et al. (2019) reported that energy-environment efficiency increased in western Guangdong and the PRD and displayed significant spatial differentiation, showing a pattern similar to that of energy intensity in this study. Soytas and Sari (2006) found some proof that China could consider decreasing its energy consumption growth without considerably hampering its economic growth. This phenomenon is especially true for Guangdong Province, not only for municipalities with high economic development but also for those with low economic development.

In November 2009, at the Copenhagen climate negotiations, China pledged to reduce its carbon intensity (carbon emissions per unit of GDP) by 40-45% from 2005 to 2020 (Liu et al., 2014). Because there are no statistical data on carbon emissions on a city scale, carbon intensity is exceptionally related to energy intensity. We calculated the energy intensity of Guangdong Province, and its energy intensity decreased by 46.0% from 2005 to 2018 (Fig. 8), which can meet the commitments made at the climate summit. The GDP of Guangdong increased by 3.38 times with decreased energy intensity from 2005 to 2018. This finding means that Guangdong can reduce its energy consumption growth without substantially sacrificing its economic growth. From the perspective of the energy structure, the proportion of coal in energy use ranged from 52.8% in 2005 to 37.2% in 2018. Although the consumption of coal has considerably declined, it is still dominant. Guangdong Province continues to promote the transformation and upgrading of the industrial structure. Notably, the peripheral municipalities need to reduce their energy intensity by increasing their fixed-asset investment and developing their tertiary industry (Fig. 7). In the PRD, there is an increasing demographic advantage (Fig. 6) in realizing an innovative renovation of the traditional sector and in integrating advanced manufacturing and high-tech industries.

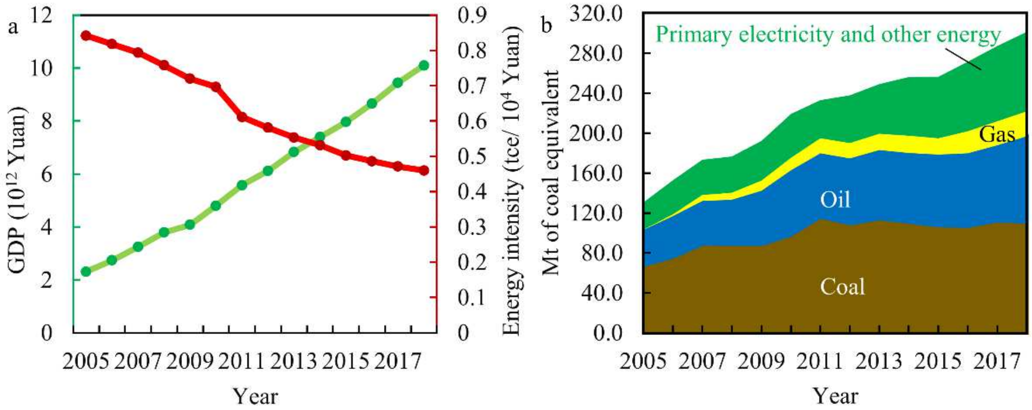

Fig. 8. Temporal change in energy consumption and related indicators in Guangdong from 2005-2018. a. GDP (green spots) and energy intensity (red spots). b. Total production of energy and its composition.

Conclusion and policy implications

Overall, this study discovers the spatial agglomeration of GDP per capita and energy intensity through hot spot analysis. Furthermore, it provides a new view of empirically testing the relationship between energy consumption and economic development under the framework of the C-D production function on a city scale.

We believe that this study contributes to several strands of the recent energy economics literature. First, conducting spatial autocorrelation analysis, we are able to quantitatively explore the spatial dependence of GDP per capita and energy intensity while observing the heterogeneity of a specific variable under different levels of socioeconomic development. Second, conducting PVAR analysis, we are able to consider the complex relationship between energy consumption and economic development. By analysing orthogonalized IRF, we are able to separate the response of energy consumption to shocks from socioeconomic factors. Third, owing to the Granger causality test, our results present the causality between different variables.

Grouped studies based on the differences in regional economic development show that there is no confirmation of Granger causality between energy consumption and economic development. Guangdong can decrease its energy consumption growth without substantially sacrificing its economic growth. Interestingly, changes in energy consumption are mainly driven by the growth rate of the population, and this conclusion is still supported based on regions with different levels of economic development. However, population has a significantly negative correlation with the energy consumption in the PRD; it presents the exact opposite correlation in the peripheral municipalities.

