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Economic Growth and the Expansion of Urban Land in China

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Abstract

This paper aims to demonstrate the relationship between economic growth and the urban core area in order to help urban planners reach a better understanding of the pressures that are leading to changes in land use. Using a unique panel dataset with measures of China's land use, it is shown that, during the late 1980s and 1990s, China's urban land area rose significantly. Descriptive statistics and multivariate analysis are then used to identify the determinants of urban land use change. In addition to using more standard regression approaches such as ordinary least squares, the analysis is augmented with spatial statistical analysis. The analysis demonstrates the overwhelming importance of economic growth in the determination of urban land use. Overall, it is found that urban land expands by 3 per cent when the economy, measured by gross domestic product, grows by 10 per cent. It is also shown that the expansion of the urban core is associated with changes in China's economic structure. If urban planners have access to forecasts of economic growth, using these results they should be able to have a better basis for planning the expansion of the built-up area in the urban core.

1. Introduction

According to experiences in most parts of the world, the process of development leads to urbanisation. Economic development is sometimes actually defined as a process that shifts a nation's population from rural to urban (Kuznets, 1966). In the earlier stages of development, the agricultural sector is always the dominant part of the economy. Transferring relatively less productive rural labour to the non-farm sector is one of the main engines of the development process (Beauchemin and Schoumaker, 2005).

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Almost axiomatically, growth-induced urbanisation is going to require that cities grow in size and utilise land. Successful urbanisation requires the expansion of the industrial and service sectors (Parker, 1996). More housing is needed. Urbanisation also requires the creation of new infrastructure (Ogu, 2000).

In addition, there are a number of other factors (which are often unobservable or difficult to measure) which also may affect the expansion of urban land, such as the fiscal motives of local governments to convert rural land into urban use. In some places, local governments can obtain substantial extra-budgetary revenue through land conversion. As a result, in some circumstances, local governments tend to promote excessive spatial growth of cities beyond what has been planned.[1] Of course, officials in upper-level governments know this and often respond with restrictions on land conversion and built-up area.

While the need for land is unambiguous, what is unclear is how much land will be shifted from other uses during the course of urbanisation. One of the main demands on urban planners who are charged with designing a future urban landscape and co-ordinating the expansion of the city with a nation's other developmental needs is an accurate estimate of the amount of land that will be converted during the period being covered by the plan. In the initial step of creating an urban land use plan, planners are typically given an expected growth rate (for example, from the Ministry of the Economy's economic planning office or from the Government Accounting Office). Based on this expected growth rate, urban planners can then begin to attempt to create a blueprint of what the city will (should) look like at some point in the future. One of the parameters of greatest interest which will be evident when the blueprint is complete (and which is also one of the key inputs into creating the urban plan) is the amount of land that will be converted from other uses into city use.[2]

Once this initial growth/urban land conversion projection is made, the second step of the planning process can proceed. During this stage, policy-makers look at how much land will be expected to be converted in a 'business as usual' scenario and determine if this amount of conversion is acceptable or not. If the level of conversion is acceptable, the plan can be launched within the bounds of the current regulatory and institutional framework that has guided urban land use in the past. Under this scenario, the main job of the planning department will be to monitor land use to ensure that their projections were correct.

However, if the amount of land to be converted to urban uses under expected economic growth rates is too high—for example, if the conversions were expected to use so much agricultural land that they would cause a threat to the nation's food security—policy-makers might ask the urban land planners to create a new plan. This new plan might be accompanied by a new set of regulations and institutions that would seek to allow the growth to continue but in a way that used less agricultural (or other types) of land.

In understanding this process, one of the most fundamental issues that needs to be understood is from what sources planners get their estimates of the area to be converted during the period covered by the urban plan. Typically, such estimates—at least in the initial planning periods—come from observations of a nation's past performance (or, in other words, the observed relationship between growth and urban land use in the past). Estimation of the impact of economic growth on urban land use, however, is not trivial, especially if the analyst only has cross-sectional data (which is the normal case). Although estimating the relationship between economic growth and urban land use in one sense is quite simple—correlation coefficients and basic regression models can provide measures of how urban land use changes with the level of wealth in an economy—social scientists and geographers know that, in fact, a full (and accurate) analysis of the determinants of urban land use is complicated. There are many different factors—some observable, others not observable—that affect the size of an urban area (Zhang, 2000; Zhang and Jia, 2001). Fortunately, there are a number of statistical tools that have been developed in recent years that can help analysts to understand the nature of a behavioural relationship (i.e. the impact of growth on urbanisation) and assess how well alternative estimates are able to capture the essence of the relationship. Econometric methods and spatial statistical analysis are two of these tools.

