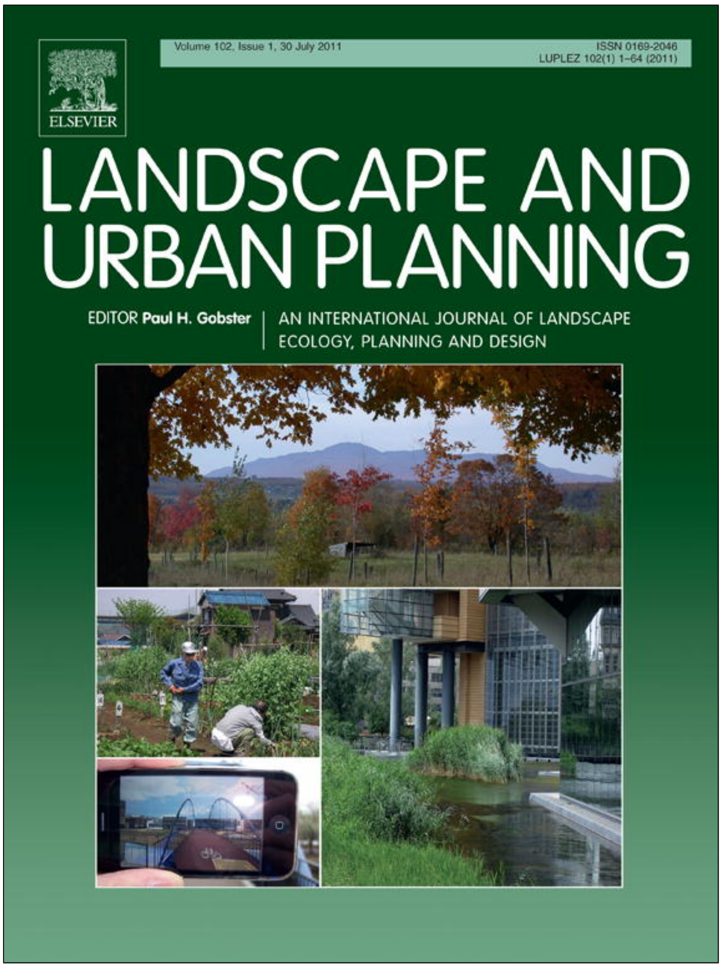
Volume 102, Issue 1, 30 July 2011
ISSN 0169-2046
LUPLEZ 102(1) 1–64 (2011)
ELSEVIER
LANDSCAPE AND URBAN PLANNING
EDITOR Paul H. Gobster
AN INTERNATIONAL JOURNAL OF LANDSCAPE ECOLOGY, PLANNING AND DESIGN

Landscape and Urban Planning 102 (2011) 33–42

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Estimating the relationship between urban forms and energy consumption: A case study in the Pearl River Delta, 2005–2008

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ARTICLE INFO

Article history:
Received 27 September 2010
Received in revised form 3 March 2011
Accepted 12 March 2011
Available online 20 April 2011

Keywords:
Urban forms
Energy consumption
Landscape metrics
Panel data analysis

ABSTRACT

Urban form, which refers to the spatial configuration of urban land use within a metropolitan area, has profound influences on energy consumption of a city. Landscape metrics are frequently used to quantify urban land use patterns, but there are limited studies reporting the implications of different urban land use patterns on energy consumption. In this study, we attempt to empirically estimate the relationships between urban land use patterns and energy consumption. Five cities of the Pearl River Delta (PRD) in south China, namely Guangzhou, Dongguan, Shenzhen, Foshan and Zhongshan, are selected as the study areas. PRD is becoming an emerging megalopolis and important manufacturing base in the world. However, the rapid and unregulated urbanization process as well as the extensive and inefficient use of energy has caused a series of problems. In this study, remote sensing images during 2005–2008 were used to reveal the dynamic distribution of urban land use based on land use classification. The urban land use patterns were then quantified using a set of landscape metrics, which further serve as explanatory variables in the estimation. The panel data analysis is implemented to estimate the relationship between urban land use patterns and energy consumption. Briefly, it is found that: (1) Urban size is positively correlated with energy consumption; (2) fragmentation/irregularity of urban land use patterns is positively correlated with energy consumption; (3) The dominance of the largest urban patch is negatively correlated with energy consumption.

1. Introduction

Urban form refers to the spatial configuration of urban land use within a metropolitan area (Anderson, 1996). Different urban forms may give rise to diverse social, ecological, and environmental consequences (Camagni, Gibelli, & Rigamonti, 2002; Holden, 2004; Wachs, 1993). Many studies revolve around the topic of sustainable urban forms (Breheny, 1992; Frey, 1999; Jabareen, 2006; Williams, Burton, & Jenks, 2000). Some researchers believe that compact urban forms (Jenks & Burgess, 2000), characterized by high density, mixed land use, pedestrian-oriented habitation and energy efficiency (Chen, Jia, & Lau, 2008), are more desirable for retaining the sustainability of development (Thomas & Cousins, 1996). Therefore, the compact urban forms become increasingly promoted by urban planners. Simulation techniques, such as cellular automata (CA), are adopted by researchers to illustrate the planning scenarios of compact development. For example, Li and Yeh (2000) proposed a constrained CA model to simulate compact urban forms of Dongguan; Ward, Murray, and Phinn (2003) integrated CA model with spatial optimization to generate the development scenario of high density and compact growth in south east Queensland, Australia. However, there are also evidences that challenge the superiority of compact urban forms. Holden and Norland (2005) indicated that lower energy consumption may be achieved by decentralized concentration. Whether the compact development policy is applicable for cities in developing countries like China, which inherently has a large population and high density, still needs further examination (Chen et al., 2008).

One important facet of the debate over sustainable urban forms is the relationship between urban forms and energy consumption. The influence of urban forms on energy consumption is profound, albeit not dominant (Anderson, 1996). Several aspects of urban forms can significantly affect urban energy consumption, such as the relationship between new developments and existing towns, the size, shape and function of new urban development, the mixing of land uses, travel patterns (Owens, 1986). Banister, Watson,

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doi:10.1016/j.landurbplan.2011.03.007