In light of these findings, the following suggestions are proposed: First, the government should continue to promote the transformation and upgrading of the industrial structure. Our results show that the energy consumption of the PRD is low and that there is spatial clustering, which has an obvious relationship with the industrial structure. The government should promote the transformation of the economic mode from the traditional factor-driven and investment-driven mode to the innovation-driven mode. To achieve this transformation of Guangdong Province, the service industry economy and high-tech industry should be the dominant industries. The spatial clustering of GDP per capita indicates that the economic gap between different municipalities decreased from 2005 to 2018, which proves that the policy under which earlier prosperous regions drive other regions to be rich plays an obvious role.

At this stage, Guangdong's policy only controls the proportion of the decrease in total energy consumption, which has led to uncertainties in the control of total energy consumption. During policy implementation, there was no strategic planning for strict implementation to decrease energy consumption. Regarding the second suggestion, we propose implementing dual control of energy intensity and total energy consumption and formulating a work plan for controlling total energy consumption as soon as possible. Furthermore, Guangdong's economic development and energy-saving plans should consider the differences between regions and adopt different strategic plans for different regions. Such plans should divide the province into the PRD and peripheral municipalities and clarify the planning objectives, tasks and responsibilities. The PRD should maximize its population and geographical advantages, while the peripheral municipalities need to increase their investment to effectively reduce their energy consumption. Unbalanced regional economic development and energy use are not unique to Guangdong; they are widespread in China. Social policies have a significant influence on development in China, and it is necessary to adopt targeted policies for regions with different development situations, which can help reduce actual energy consumption while ensuring economic growth.

Guangdong is a province with substantial regional heterogeneity and unbalanced economic development. The development of the regional economy depends on its own "assembling effect". The GDP per capita of the PRD is significantly higher than that of the peripheral municipalities; energy intensity shows an entirely different spatial distribution and low energy intensity in places with high economic development. Furthermore, the relationship between energy consumption and GDP cannot be evaluated simply to draw a single conclusion; it should be discussed regionally from multiple perspectives. The limitation of this study is that the causal relationship between energy consumption, economic growth, and carbon emissions is not considered.

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Authors contributions

Mengmeng Hu: Conceptualization, Methodology, Software, Writing - original draft. Yafei Wang: Formal analysis, Data curation, Resources. Beicheng Xia: Supervision, Writing - review & editing. Guohe Huang: Writing - review & editing.

Ethics declarations

Ethical approval

Not applicable

Consent to participate

All authors consent to participate.

Consent to publish

All authors consent to publish.

Competing interests

The authors declare that they have no conflict of interest.

Data availability

Any data that support the findings of this study are included within the article.