The overall goal of this paper is to understand how growth affects urban land use, which among other things, can be used to help urban land planners to produce better designs of future urban areas. To meet this goal, we have three specific objectives. First, we will describe the relationship between economic growth and urban land use, a process that can most accurately be called laying out the observed facts. Secondly, we will use econometric analysis to identify the determinants of urban land use with a focus on the role of economic growth. In doing so, we will have access to three years of urban land use data (1988, 1995 and 2000) and two years of data on a set of explanatory variables, including measures of economic growth. Having access to information over time will, among other things, allow us to isolate the importance of accounting for the historical legacy of a city in explaining its current land area and identify more accurately the effect of economic growth on urban land use. Thirdly, we will use recent techniques in spatial statistical analysis (or more precisely spatial econometrics) to understand how accounting for patterns of spatial associations embodied in cross-section data can help to isolate the effect of economic growth on urban land use. By approaching the analysis in two different ways, we can compare (at least in the context of our particular study) the relative importance of historical legacy against that of spatial associations in helping to explain the determinants of urban land use.

To meet these objectives, we will focus on the case of China. We do so for several reasons. First, the rapid, but heterogeneous, urbanisation of China, as well as other socioeconomic changes, across time and space provide a veritable laboratory for analysing the determinants of urban land use. Our focus on China also allows us to utilise a unique set of land use data from Landsat TM/ETM digital images. Specifically, this study uses land use information for all of China at the 1×1 square kilometre observation level for 1987/88/89, 1995/96 and 1999/2000 (henceforth, 1988, 1995 and 2000). The GIS database also contains information on traditional geophysical factors at the 1×1 square kilometre level. In addition, this study combines the land use and other GIS information with a set of county-level, socioeconomic data that have been assembled by the authors. Such a dataset allows us to use econometric methods to explain variations in land use across space and over time which consider a comprehensive set of factors including economic growth and demographical expansion. Unfortunately, since consistent data on economic growth at the county level only go back to the early 1990s, the multivariate analysis is conducted only with the data from 1995 and 2000.

The rest of this paper is organised as follows. The next section introduces the data used in this study. The third section illustrates the changes of urban land in China during the study period between 1995 and 2000. The fourth section introduces the empirical models and results from regression analysis. The fifth section illustrates the spatial statistical analysis and the GDP–urban core relationship. The final section concludes.

2. Data

2.1 Creating the Sample

One of the most onerous tasks in preparing the data was to create a set of county-level observations that were consistent over the time of the study. The problem of consistency of county-level units over time arises because of changes in jurisdictional areas in China's administrative regions. The boundaries of some counties change over time. In other cases, towns/townships in a single county are divided into two groups and made into two counties between the mid 1980s and late 1990s. Occasionally the city core of a county is removed from the jurisdiction of the original county government and becomes an independent county-level administrative unit.

Because of these changes, the number of counties rose over the study period. For example, in 1988 China had 2156 administrative units at the county level, whereas in 2000 the number had expanded to 2733.[3] The organisational shifts of county-level administrative units are problematic for this study since data within each county observational unit need to be comparable over time.

In order to overcome this problem, we use the geo-coding system of the National Fundamental Geographical Information System (NFGIS, 2000) and a 1995 administrative map of China from the Scientific Data Centre of the Chinese Academy of Sciences, which included a consistent geo-coding system with that of NFGIS. Using these tools, if two counties had been subject to border shifts (for example, one county ceded jurisdictional rights to another), we combined them into a single unit for the entire sample period. In cases in which the city core of a county had been removed from the jurisdiction of the original county-level government, we reaggregated the municipal administrative zone back into the county proper. In the case of large metropolitan areas (i.e. China's four provincial-level municipalities—Beijing, Tianjin, Shanghai and Chongqing; provincial capitals; and other large cities), the districts within the city's administrative region were combined into a single, sample-period-consistent observational unit. In this way, we ended up with a sample that includes 2348 observational units (excluding Taiwan, Hong Kong and Macao) at the county level that are consistent in size and jurisdictional coverage over time. In the rest of the paper, even though the observations will include municipality districts, cities and other administrative units that are larger (and more complex) than counties, for brevity we call all observations county sampling units (or simply counties).