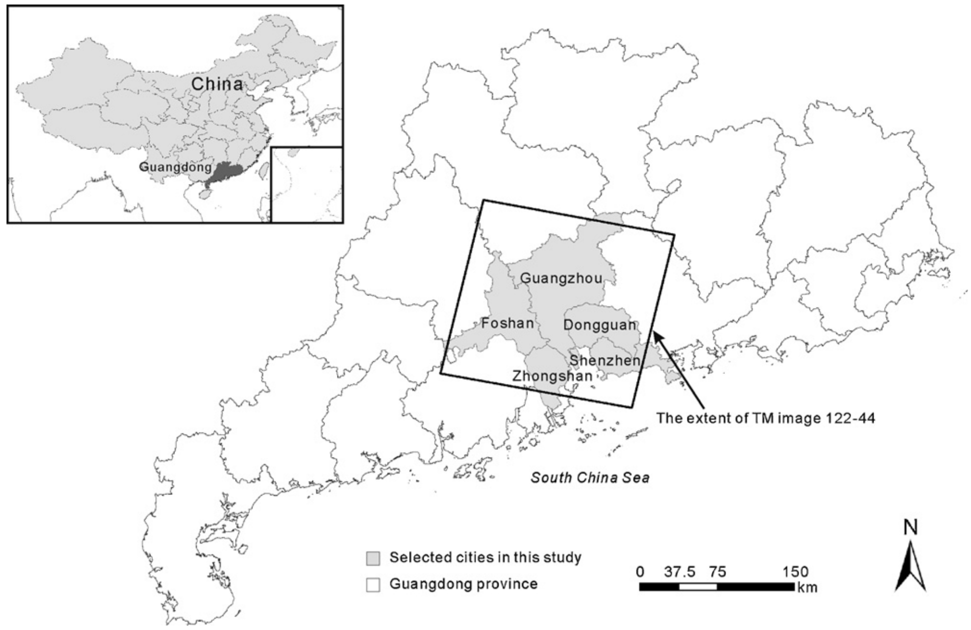

Fig. 1. Location of the study area.

and Wood (1997) tried to reflect the links between energy use in transport and urban forms, based on six case studies in United Kingdom and Netherland. Factors significantly affecting urban energy consumption were identified, such as density, employment and car ownership. But the data involved were coarse and the inconsistency of variables prevented the comparative analysis of different cities. In another empirical study on three cities in Netherland, Dieleman, Dijst, and Burghouwt (2002) found that the dependency of private cars related to factors of car ownership, household type, abundance of public transport and local residential environments. Ratti, Baker, and Steemers (2005) devised several algorithms to reflect the effects of urban texture on the energy consumption of buildings, using digital elevation models (DEMs).

Different from the studies mentioned above, we attempt to empirically estimate the relationship between urban forms and energy consumption from the perspective of spatial patterns of urban land use. With the advances in remote sensing and geographical information systems (GIS), extensive studies have demonstrated the use of landscape metrics to quantify the spatial characteristics (Alberti & Waddell, 2000; Luck & Wu, 2002; Seto & Fragkias, 2005; Xie, Yu, Bai, & Xing, 2006) and the change of urban land use patterns (Dietzel, Oguz, Hemphill, Clarke, & Gazulis, 2005; Herold, Scepan, & Clarke, 2002; Liu et al., 2010). Landscape metrics are also considered very useful in assisting urban planning. Botequilha Leitão and Ahern (2002) developed a conceptual framework for sustainable landscape planning, and the landscape metrics were utilized in order to address the ecological concerns. To our knowledge, less attention has been paid to the link between urban landscape and energy consumption. Especially, such studies have not been reported for the rapidly growing cities in China.

In this study, five cities of the Pearl River Delta (PRD) in south China, namely Guangzhou, Dongguan, Shenzhen, Foshan and Zhongshan, are selected as the study area. As an emerging megalopolis, PRD becomes an important economic region and manufacturing base in the world. Despite its economic success, the rapid and unregulated process of urban growth has resulted in a series of environmental problems (Li & Yeh, 2004; Seto et al., 2002). Meanwhile, the extensive and inefficient use of energy causes a serious degradation of environment (Fang, Chan, & Yao, 2009; Guo et al., 2006). This study attempts to reveal the relationship between urban land use patterns and energy consumption in PRD. Urban land use patterns are retrieved from multi-temporal images during 2005–2008. Afterward the spatial patterns of urban land use are quantified by a set of landscape metrics, which are further taken as the explanatory variables for energy consumption. The panel data analysis is then implemented to estimate the relationship between urban land use patterns and energy consumption.

2. Study area and data

2.1. The Pearl River Delta

The Pearl River Delta is situated in the central part of Guangdong province in south China. This region is mainly dedicated to agricultural production until the economic reform started in 1978. Since then the region has attracted large amounts of foreign direct investments (FDI), which is the critical support to the take-off of regional economy. The continuing development of manufacturing plants and joint ventures demands a large quantity of land. As a result, a lot of land was converted from agricultural use to infrastructure, real property or industrial uses. The unregulated urbanization process gave rise to a series of problems, e.g. the loss of large amount of fertile agricultural land (Li & Yeh, 2004; Seto et al., 2002). Many researchers were therefore devoted to developing effective methods for monitoring and quantifying the fast changing landscapes of the PRD (Seto & Fragkias, 2005; Sui & Zeng, 2001).

The economic growth of the region requires a vast volume of natural resources, especially energy. Although the Pearl River Delta only occupies 20% of the territory of Guangdong province, it consumes 67% of the coal and 85% of the oil that are consumed by the entire province (Shao, Tang, Zhang, & Li, 2006). Moreover, the efficiency of energy consumption is very low compared with other developed regions in China (like the Yangtze River Delta), not to mention the industrialized countries like US or Japan (Fang et al., 2009). The air quality here seriously deteriorates as a result of such extensive and inefficient use of energy (Fang et al., 2009; Guo et al., 2006). Thus, substantial efforts should be paid to reduce the energy consumption and improve the environmental quality.

In this study, we attempt to analyze the relationship between spatial patterns of urban land use and energy consumption. Five

Table 1
Population, GDP, the number of cars, the proportion of the secondary industry and the tertiary industry of Dongguan, Foshan, Guangzhou, Shenzhen and Zhongshan in 2005 and 2008.