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Figures

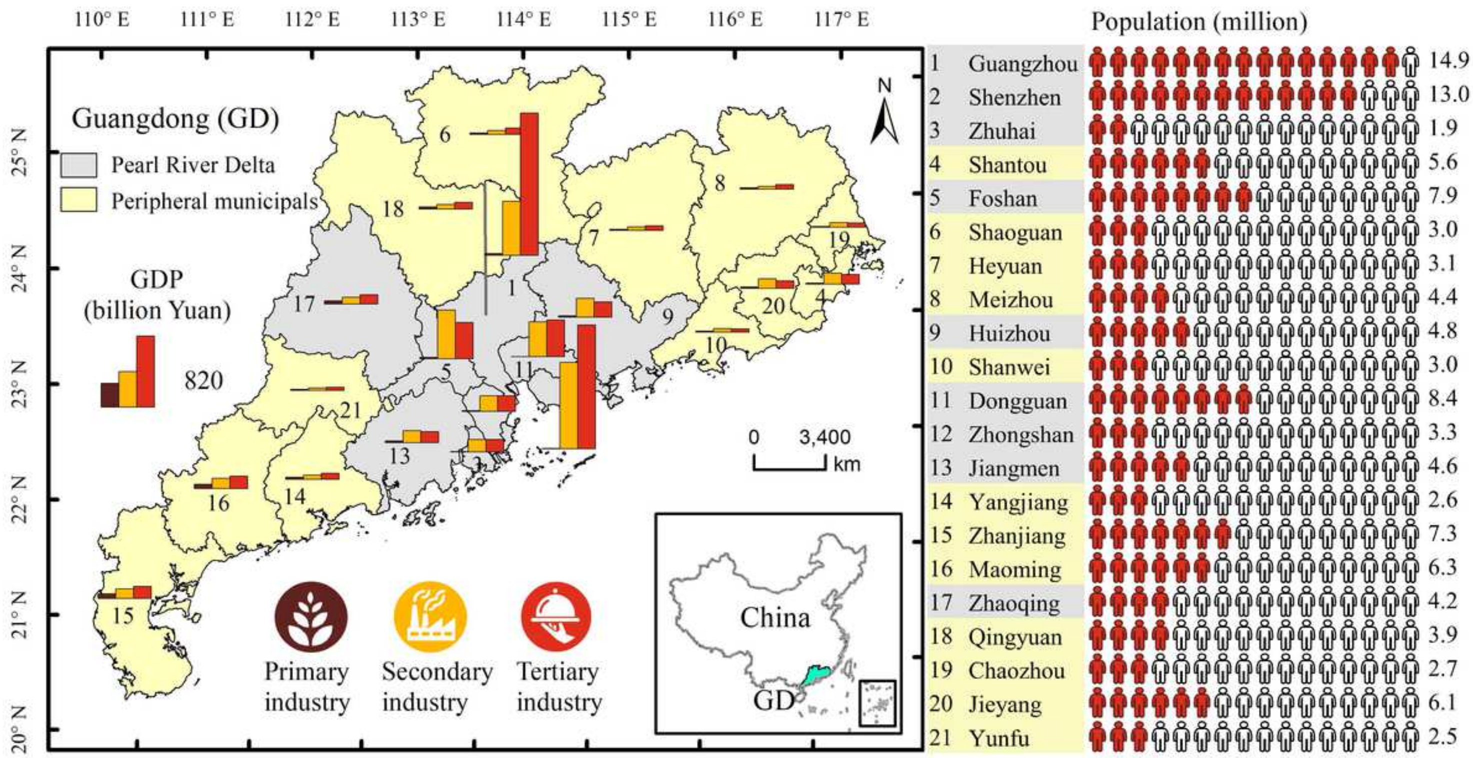

Figure 1

The location, population and industrial structure of the study area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square Company concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