Because spatial analysis cannot be carried out effectively when there are missing data, we had to drop several provinces from our analysis. The basic problem of missing values in our spatial econometric approach is that, if just one county has a missing value, then some or all of the spatially weighted variables cannot be created. Ignoring this problem results in an errors-in-variables bias (Cressie, 1993). It is less of a problem in ordinary least squares (or traditional regression) estimation since most programmes drop the observations for which a variable has a missing value.

In the case of our analysis, the problem arises due to missing observations on the economic variables. After looking in as many published sources as possible (both national and provincial yearbooks and statistical compendia), the economic data were not complete for a number of counties in Xinjiang, Tibet, Qinghai and Gansu. In the case of the rest of the provinces, we were able to create a complete series of county-level data for 1995 and 2000 for all counties. After eliminating the counties from Xinjiang, Tibet, Qinghai and Gansu from the analysis, we are left with a final sample size that includes 2063 counties.[4]

2.2 Land Use Data

One of the strengths of our study is the nature and quality of the data that we use to estimate changes in urban land use. For our purposes, satellite remote sensing digital images are the most suitable data for detecting and monitoring land use change (LUC) at global and regional scales (Kok, 2004). In previous studies, satellite sensors, such as Landsat TM and the French SPOT system, have been used successfully for measuring deforestation, biomass burning and other land use changes, including the expansion and contraction of deserts (Skole and Tucker, 1993). Remote sensing techniques also have been used widely to monitor the conversion of agricultural land to infrastructure (Palmera and Lankhorst, 1998; Woodcock *et al.*, 2001; Milesi *et al.*, 2003).

In our study, we use a land use dataset developed by the Chinese Academy of Sciences (CAS). Our study's data are from satellite remote sensing data provided by the US Landsat TM/ETM images which have a spatial resolution of 30 by 30 metres (Vogelmann *et al.*, 2001). The database includes time-series data for three time-periods: the late 1980s, including Landsat TM scenes from 1987 to 1989 (henceforth, referred to as 1988 data for brevity); the mid 1990s, including Landsat TM scenes from 1995 and 1996 (henceforth, 1995); and the late 1990s, including Landsat TM scenes from 1999 and 2000 (henceforth, 2000). For each time-period, we used more than 500 TM scenes (514 scenes in 1988, 520 scenes in 1995 and 512 scenes in 2000) to cover the entire country.

The Landsat TM images are geo-referenced and ortho-rectified. To do so, the data team used ground control points that were collected during fieldwork as well as high-resolution digital elevation models. Visual interpretation and digitisation of TM images at the scale of 1:100 000 were made to generate thematic maps of land use (Deng *et al.*, 2002 and 2004). A hierarchical classification system of 25 land-cover classes was applied to the data. In this study the 25 classes of land use were aggregated further into six classes of land use—cultivated land, forestry area, grassland, water area, built-up area and unused land.

The interpretation of TM images and land-cover classifications was validated against extensive field surveys (Liu *et al.*, 2003). The interpretation team from CAS conducted ground-truth checks for more than 75 000 km of transects across China. During ground-truthing, more than 8000 photos were taken using cameras equipped with a global position system. The average interpretative accuracy for land use classification is 92.9 per cent for 1988, 98.4 per cent for 1995 and 97.5 per cent for 2000. By comparing land use patterns between 1988 and 2000 (or 1995 and 2000), we determined the changes in land use for the entire country between 1988 and 2000. Additional details about the methodology which we used to generate the databases of land use from Landsat TM are documented in Liu *et al.* (2002).

2.3 Other Data Sources

Several datasets were used to generate variables that measure the geophysical and socio-economic attributes of each county. In the LUC literature, a number of geophysical variables have been used in research that has attempted to understand urban land use (Fischel, 1982; Ewing, 1994; Tang, 1994; Dredge, 1995; Squires, 2002; Sudhira *et al.*, 2004; McGrath, 2005). We include a subset of these in our analysis.