		Dongguan	Foshan	Guangzhou	Shenzhen	Zhongshan	Total
Population (million)	2005	6.56	5.80	9.50	8.28	2.43	32.57
	2008	6.95	5.95	10.18	8.76	2.52	33.32
GDP (10^3 bellion yuan)	2005	0.22	0.24	0.52	0.50	0.10	1.56
	2008	0.37	0.43	0.82	0.78	0.14	2.55
Number of private cars (million)	2006	0.36	0.39	0.62	0.64	0.16	2.18
	2008	0.54	0.55	0.87	0.93	0.22	3.13
Proportion of the secondary industry (%)	2005	56.7	60.4	39.7	53.2	61.3	50.76
	2008	52.8	65.6	38.9	48.9	60.4	49.72
Proportion of the tertiary industry (%)	2005	42.4	36.4	57.8	46.6	35.2	47.53
	2008	46.9	32.2	59.0	51.0	36.5	49.00

cities within this region are selected, including Guangzhou, Shenzhen, Foshan, Dongguan and Zhongshan (Fig. 1). Table 1 lists the selected statistics of these five cities in 2005 and 2008, including population, GDP, the number of cars, the proportion of the secondary industry and the tertiary industry. These five cities are the largest cities in the PRD. The sum of the population of these five cities was 32.57 million in 2005, and further increased into 33.32 million in 2009, which accounts 75.57% of PRD's total population and 36.00% the province's total population. Also, these five cities are the most developed cities in the PRD and Guangdong province. The sum of the GDP of these five cities was 1.56×10^3 bellion yuan in 2005, and rapidly increased into 2.55×10^3 bellion yuan in 2008. This accounts 85.62% of PRD's total GDP and 67.96% of the province's total GDP. Recently the PRD has the highest GDP per capita among several most developed regions in China (Shao et al., 2006). The increase of personal wealth stimulates the possession of private cars. The sum of private cars was 2.18 million in the five cities in 2006, and grew into 3.13 million in 2008, with the annual growth rate of 19.87% which was even higher than that of GDP (17.79%).

Besides the rapid growth of economic size, significant changes are also witnessed in the economic structures of these five cities. It is found that the proportion of the secondary industry gradually decreases in some of these cities in recent years. For example, the proportion of the secondary industry in Donggguan and Shenzhen were 56.7% and 53.2% respectively in 2005; but they rapidly declined into 48.4% and 46.7% in 2008. While for Foshan and Zhongshan, their proportion of the secondary industry were stilled as high as 65.6% and 60.4% in 2008. The economic structure of Guangzhou is most distinct from the other four cities. The proportion of secondary industry was only 37.2% in Guangzhou while the proportion of the tertiary industry was 60.9% in 2008.

2.2. Data preparation

2.2.1. Approximating the energy consumption

It is very difficult to obtain the precise data of energy consumption. In general, the energy data in other studies are collected in three major ways: (1) collect data from previous studies. For example, in (Banister et al., 1997) the comprehensive analysis of the relationship between urban forms and energy consumption over six cities was on the basis of data collected from a sample of previous studies. Similarly, Mindali, Raveh, and Salomon (2004) cited the data in (Newman, Newman, & Kenworthy, 1989). (2) Use the surveyed data. Examples can be found in (Banister, 1996; Dieleman et al., 2002). (3) Approximate energy consumption by related statistical data. This is a useful method for those study areas like China that energy consumption data are not rich. For example, Dhakal (2009) illustrated how to estimate the total amount of energy consumption of a city using the statistics of energy consumption per unit Gross Regional Product (GRP).

We attempt to estimate the relationship between energy consumption and urban forms, thus we follow Dhakal's approach in this study. We use two statistics from Guangdong Statistical Year Book (http://www.gdstats.gov.cn/tjnj/ml_c.htm) to approximate the energy consumption of the study area. Urban energy consumption is separated into two major sources in Guangdong Statistical Year Book: production and living. At city level, Guangdong Statistical Year Book provides the energy consumption per unit gross domestic production (GDP) (t. of Standard Coal Equivalent/10^4 Yuan) during 2005–2008, here denoted as e_{GDP}; and the annual average energy consumption for living per capita as well (kg. of SCE), denoted as e_{Living}. These two statistics represent energy intensity in production and living respectively. Specifically, the e_{GDP} refers to the energy intensity in material production and non-material production; while e_{Living} refers to a resident's average yearly energy consumption that comes from living activities. So energy uses by sectors like industrial production and logistics are considered in e_{GDP}; while energy uses by using household appliances are accounted in e_{Living}. There might be the risk of double counting when data comes from different statistics. However, based on the definition of statistics, e_{GDP} and e_{Living}, we think the problem of double counting is quite unlikely here. Although the detailed composition of energy consumption sectors (such as industry, transportation, residential) is also very important to the analysis, we cannot find such statistical data at city level for the selected five cities and hence didn't involve this variable in this study. The two statistics, e_{GDP} and e_{Living}, are used to estimate the total energy consumption, which is considered as the dependent variable in estimation of the relationship between urban forms and energy consumption:

$$E = e_{GDP} \times V + e_{Living} \times P \quad (1)$$

where V represents the amount of GDP and P is the size of population of a city.

2.2.2. Quantifying urban forms by combining remote sensing data and landscape metrics

In this study, the urban forms of the five cities, Guangzhou, Shenzhen, Foshan, Dongguan and Zhongshan, are quantified using a set of landscape metrics. Landscape metrics are developed from information theory and fractal geometry (Mandelbrot, 1983; Weaver & Shannon, 1963) and commonly used in landscape ecology (Herold, Couclelis, & Clarke, 2005). They can be used to quantify spatial heterogeneity and its changes within a landscape. Herold et al. (2005) have made comments on applying such metrics in the context of urban landscapes. They summarized several advantages of using landscape metrics for urban analysis: (1) improving the representation of heterogeneous urban landscapes; (2) bridging the gap between urban land use patterns and the governing processes; (3) facilitating the analysis of impacts of urban development on the surrounding environment; and so on. Besides, they recommended the combination of remote sensing and landscape metrics to improve the modeling of urban land use, because "remote sensing can provide the spatially consistent, high-resolution datasets that are required for the analysis of spatial structure and pattern through spatial metrics" (Herold et al., 2005). We follow such method in this study that first acquire the spatial distribution of urban land use from remote sensing images and further use landscape metrics to quantify the urban land use patterns.

Multi-temporal Landsat TM5 images acquired in 2005, 2006, 2007, and 2008 were used to obtain the dynamics of urban land use patterns in the study area. A single scene of Landsat TM image (path 122, row 44) can approximately cover this area (Fig. 1) except that part of Shenzhen is within the east adjacent scene of image (path 121, row 44). The images were georeferenced to the UTM projection with the registration error of less than 0.5 pixels. We identified six land use classes from the images: built-up areas, farm land, forest, water, fishpond and bare soil. We think such scheme of land use classes is most appropriate considering the 30 m-resolution of TM images. In fact, this scheme is very similar in many other studies using TM images, such as (Seto et al., 2002). Some may be curious about the classes of water and fishpond, both of which could have been identified as the same class. Actually, the water class includes rivers, lakes and reservoirs, which are large and continuous water area. Fishponds are adjacent small pools, which look like 'dark' grids (some times irregular) in the space. Therefore it is easy to differentiate these two classes in the images, especially using object-based classification methods. Such methods are provided in the software Definiens Developer 7.0. The classification procedure contains four steps: image segmentation, sample selection, feature optimization, and objects classification. First, the image segmentation aggregated similar pixels into objects. Afterward samples (image object) were selected manually by the user for each land use class. Before categorizing all objects into given classes, a set of features should be determined with the objective of maximizing the distance between one land use class and another. This step was executed automatically by the software using the tool of Feature Optimization. Finally, the nearest neighbor classification was performed based on the selected samples and features. After the land use classification, the output images were further converted into binary grids of urban/non-urban for the quantification of urban forms using landscape metrics. The resolutions of grids are resampled from 30 m to 150 m through the nearest neighbor method in order to reduce the computation time in subsequent analysis. We choose the resolution according to the extent of study area and other literature on this topic, such as (Dietzel et al., 2005). We admit that the values of the landscape metrics will change once the resolution is resampled into 150 m, but we think the change should be consistent among all cities and hence such change may not significantly affect the analysis results.