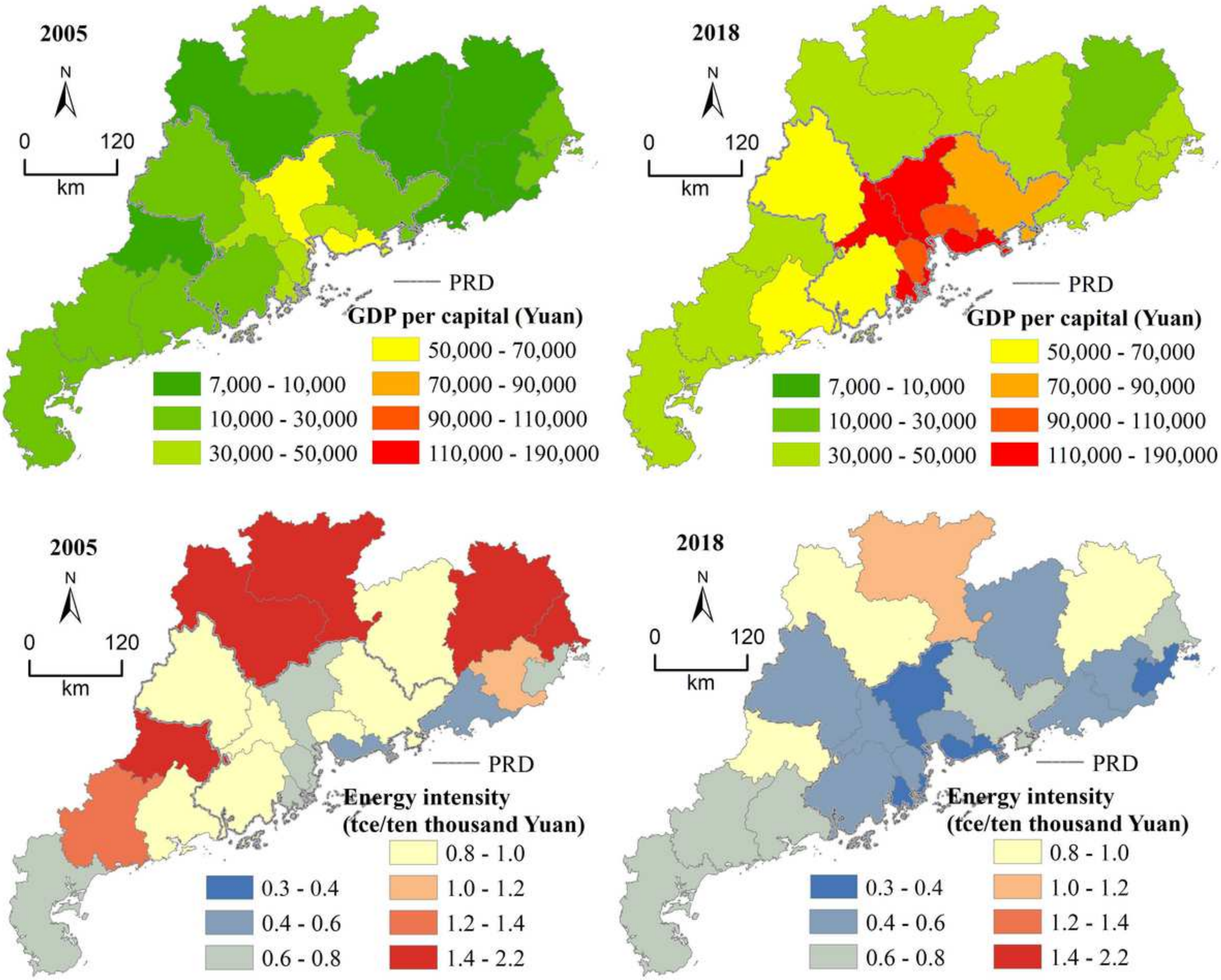

Figure 2

Spatial-temperal changes in Guangdong's GDP per capita and energy intensity. tce means ton of coal equivalent. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square Company concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

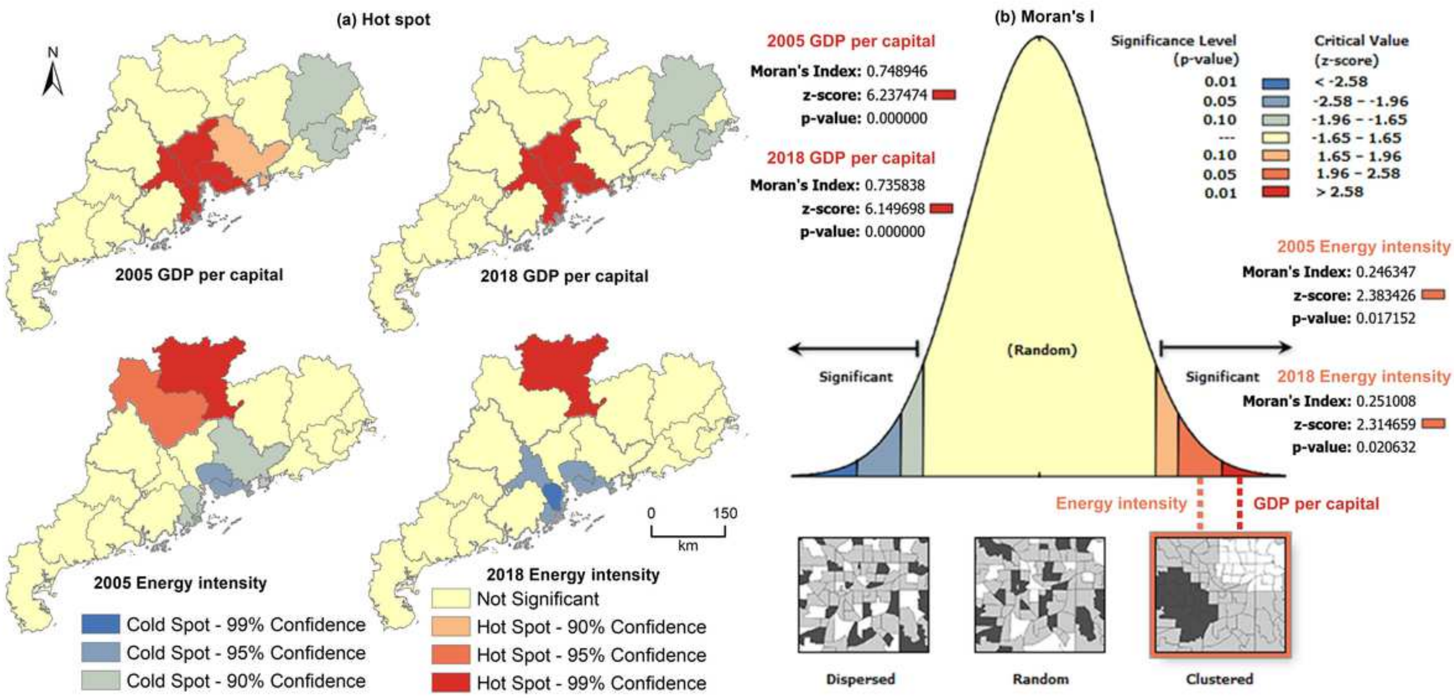

Figure 3

Hot spot map of GDP per capita and energy intensity. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square Company concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