The geophysical data that we use in our analysis come from several sources of data. The terrain variables are generated from a dataset created from a digital elevation model of China (which is housed in the Chinese Academy of Sciences—CAS, Institute of Geographical Sciences and Natural Resource Research). The distance of each county (county seat) to the provincial capital and the distance of each county to the nearest port city also are calculated using data from the CAS data centre. The data documenting the location of the county seat (and the provincial capital and port cities) are originally from the State Bureau of Surveying and Mapping of China. Climatic variables are generated by the authors based on the site-based climatic data from the China Meteorological Bureau from 1950 to 2000. All of the geophysical data, which are available in their most disaggregated form at the 1×1 square km level, were spatially referenced to the county level using GIS geo-coding methods. The specific variables used in the analysis are defined later.

Socioeconomic variables, unlike the GIS-based data, do not require aggregation from sub-county levels (and, in fact, are not available at the sub-county level). Information on gross domestic product (GDP) for each county for 1995 and 2000 are from the *Socioeconomic Statistical Yearbook for China's Counties and Cities* (NBSC, 2001a) and are supplemented by each province's annual statistical yearbook for 1995 and 2000. Investment in the agricultural sector accounts for one of the most important sources of the total fixed investment for a county. It is often used in the urban studies literature to proxy for the value of agricultural land (for example, Firman, 1997; Seto and Kaufmann, 2003). The data on investment into the agricultural sector for each county are from each province's annual statistical yearbook for 1995 and 2000. The database was provided to the authors by the Academy of Macroeconomic Research (*hongguan jingji yanjiuyuan*) of the National Development and Reform Commission (NDRC). These data originally come from NBSC and are collected as part of their annual survey of counties. The demographic data for 1995 and 2000 are from the *China Counties and Cities' Population Statistical Yearbook* (Ministry of Public Security of China, various years), which is published by the Ministry of Public Security of China.

3. Changes in China's Urban Land

Studies that examine urban land change using Landsat images need to make an important choice regarding the definition of 'urban land'. Our dataset includes three classifications of built-up area: the urban core, rural settlements and other built-up areas.[5] In constructing our dataset, the urban core is defined as all built-up area that is contiguous to urban settlements. Therefore, each county in our sample, by definition, has at least one urban settlement. The expansion of the urban core from one time-period to another is defined as all new built-up area that has appeared, for example, between 1988 and 1995, which is contiguous to the urban settlement in 1988. Rural settlements in our dataset include all built-up area in small towns and villages. Rural settlements can become urban settlements in two ways: by being surrounded by new built-up area and thereby becoming part of the contiguous urban core; and by growing themselves to the point that the Landsat image interpretation pushes them into the urban settlement category. The 'other built-up area' category includes roads, mines and development zones that are not contiguous with the urban core.

3.1 Measuring the Expansion of the Urban Core: An Illustration

To illustrate the nature of our data (and the scope of the urban expansion that we are interested in), we show maps created from Landsat images for the two years (1995 and 2000) from three selected cities (Figure 1). Beijing is included as an example of a large metropolitan region in China's rapidly developing coastal area. Guiyang is included as an example of a large city in China's inland region. Mianyang, which is located 115 km to north-east of Chengdu in the province of Sichuan, is included to illustrate changes in a small, prefectural-level city. Although the scales of the maps are not the same, examining their change over time allows us to see that there are differences among the county sample units in the level and rate of their urbanisation. According to the data, we can see that there are differences in the rates of growth of the urban core. For example, Beijing's urban land expanded by 5 per cent between 1995 and 2000. During the same period, the urban land in Guiyang expanded by 14 per cent; Mianyang expanded by 15 per cent.