The landscape metrics were chosen based on published literature on this theme (Dietzel et al., 2005; Seto & Fragkias, 2005; Xie et al., 2006), including total urban class area (CA), number of urban patches (NP), mean perimeter-area ratio (PARA_MN), mean Euclidean nearest neighbor distance (ENN_MN) and largest patch index (LPI). CA represents the area of a particular class in a landscape, thus this metric is equivalent to the area of urban land use in this study. The unit of CA is transformed from ha into km^2. NP is the total number of urban patches. Here urban patches are defined as homogenous regions of urban land use (Herold et al., 2005). In the early phase of urbanization process, especially for those experiencing rapid urban growth, the value of NP is expected to increase until in later stage individual urban patches gradually merge into continuous areas (Seto & Fragkias, 2005). ENN_MN (m) is the average distance between any two nearest neighboring urban patches. ENN_MN can be interpreted as the measure of spatial connection between urban patches. Given the same amount of new developed urban areas, high values of NP and ENN_MN indicate a fragmented/scattered pattern. PARA_MN is the mean value of the perimeter (m)-area (m^2) ratio of urban patches in the landscape, providing information about the shape of urban patches. The higher the value of PARA_MN is, the lower the overall regularity of the urban landscape is. LPI (%) means the percentage of landscape occupied by the largest patch. In the context of urban landscape, LPI can be used to measure the dominance of the largest urban patch.

3. Panel data analysis

The panel data analysis is adopted for estimating the relationship between urban land use patterns and energy consumption. Panel data analysis is a sort of regression models that can deal with observations from multiple individuals over multiple periods. Panel data analysis has more advantages compared with conventional statistical analysis using only either cross-sectional or time-series data. For example, more data points can be involved for analysis so that the degrees of freedom are increased while the collinearity among explanatory variables are reduced (Hsiao, 2003). Therefore, the estimation efficiency can be improved by using panel data analysis. Moreover, spatial heterogeneity and influence not accounted by explanatory variables may cause the relation to vary among individuals (Seto & Kaufmann, 2003). This can be solved by varying the intercepts and/or coefficients in panel data analysis.

The implementation of panel data analysis contains three steps. The first step is to select a model form because there are different model forms in panel data analysis. The model form cannot be chosen arbitrarily, but based on the results of *F*-test. Secondly, if the test results suggest that intercepts and/or coefficients should not be constant, the Hausman test is implemented to decide whether such effects are fixed or random. Finally, the model is estimated using generalized least squares (GLS) (Hsiao, 2003). The details of *F*-test and Hausman test are specified as follows:

The forms of regression model for panel data analysis vary according to different assumptions. There are three major types of model form: pooled regression model, variable intercepts and constant coefficients model, variable intercepts and variable coefficients model. In pooled regression model, both intercepts and coefficients are held constant for all individuals over the entire period. The form of pooled regression model can be specified as Eq. (2):

$$y_{it} = a + bx_{it} + \varepsilon_{it} \tag{2}$$

where i and t are indices for individuals and time; y_{it} and x_{it} represent the dependent variable and independent variable respectively; and ε_{it} is the error term.

If it is assumed that there are influences not accounted by explanatory variables and vary among individuals but time invariant, the variable intercepts can be introduced as a_i:

$$y_{it} = a_i + bx_{it} + \varepsilon_{it} \tag{3}$$

where a_i is specified as fixed effects or random effects.

In fixed effects model, a_i is a constant for individual i; while in random effects model, the intercept for individual i is formulated as a constant plus a random term. Moreover, the coefficients also can vary among individuals, denoted as b_i:

$$y_{it} = a_i + b_i x_{it} + \varepsilon_{it} \tag{4}$$

Similar to the specification of a_i, b_i can be treated as fixed or random effects. Decision of choosing a form among 2, 3 and 4 depends on the result of *F*-test by comparing the residual sum of squares (RSS) of Eqs. (2)–(4) (Hsiao, 2003):

$$H_1 : \beta_1 = \beta_2 = \cdots = \beta_N$$

$$F_1 = \frac{(S_3 - S_1)/[(N-1)K]}{S_1/(NT - N(K+1))} \sim F[(N-1)K, N(T-K-1)] \tag{5}$$

$$H_2 : \alpha_1 = \alpha_2 = \cdots = \alpha_N$$
$$\beta_1 \neq \beta_2 \neq \cdots \neq \beta_N$$

$$F_2 = \frac{(S_2 - S_1)/[(N-1)(K+1)]}{S_1/(NT - N(K+1))} \sim F[(N-1)(k+1), N(T-K-1)] \tag{6}$$

where F_2 is the statistic for H_2 that intercepts are variable and coefficients are constant; F_1 is the statistic for H_1 that intercepts and coefficients are held constant over individuals and time. S_1, S_2 and S_3 are RSS for Eqs. (4), (3) and (2). N, T and K represent the number of observations, the number of periods and the number of explanatory variables respectively. Given the confidence level and condition that $T > K + 1$ (T represents years and K represents the number of variables), if F_1 is greater than or equal to the critical value, H_1 is rejected and H_2 is tested; otherwise the pooled regression model should be used. If F_2 is greater than or equal to the critical value, H_2 is rejected and both intercepts and coefficients are variable; otherwise intercepts are variable and coefficients are held constant.

Hausman test is further used to decide whether effects are fixed or random. Assumed that β and $\hat{\beta}$ are estimation results of fixed effect model and random effect model respectively, the variance is then formulated as:

$$Var[\beta - \hat{\beta}] = Var[\beta] + Var[\hat{\beta}] - Cov[\beta, \hat{\beta}] - Cov[\beta, \hat{\beta}]' \tag{7}$$

And:

$$Cov[(\beta - \hat{\beta}), \hat{\beta}] = Cov[\beta, \hat{\beta}] - Var[\hat{\beta}] = 0 \tag{8}$$

Thus the covariance should be:

$$Cov[\beta, \hat{\beta}] = Var[\hat{\beta}] \tag{9}$$

Finally, we get:

$$Var[\beta - \hat{\beta}] = Var[\beta] - Var[\hat{\beta}] = \Psi \tag{10}$$

The Hausman test is then based on the Wald statistics formulated as:

$$W = [\beta - \hat{\beta}]' \Psi' [\beta - \hat{\beta}] \sim \chi^2(K-1) \tag{11}$$

where K is the degree of freedom. If the value of W is not equal to zero, the fixed effect model should be used; otherwise the random effect model should be used.