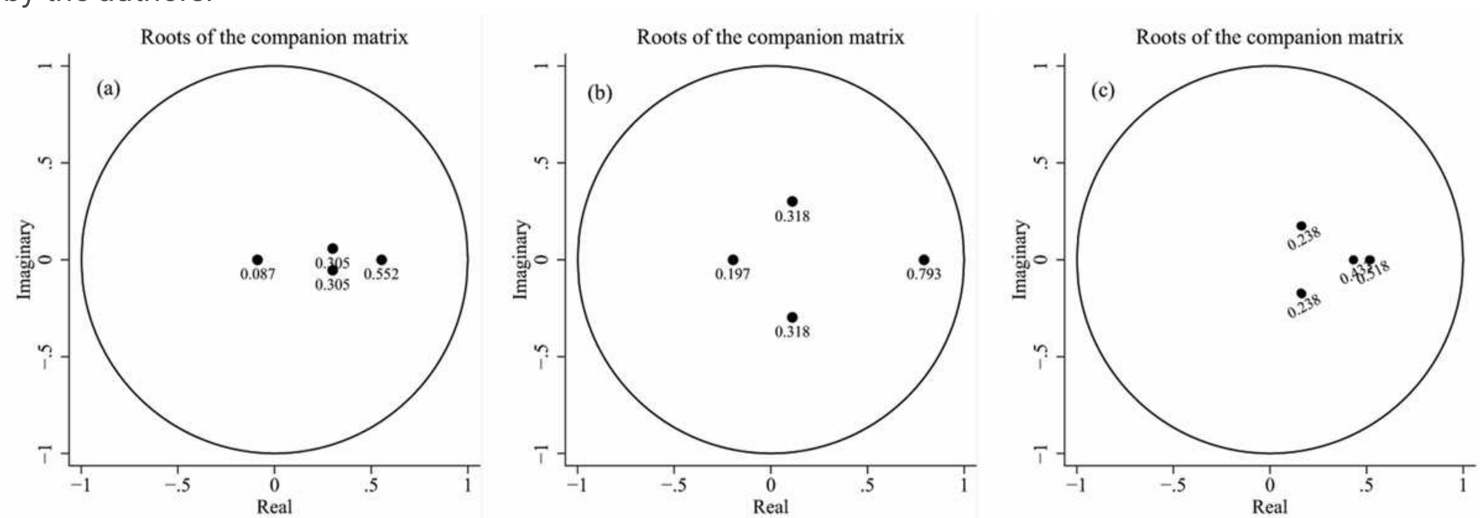

Figure 4

Stability test of the PVAR model. Panel data in (a) Guangdong (all); (b) Pearl River Delta; and (c) peripheral municipalities.