3.2 Appropriateness of Choice of Urbanisation Variable

In our paper, we focus on explaining the expansion of the urban core for several reasons. First, the expansion of the urban core is the fastest-growing component of the built-up

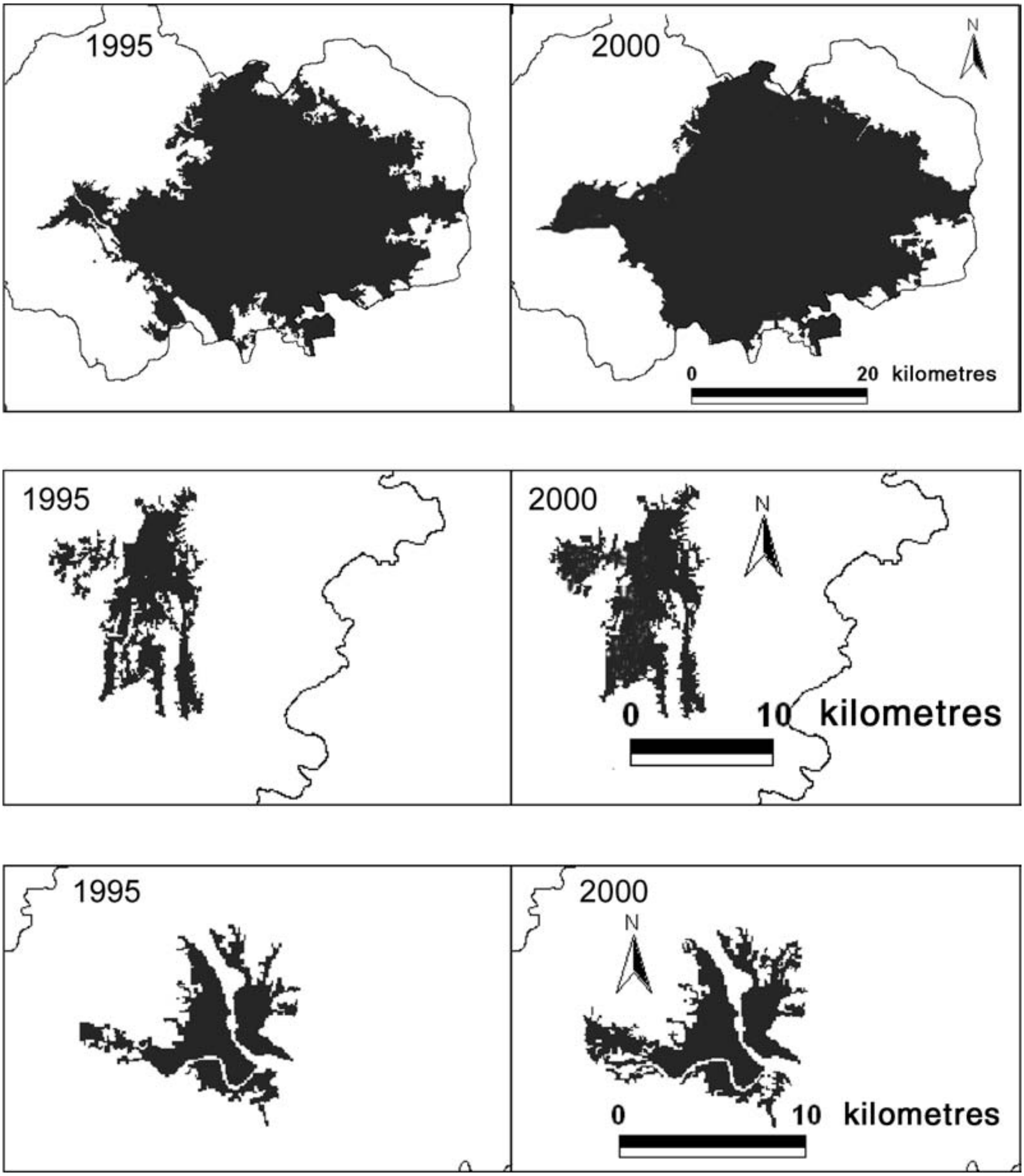

Figure 1. The expansion of the urban core of Beijing, Guiyang and Mianyang from 1995 to 2000. *Above*: Beijing; *centre*: Guiyang; *below*: Mianyang. *Data source*: Landsat TM/ETM images, Chinese Academy of Science Database.

area. Although the land area included in 'other built-up area' in 1988 was larger than that in the urban core, the rate of expansion of the urban core is larger in both absolute amount (+817 000 hectare expansion for the urban core between 1988 and 2000 versus +235 000 hectares for other built-up area) and in percentage terms (25.40 per cent for the urban core; 1.26 per cent for other built-up area). Since we also are interested mainly in the process of urbanisation, we do not include the area built-up in rural settlements, although this is analysed in Huang *et al.* (2004). Finally, unlike many studies in developed countries that are interested in urban sprawl (for example, Burchfield *et al.*, 2006), we focus on the urban core since the fragmented pattern of growth is not the major issue at this point in China's development process. By ignoring urban sprawl, we do not include the expansion of the built-up area that appears in non-contiguous areas of counties.