4. Results and discussion

4.1. Urban forms and landscape changes during 2005–2008

Multi-temporal remote sensing images of the study area during 2005–2008 are classified into six land use classes using Definiens Developer 7.0. The classification accuracy at each period is shown in Table 2. The accuracies of built-up areas are over 83% for all images and hence the quality of input data is ensured for subsequent estimation. The classification results are then converted into binary images as urban and non-urban (Fig. 2).

Urban forms of the five cities are quantified based on the selected landscape metrics, namely CA, NP, LPI, ENN_MN and PARA_MN. These metrics are computed using FRAGSTATS (McGarigal, Cushman, Neel, & Ene, 2002), a spatial pattern analysis program for quantifying landscape structure. Fig. 3(a)–(e) shows the computation results of the selected metrics for the five cities during 2005–2008.

It can be seen from Fig. 3(a) that the values of CA are rapidly increasing during the study period. Such fast urbanization process can be dated back as early as 1980s when market-oriented reform in China was implemented. Triggered by the fast economic development, the urbanization process accelerates in a high rate. For example, the average annual rate of urban land use growth was as high as 17% during 1988–1999 (Seto & Fragkias, 2005); and nearly 9% during 1998–2003 (Fan, Wang, & Wang, 2008). The computation results of CA in this study suggest that the urbanization process is still accelerating during 2005–2008 (Fig. 3(a)). The sum of urbanized area of the five cities is 2894.09 km^2 in 2005, and rapidly grows into 3742.99 km^2 in 2008. The average annual growth rate during this period is 8.95%, which is very close to the rate during 1998–2003 (Fan et al., 2008).

It is unexpected that Dongguan has the highest value of LPI instead of Guangzhou, as shown in Fig. 3(b). As the primate city in this region, Guangzhou was the most densely settled city measured by Seto and Fragkias (2005). However, in this study the LPI of Guangzhou is not significantly higher than other cities during 2005–2008; this may due to that the analysis of Guangzhou was based on the restructured administrative divisions. After the restructure of administrative divisions began in 2000, the total area of Guangzhou was tremendously enlarged from 1662 km^2 to 7263 km^2 (http://en.wikipedia.org/wiki/Guangzhou). As a result, besides the witnessed largest urban patch in the city proper, there are several other massive urban patches distribute in Huadu and Panyu (Fig. 2); and thus the value of LPI is not as high as expected.

Fig. 3(c)–(e) shows the computation results of NP, ENN_MN and PARA_MN. They are used to reflect three important features of the urban landscape: composition, average spatial connection and average shape. NP and ENN_MN measure how scattered the spatial pattern of urban land use is. Higher values of both NP and ENN_MN may suggest a more scattered pattern. While PARA_MN measures the regularity of the shape of urban patches at average level. If a patch has a high value of PARA_MN, the shape of this patch is irregular; otherwise this patch is regular.

It can be seen that Guangzhou has the highest values of NP and ENN_MN (Fig. 3(c) and (d)). Drivers lead to such scattered urban land use patterns may include hosting sport games (such as Asian Games 2010), the booming real estate development in sub-urban area, the expanded administrative division as well as construction of large projects such as infrastructure, industrial parks (Su, Wei, & Guo, 2005). The value of NP is also very high in Foshan. There is a long tradition of fish pond culture in Foshan; but during the rapid industrialization process, many fish ponds were filled up for the construction of new factories or infrastructures. As a result, the urban land use pattern in Foshan becomes very scattered.

The urban land use patterns are most irregular in Dongguan and Shenzhen because the values of PARA_MN are highest in these two cities (Fig. 3(e)). Visually, the urban land use patterns are quite similar in Dongguan and Shenzhen (Fig. 2) that almost all urban patches are along the major roads. Some researchers believe that the urban land use patterns in Dongguan and Shenzhen belong to "Desakota" ("desa" means village and "kota" is town) in McGee-Ginsburg's model (McGee, 1991; Sui & Zeng, 2001). "Desakota" is very common in many fast developing regions in Asia, and one typical feature of "Desakota" is that urban land use "often stretches along corridors between large city cores" (Sui & Zeng, 2001). The formation of such patterns in Dongguan and Shenzhen is due to their close links to Hong Kong. In the early phase of development in Dongguan and Shenzhen, the establishment of industries were mainly supported by investments came from Hong Kong (Li & Yeh, 2004; Seto et al., 2002). Today there are still many Hong Kong-invested enterprises in Dongguan and Shenzhen. Moreover, both the import of raw materials and the export of industrial products need to come through the ports in Hong Kong and Shenzhen; thus

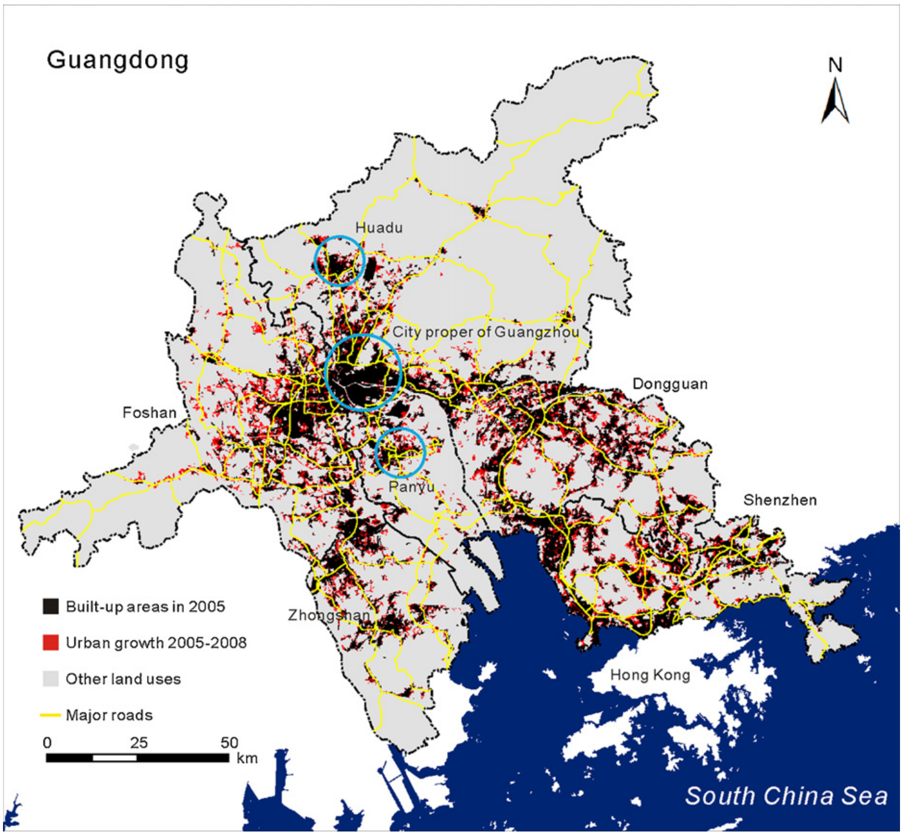

Fig. 2. Urban growth in the Pearl River Delta (2005–2008).