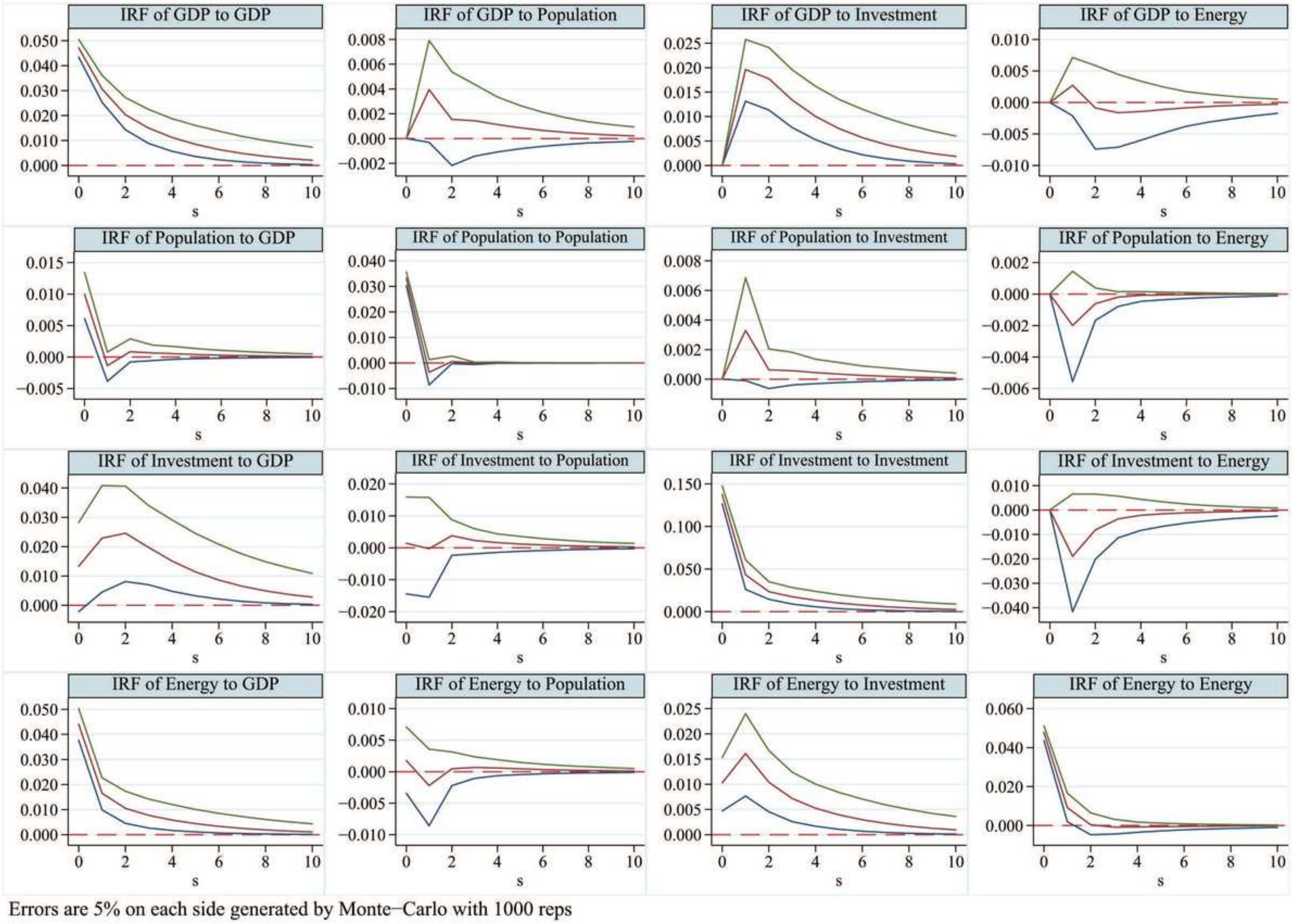

Figure 5

Impulse responses for all samples (Guangdong).