In this study, we use the county as the analytical unit. The county is the third level in the administrative hierarchy in China, below the province and prefecture. Although we generically use the term county for all of our observations (as discussed earlier), our choice of analytical unit includes (autonomous) counties, county-level cities, banners (which are county-like administrative regions in northern China) and districts. We use the county as the analytical unit because in China we believe each county can be regarded as an administrative as well as an economic region. The average area of a county is between 3000 and 4000 square km. Historically, counties grew up around an urban centre, the county seat. Today, each county hosts an important administrative level of government (the county government) and in almost all cases one of the functions of the county government is to create its own land use plan and thus the county constitutes a region that can be used to study land use changes—especially of the expansion of the urban core.

Comparisons of our data and information on urbanisation that have been collected by China's statistical system provide evidence that our choice of the variable that we use to study urbanisation is appropriate. Since the early 1980s, NBSC has collated and reported a variable at the city level called "area affected by the construction in urban area" (*jianchengqu*). In discussions of urbanisation, statistics based on this variable are often quoted (for example, Liang and Jin, 2005). The correlation coefficient between our measures of urbanisation (aggregated to levels that are comparable with the NBSC data) and those of NBSC are relatively high—0.75.

Unfortunately, the NBSC data on urbanisation have several shortcomings that preclude its use in rigorous analysis of the determinants of urbanisation. Above all, the coverage is limited. NBSC only reports *jianchengqu* for large cities (for example, 40 cities in 2000). In addition, the source of the information for this variable is not clear. There is no rigorous definition that is used to collect uniform information across China's cities. Finally, comparisons with our data suggest that the NBSC data are underreported. For example, based on NBSC's statistics, the *jianchengqu* area of Beijing increased from 391 square km in 1988 (NBSC, 1989) to 488 square km in 2000 (NBSC, 2001b), while based on our data, the urban core areas of Beijing at the corresponding periods were 547 and 788 square km respectively.

3.3 The Expansion of the Urban Core in China

Although it is clear from our data (and NBSC data) that the area of land used for urbanisation is increasing over time, using our data for the 2063 county-sampling units, we find that the expansion of the urban core is variable across time and space. Distributions of growth rates of urban core for the two periods show that the growth rate ranges from zero per cent to over 90 per cent, indicating a wide variability across space.

Moreover, we find that more counties experienced higher growth rates in 1988 to 1995 compared with 1995 to 2000. The distributional maps suggest that, on average, the urban core expanded rapidly from 1988 to 1995 and then decelerated. We also find that all provinces except those of north-western and north-eastern China experienced faster urban core growth in the earlier period. The provinces of north-west and north-east China are poorer compared with the rest of the nation. The fact that the urban cores in the provinces of north-western and north-eastern China are expanding faster in the later period may be one indication that they are catching up with the rest of the economy.

3.4 Economic Growth and Expansion of the Urban Core

In the same way that our data show that the expansion of the urban core differs over time and across space, the descriptive evidence also shows that economic forces may be associated with the changing urban landscape. In most aggregated terms during the late 1990s as the urban core of the average county expanded, counties were experiencing dramatic changes in their socioeconomic environment (Table 1). For example, during the time that the urban core of the average county expanded by 3.64 per cent (from 1792 hectares to 1857 hectares; row 2), GDP also was rising rapidly (from 2.82 billion yuan to 5.00 billion yuan; row 3). During the late 1990s, other factors were also expanding, including population, agricultural investment and the rate of industrialisation and service-sector expansion (rows 3–6). In short, the factors that have been identified by studies in other countries that affect urbanisation (Alonso, 1964; Mills, 1967; Muth, 1969; Brueckner and Fansler, 1983; Glaeser and Kahn, 2004; Brueckner, 2005; McGrath, 2005) are all changing in China and must be considered as possible drivers of urban core expansion. Importantly, as a way of showing the consistency of our data, Table 1 also demonstrates that, in cases in which there are comparable data available from our dataset (columns 2 and 3) and from published sources using national statistics (columns 4 and 5), variables from the two sets of data are correlated, especially across time.