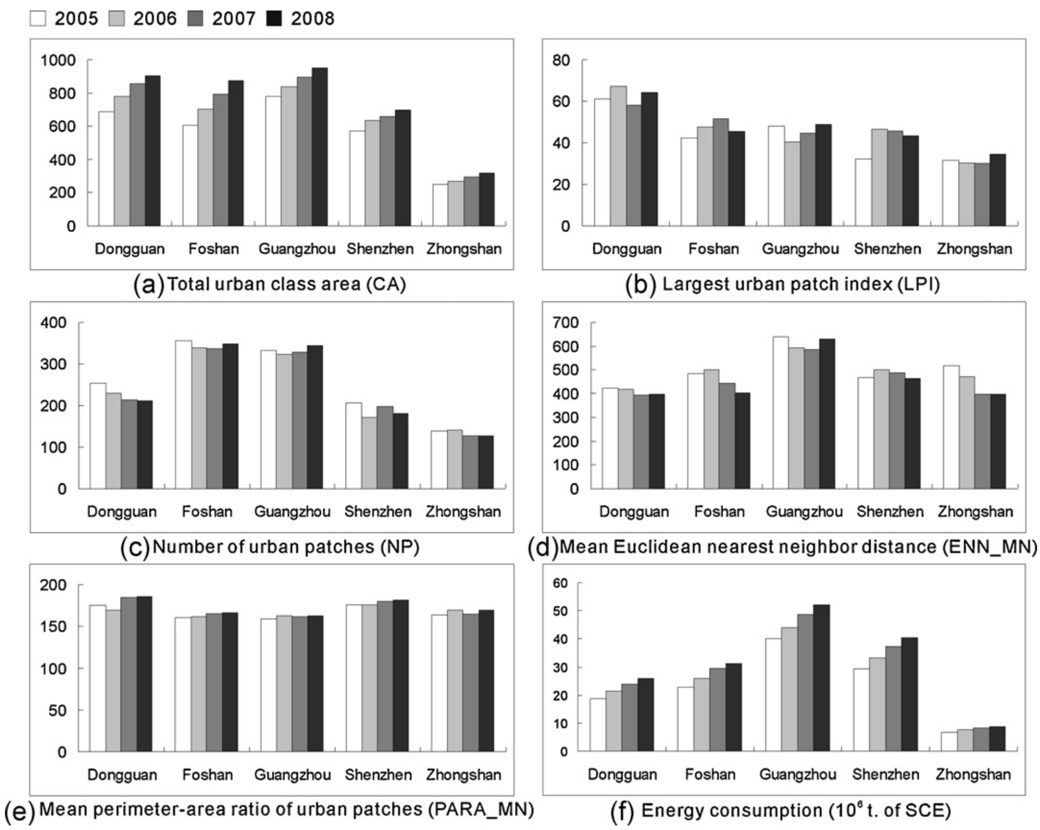

Fig. 3. Energy consumption and values of landscape metrics.

Table 2
Accuracies of classification results 2005–2008 (%).

	2005	2006	2007	2008
Built-up areas	83.33	86.81	88.39	89.51
Bare soil	82.34	80.00	81.87	83.30
Water	96.67	93.50	94.40	98.13
Farm land	70.01	73.33	76.25	70.55
Forest	86.67	91.00	90.66	89.83
Fishpond	80.79	76.67	77.73	82.12

locations near major roads can provide better accessibility to the ports for import/export of goods.

4.2. The relationship between urban forms and energy consumption

The energy consumption of the five cities during 2005–2008 is approximated using Eq. (1), and the results are shown in Fig. 3(f). As the biggest city in the PRD, Guangzhou consumes the largest volume of energy (51.93 million tons of SCE), about 32.79% of total energy consumed by all of the five cities. While Zhongshan, with smaller city size and very high energy efficiency in Guangdong Province, has the minimum energy consumption. The other three cities, Dongguan, Foshan and Shenzhen, which are characterized by numerous manufacturing plants and a mass population of migrant labors, consume 97.63 million tons of SCE, contributing 61.63% of total energy consumption of the study area.

The approximated energy consumption is then served as dependent variables to estimate its relationship with urban land use patterns. The hypothesis is that the larger the city size, the more energy is needed; but given the same size, cities with different land use patterns may have different energy consumption. The estimation is accomplished using panel data analysis. The observation units are cities. The estimation is based on the data of the five cities during 2005–2008, thus there are twenty observations. Given the condition that $T > K + 1$, here $T = 4$, the maximum value of K is 2. This means there are at most two explanatory variables in a regression model. In this study five landscape metrics are selected to reflect different aspects of urban land use patterns. Thus they have to be divided into several combinations and estimated separately. The combination of landscape metrics is chosen based on the correlation analysis. The Pearson's correlation coefficients are computed for five landscape metrics and all combinations of non-correlated metrics are used to establish the models. The result of correlation analysis is shown in Table 3. It can be seen that several pairs of metrics, such as CA and NP, NP and ENN_MN, PARA_MN and ENN_MN are highly correlated. There are five combinations of non-correlated metrics, i.e. (1) CA and LPI; (2) CA and ENN_MN; (3) CA and PARA_MN; (4) LPI and NP; (5) LPI and ENN_MN. Therefore, five models are established according to these five combinations of metrics.

The F-tests are first operated to decide the regression form for these five models. F_1 and F_2 are calculated according to Eqs. (5) and (6). The results are shown in Table 4. For Model 1, F_1 (1492.56) is greater than $F(12,5)$, and hence the hypothesis of constant intercepts and coefficients is rejected. While F_2 (68.41) is less than $F(8, 5)$, and hence the hypothesis of variable intercepts and constant coefficients is accepted. Therefore, Eq. (3) should be adopted for Model 1. The F-test results for the other four models are similar to those of Model 1, thus Eq. (3) was used for estimation.