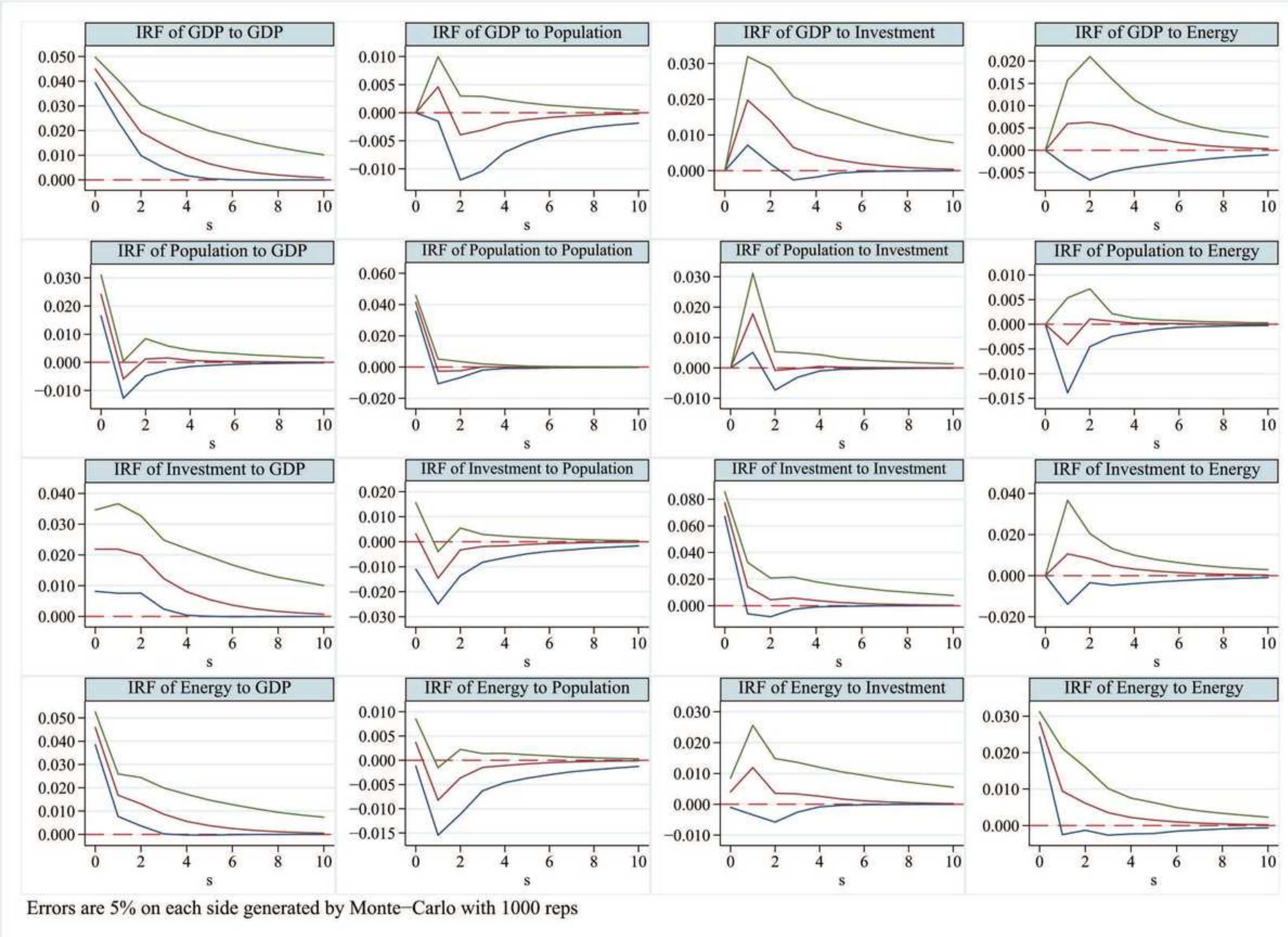

Figure 6

Impulse responses for the high economic development samples (Pearl River Delta).