When we use disaggregated data, we find that the size of the urban core is associated with

Table 1. Descriptive statistics of key variables

		Authors' data[a]		*NBSC*[b]	
Variable	*Unit*	*1995*	*2000*	*1995*	*2000*
Urban core	Hectare	1792	1857	N.A.	N.A.
Real GDP[a]	Billion yuan	2.82	5.00	2.53	3.67
Population	Thousand persons/county	553.8	568.9	495	520
Agricultural investment per capita[a]	Yuan	7.7	9.8	N.A.	N.A.
Share of GDP2	In ratio	0.44	0.47	0.48	0.5
Share of GDP3	In ratio	0.30	0.35	0.31	0.33

[a] All numbers exclude Taiwan, Hong Kong, Macao, Xinjiang, Tibet, Qinghai and Gansu. Sample size of this study includes all China's counties excluding these seven administrative regions (including prefectural and provincial capitals). For simplicity, we still call them 'counties'. All numbers in 2000 real terms.
[b] For average real GDP and population, we calculated the averages using total number of counties (including prefectural and provincial capitals) from NBSC.

Table 2. Income, population and other explanatory factors and sizes of urban core in China, 1995 and 2000

		Relatively small urban core		*Relatively large urban core*	
Variable	*Unit*	*1995*	*2000*	*1995*	*2000*
UrbanCore	Hectare	437	463	3090	3194
GDP	Billion yuan	0.96	1.57	4.62	8.35
Population	Million persons	364.89	376.90	744.03	758.59
AgriInvest	Yuan	5.76	7.26	9.67	11.94
HwyDensity	Square metres per 1000 hectares	10.62	56.40	10.62	56.40
GDP2	Billion yuan	0.33	0.58	2.09	3.85
GDP3	Billion yuan	0.25	0.49	1.65	3.27

other economic and demographic factors (Table 2). When dividing our counties into two parts based on the size of the urban core (relatively small urban cores, column 2; relatively large urban cores, column 3), the absolute scales of GDP changes shift systematically. On average, the GDP of a county with a relatively small urban core is 0.96 billion yuan, which is lower than the GDP of a county with a relatively large urban core (4.62 billion yuan in 1995). We find a similar pattern in 2000.

It should also be noted that other dimensions of the economy also are changing with the size of urban core—for example, population (Table 2, row 4); agricultural investment (row 5); and highway density (row 6). In addition, the share of industry in GDP (row 7) and the share of the service sector in GDP (row 8) are also higher in the counties with larger urban cores. Clearly, given these descriptive statistics (and the experience of the rest of the literature in isolating the factors that affect urban land use), there is descriptive evidence that China's cities are expanding as the economy grows.

4. Empirical Model and Results from Regression Analysis

4.1 Empirical Model

In this section, we specify an empirical model to estimate the relationship between urban land uses and economic growth over time. Lessons from previous studies in the US (Brueckner and Fansler, 1983; Brueckner, 2005; McGrath, 2005) and our observations of China's growth (as discussed in the previous section) lead us to consider measures of economic growth, demographic change, public investment and variables that represent shifts in the structure of the economy. We also believe that geography should play an important role in the differences among the different levels of development of urban areas across space (Burchfield *et al.*, 2006; Deng *et al.*, 2006).

Following an empirical study by McGrath (2005), we include the variable of GDP to measure the effect of the overall level of economic development of the county unit (on the right-hand side of the model) on urban land use. GDP measures the value of all goods and services produced in the county during the year. After the early 1990s, GDP measures generated by China's National Bureau of Statistics are consistently collected.

To isolate the effect of GDP, we want to hold constant the effect of other factors that are associated with the transformation of economic and demographic changes in the urban core area. As in Seto and Kaufman (2003), our measure of industrialisation is constructed as the value of GDP created in the industrial sector divided by total GDP (*GDP2_share*).