The Hausman test is then implemented to determine whether fixed or random effects should be adopted (Eq. (11)). Table 5 shows the results of the Hausman test for the five models. The values of W for Models 1–5 are all greater than zero. Therefore, we used the fixed effect model for estimation. The estimation was performed using generalized least squares (GLS) and the results are shown in Table 6.

The estimated coefficients demonstrate a significant relationship between urban land use patterns and energy consumption. As shown in Table 6, CA, NP, ENN_MN and PARA_MN are positively correlated with energy consumption; LPI is negatively correlated with energy consumption (coefficients of LPI are positive in Models 4 and 5, but they are not significant).

The positive correlation between the urban size and energy consumption can be explained from three aspects: economic development, population growth, and urban transportation. Economic development is recognized as the leading driver of urban growth in PRD by many researchers (Fan et al., 2008; Seto & Kaufmann, 2003). The input of large amount of land resources contributes the take-off of regional economy. During last twenty years, a lot of farm land was converted into to infrastructure, real property or industrial uses. Manufacturing industries, especially the processing industries, which are characterized as labor-intensive and low energy efficiency (even lower than other developed areas like the Yangtze River Delta in China (Fang et al., 2009)), used to be the predominant sector in regional economy. Observed from the Guangdong Statistical Year Book 2009, 66.64% of total energy was consumed by the secondary industry in Guangdong in 2008. We cannot find such data at city level so far, but given that the five cities playing the most critical role in the province's economy, it is very likely that the proportion of energy consumption by the secondary industry is higher than 66.64%. Recently the secondary industry is still very important to the regional economy. The average proportion of the secondary industry for the five cities is still near 50% (Table 1); and it is even over 60% in Foshan and Zhonshan. Therefore, the growth of regional economy (especially the secondary industry) should be the most important factor to the increase of energy consumption.

The increasing population, which is also the driver of urbanization (Fan et al., 2008), should be another reason of growing energy consumption. Daily living, commuting, working and traveling of the population create a large demand for energy. Moreover, the annual energy consumption per capita is increasing during the past decade. It was only 148.90 kg of SCE in 2000; and rapidly increased into 285.76 kg of SCE in 2008, almost double times. This could be the result of economic development, which leads to the growth of personal wealth. One typical example is the fast growing number of private cars, as shown in Table 1. "If people own a car, they use it" (Dieleman et al., 2002). The increasing possession of private cars significantly change the patterns of residents' daily activities (Zhou, Yang, & Deng, 2010), and at the same time raises some problems in urban transportation. As reported by Zhou and Liu (2010), the increasing traffic demand and the mismatch of jobs-housing are the major factors of the serious traffic jam in Guangzhou. Thus, urban energy consumption in transportation sector is expected to increase in the future, because on the one hand the number of vehicles is persistently increasing that demands more energy, on the other hand urban transportation systems cannot fully adapt to such change of traffic demand and hence may reduce the energy efficiency.

Table 3
Pearson's correlation coefficients of the spatial metrics.

	CA	LPI	NP	ENN_MN	PARA_MN
CA	1				
LPI	0.324	1			
NP	0.725**	−0.265	1		
ENN_MN	0.265	−0.439	0.476*	1	
PARA_MN	0.103	−0.777**	−0.508*	0.583**	1

Note: CA, LPI, NP, ENN_MN and PARA_MN are landscape metrics, representing total urban class area (km^2), largest patch index (%), number of urban patches, mean Euclidean nearest neighbor distance (m) and mean perimeter-area ratio respectively.
* Significant at 0.05.
** Significant at 0.01.

Table 4
F-test results for Models 1–5.

F-test	Model 1	Model 2	Model 3	Model 4	Model 5
Constant intercepts and coefficients	$F(12,5) < 1492.56$ (0.000)	$F(12,5) < 2057.29$ (0.000)	$F(12,5) < 5968.71$ (0.000)	$F(12,5) < 51.47$ (0.01)	$F(12,5) < 121.67$ (0.01)
Variable intercepts and constant coefficients	$F(8, 5) > 68.41$ (0.000)	$F(8,5) > 59.55$ (0.000)	$F(8,5) > 188.07$ (0.000)	$F(8,5) > 2.12$ (0.01)	$F(8,5) > 5.00$ (0.01)

Notes: The combinations of metrics in these five models are: CA and LPI (Model 1); CA and ENN_MN (Model 2); CA and PARA_MN (Model 3); LPI and NP (Model 4); LPI and ENN_MN (Model 5).

Table 5
Hausman test results for Models 1–5.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β	$\hat{\beta}$	β	$\hat{\beta}$	β	$\hat{\beta}$	β	$\hat{\beta}$	β	$\hat{\beta}$
CA	0.422	0.044	0.476	0.049	0.042	0.045				
LPI	0.108	0.037					0.306	0.363	0.433	0.370
NP							−0.067	0.004		
ENN_MN			0.014	0.021					−0.050	−0.019
PARA_MN					−0.0023	−0.0184				
COV	−0.008		0.041		0.106		−0.727		−0.759	
W	57.99		70.11		69.56		2.93		3.07	

Notes: CA, LPI, NP, ENN_MN and PARA_MN are landscape metrics, representing total urban class area (km^2), largest patch index (%), number of urban patches, mean Euclidean nearest neighbor distance (m) and mean perimeter-area ratio respectively.

One interesting finding from the empirical analysis in this study is the correlation between increasing fragmentation/irregularity of patterns and growing energy consumption. The explanation of positive correlation between fragmentation and energy consumption may be that (1) the potential traffic demand increases when activities are distributed in many different urban patches (high NP); and (2) if the spatial connection between patches is weak (high ENN_MN), probably more energy would be spent because the traveling distance increases. For instance, many newly built residential areas in Guangzhou are within two important sub-centers of the city, namely Panyu and Huadu (Fig. 2), which are distant from the city proper. However, the construction of facilities there is lagged behind. The residents have to commute long distance between the city proper and where they live. The study presented by Yeh and Li (2001) provide another example. They conducted several scenario simulation of urban development in Dongguan based on 'grey-cell' CA model. They found that compared with compact development, the infrastructure costs, such as electricity and gas, were about

Table 6
Coefficients estimated from panel data analysis.