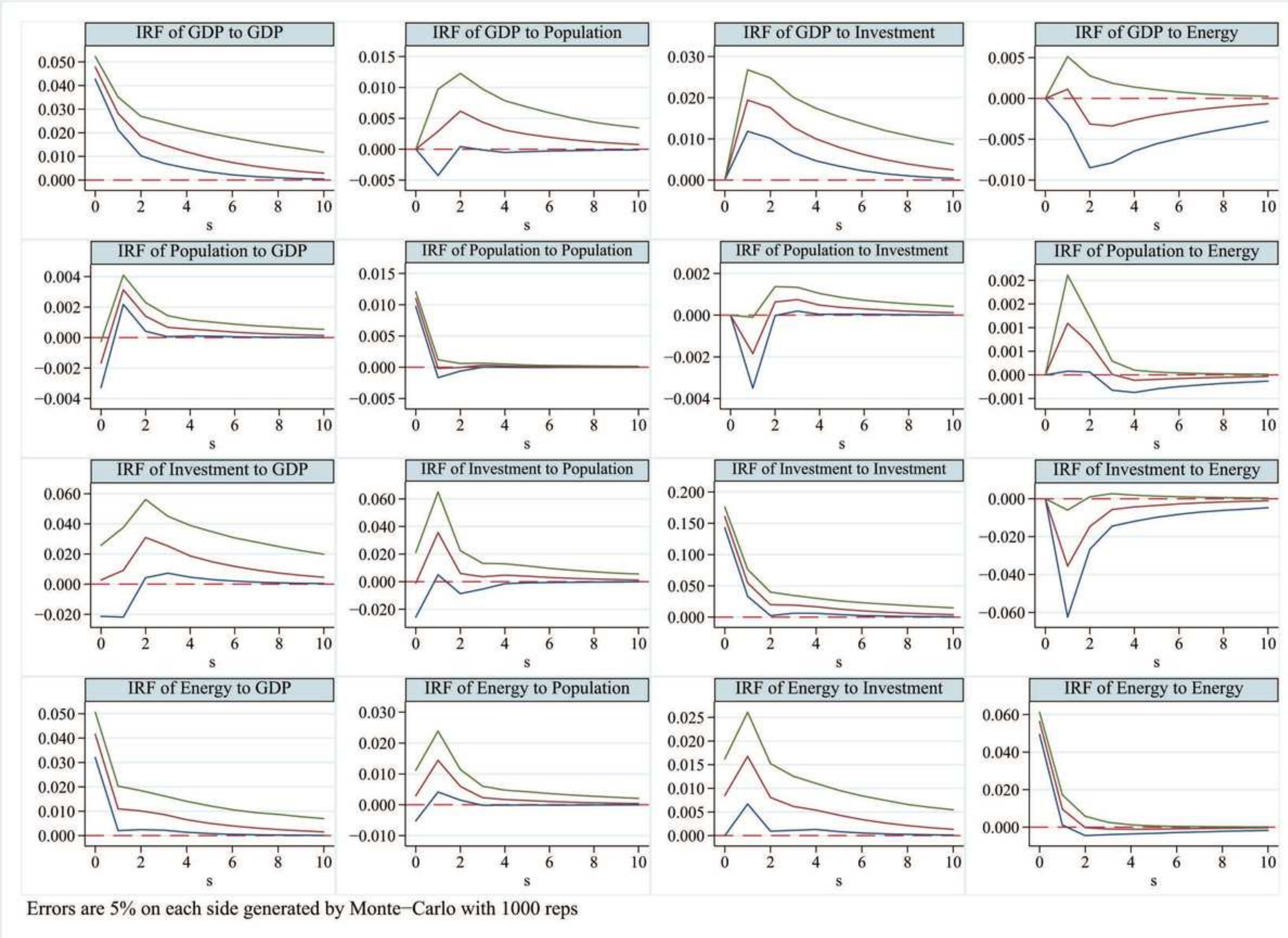

Figure 7

Impulse responses for the low economic development samples (peripheral municipalities).

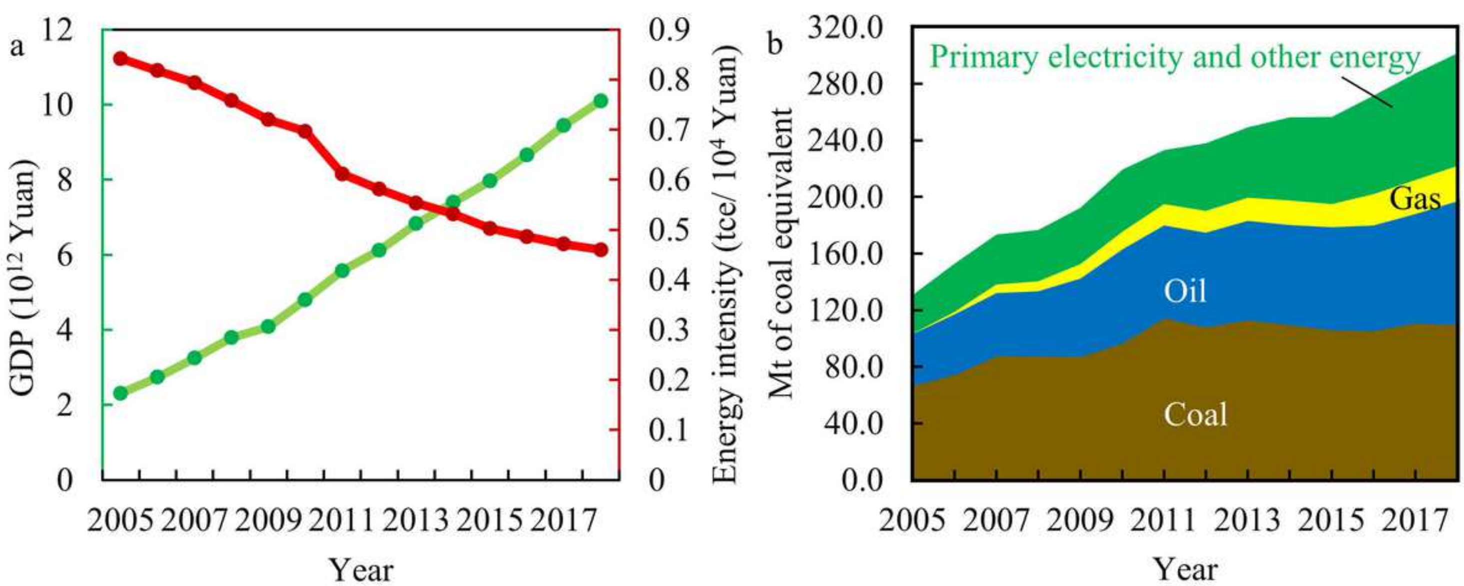

Figure 8

Temporal change in energy consumption and related indicators in Guangdong from 2005-2018. a. GDP (green spots) and energy intensity (red spots). b. Total production of energy and its composition.