	Model 1	Model 2	Model 3	Model 4	Model 5
CA	0.0798*** (13.29)	0.0460*** (10.14)	0.0203*** (9.48)		
LPI	−0.8025*** (−5.49)			0.0401 (0.24)	0.0515 (0.3)
NP				0.1157*** (4.16)	
ENN_MN		0.0783*** (7.27)			0.0591** (2.1)
PARA_MN			0.0098* (1.74)		
Constant	10.9677*** (2.96)	−40.2698*** (−7.69)	−6.0507 (−6.37)***	−4.8334 (−0.55)	−2.2893 (−0.14)

Notes: CA, LPI, NP, ENN_MN and PARA_MN are landscape metrics, representing total urban class area (km^2), largest patch index (%), number of urban patches, mean Euclidean nearest neighbor distance (m) and mean perimeter-area ratio respectively.
* Significant at 0.10.
** Significant at 0.05.
*** Significant at 0.01.

24% for the dispersed development in Dongguan; and the dispersed development also costs more in transport maintenance and energy consumption.

The irregularity of urban land use patterns is also positively correlated with energy consumption. As mentioned in Section 4.1, highly irregular patterns are observed in Dongguan and Shenzhen (Figs. 2 and 3(e)). Such patterns were also witnessed in other fast industrializing regions in Asia (McGee, 1991; Xie et al., 2006). Therefore the explanation of positive correlation between irregularity and energy consumption perhaps lies in the process of fast industrialization in Dongguan and Shenzhen, or the so-called "urbanization from below" (Shen, Wong, & Feng, 2002), which refers to the rapid, unplanned and spontaneous development of towns. During this process, the governments were so eager to attract investments and promote the local economy. They loosened their control and management on land use development. As a result, many factories and plants were built-up for economic interests but regardless about their environmental impacts, not to mention their low energy efficiency (Fang et al., 2009). Recently the secondary industry is still a very important sector in Dongguan (Table 1). However, the energy consumption per unit growth of industrial production was 0.82 t. of SCE/10^4 yuan in Dongguan in 2008, even higher than that of Foshan (0.58 t. of SCE/10^4 yuan) (Guangdong Statistical Year Book 2009). The energy efficiency of Dongguan thus needs further improvement. One possible way is to gradually substitute industries of low energy consumption for those of intensive energy consumption.

The negative correlation between LPI and energy consumption may in some degree support the viewpoint of compact development (Jenks & Burgess, 2000). Generally, the range and number of functions of an urban patch are related to its size. The larger an urban patch is, the more functions it can provide. The estimation result suggests that the distribution of urban functions should be concentrated rather than decentralized. The compact development may have lower interzonal interactions (Yeh & Li, 2001) and thus can reduce more energy consumption. However, the implication from the negative correlation between LPI and energy consumption should not be overstated since the limitation of the metric LPI is also apparent. LPI only consider the size of a patch and cannot address the heterogeneity within a patch, such the distribution of population. Therefore, even though the LPI of Dongguan is higher than Guangzhou (Fig. 3(b)), it is problematic to say the development of Dongguan is more compact than that of Guangzhou. Nevertheless, the LPI is still used in this study for analysis since it is difficult to find another metric that can describe the compactness of a city at patch level.

5. Conclusion

With the advances in remote sensing and geographical information systems (GIS), the quantification of urban forms has been significantly improved by many new methods, such as landscape metrics (Herold et al., 2005). Compared with the progress in quantification of urban forms, the impacts of urban forms on environment and ecosystem are not yet fully understood (Fragkias & Seto, 2009). This study presents an empirical analysis on this realm from the perspectives of the relationship between urban forms and energy consumption. We select five rapidly growing cities in the Pearl River Delta as the case study area, namely Dongguan, Foshan, Guangzhou, Shenzhen and Zhongshan. The rapid urbanization and fast changing urban landscapes in the PRD have been reported by many authors based on GIS and remote sensing (Fan et al., 2008; Li & Yeh, 2004; Seto et al., 2002). In this study we try to link the characteristics of urban landscapes with urban energy consumption.

The urban land use patterns in the study area during 2005–2008 were obtained through classification of remote sensing images. Five selected landscape metrics were then used to quantify the urban land use patterns. The panel data analysis was implemented to estimate the relationship between urban land use patterns and energy consumption. In brief, there are three major findings from the analysis: (1) urban size is positively correlated with energy consumption. The increase of urban size in the PRD relates to the phenomena of economic development, population growth (Fan et al., 2008; Seto & Kaufmann, 2003), and increasing traffic demand (Zhou et al., 2010). All of these are probable factors to stimulate the energy consumption of PRD. (2) Fragmentation of urban land use patterns is positively correlated with energy consumption. The fragmented pattern of urban land use may cause the increase of traveling distance, which was confirmed by other researchers (Yeh & Li, 2001). The irregularity of urban land use patterns is also positively correlated with energy consumption. Perhaps this correlation relates to the formation of the irregular patterns. The critical driver is the fast industrialization, which brought many industries that are labor-intensive and low energy efficiency. (3) The dominance of the largest urban patch is negatively correlated with energy consumption. Such result may support the viewpoint of compact development in PRD, as suggested by Jenks and Burgess (2000).

In fact, this paper only presented the results of the first stage in our study about the relationship between urban forms and energy consumption. There are several limitations that should be acknowledged regarding present study. For example, the mechanism behind the empirical results is still not fully clear and needs thorough examination in future study. This is mainly caused by the limited data availability, i.e. the urban land use data and energy consumption data. The spatial distribution of industrial, residential or commercial uses is important in analyzing the relationship between urban forms and energy consumption. However, it is almost impossible to identify such land uses in Landsat TM images with a resolution of 30 m. Therefore, we have to assume that there are not too much variations of spatial distribution of these different land use patterns between these five cities. Another limitation is in the data of urban energy consumption. To the best of our knowledge, there is very few data about urban energy consumption for most of the cities in PRD until 2005. Even at present the energy data at city level are still quite limited. Data such as the detailed composition (transportation, office/commercial building, household) of energy consumption is not fully available.

We hope we can find more data in future study so that questions like "How such urban land use patterns evolve? Why and in what ways such urban land use patterns can influence the energy consumption?" can be addressed much better. Besides, other methods or techniques may also be considered in future study. The panel data analysis is capable of capturing strength of relationship between explanatory variables and the dependent variable; but cannot directly guarantee the causation among them. Perhaps the simulation methods are a considerable option (Li & Yeh, 2000). Based on the simulation methods, experiments can be carried out and replicated in a standard platform to investigate non-linear and self-organizing dynamics of complex systems (such as cities) (Wu, 1999). Therefore, the simulation methods may be adopted to address the interactions between changing urban forms and energy consumption in next stage of our study.

Acknowledgements

This study was supported by the National Basic Research Program of China (973 Program, 2011CB707103), the Key National Natural Science Foundation of China (Grant No. 40830532), the

National Outstanding Youth Foundation of China (Grant No. 40525002), the National Natural Science Foundation of China (Grant No. 40901187), and the Sun Yat-sen Innovative Talents Cultivation Program for Excellent Tutors.

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