A similar measure was created for the service sector (*GDP3_share*). Following the empirical studies by Brueckner and Fansler (1983) and Burchfield *et al.* (2006), we also include a measure of the level of the population of the county sampling unit (*Population*). These data include non-rural residents who have their official residence permit (*hukou*) in the county sampling unit (regardless of whether they reside in the urban core or not). People with rural *hukou* and those from other county sampling units that have not officially moved their *hukou* or who have not registered with the local bureau of public security are not included.

In addition to a set of variables from the spatial size of the city literature, there are other economic variables and geophysical variables that also might affect the size of the urban core (Brueckner and Fansler, 1983; McGrath, 2005; Burchfield *et al.*, 2006). Although we would ideally like to have comprehensive measures of public investment, due to data limitations we only include a measure of the amount of investment allocated to agriculture (*AgriInvest*). It is also well known that agricultural investment has an important effect on a region's development. The variable (henceforth *AgriInvest*) is measured as the investment per capita for each county, as a proxy for agricultural rent to identify the opportunity cost of converting to urban area (Wei, 1993; Deng *et al.*, 2008).

The nature of the geophysical landscape might also affect the expansion of the urban core. Studies by Burchfield *et al.* (2006) and Braimoh and Onishi (2007) have included geophysical variables in their models. The geophysical variables used in our study can be divided into four broad categories. In our dataset none of these variables varies over time. The first category of variables includes distance and transport variables (McGrath, 2005). Two variables, both denominated in kilometres, control for the distance of county sampling units from specific types of locations: *DistPort* measures the distance to the nearest port city; and *DistPvCapital* measures the distance of the county to the capital of the province to which the county belongs. Brueckner and Fansler (1983) and McGrath (2005) also empirically account for the effects of the nature of the transport system on the growth of urbanised area. In this paper, we include a non-time-varying measure of the density of each county's highway system in 1995 (*HwyDensity*, from the CAS digital transport map).

Besides distance and transport variables, we also include geographical variables to account for differences in climate and terrain. Burchfield *et al.* (2006) have explored the effects of climatic conditions on urban land expansion and have concluded that temperate climate and rugged terrain are associated with urban land sprawl in the US. In our study, measures of *Rainfall* (average annual rainfall in a county over a 50-year period, 1950 to 2000) and *Temperature* (average annual air temperature, calculated as the sum of daily average temperature in a county over a 50-year period, 1950 to 2000) also are used. Coming from the China Bureau of Meteorology, measurement of *Rainfall* and *Temperature* are available for over 400 national meteorological stations. We use these readings and our own China-specific climate interpolation models to interpolate the data from specific meteorological stations, changing them into spatial data (at the 1x1 km level) and then aggregating them to county-specific measures.

Also following Burchfield *et al.* (2006), we include terrain variables to estimate the impact of terrain on urban land use. Three kinds of terrain variables are used here. The first, *Elevation*, is measured as the average elevation of the county's entire land area (both urban core and non-urban-core area). *Slope* is the average slope of a county and is intended to measure the steepness of the county's hills and mountains. *SharePlain* is a variable that is created by dividing the land area in a county that has a slope that is less than eight degrees by the total land area of the county. Taken together, these three variables provide a control for the ruggedness of a county's terrain, which should be correlated with the difficulties of constructing urban infrastructure and buildings.

Finally, in addition to the economic and geophysical variables of interest, the model includes one other variable—$UrabanCore_{1988}$, a measure of urban core area in 1988. This variable is needed to control for the overall size of the county sampling unit since we are explaining the expansion of the urban core in hectares. In some sense, this variable is controlling for the past legacy of the expansion of the urban core.

In sum, we use the following reduced form model:

$$UrbanCore_{it} = f(GDP_{it}, GDP2\_share_{it}, GDP3\_share_{it}, AgriInvest_{it}, Population_{it}, DisPort_i, DistPvCapital_i, HwyDensity_i\ SharePlain_t, Rainfall_i, Slope_i, Temperature_i, Elevation_i, UrbanCore_{i1988}) \quad (1)$$

We first estimate the model using ordinary least squares (OLS). Later in the paper, we discuss the model and modelling approach that we use with an alternative approach (a spatial statistical approach).

4.2 Results of the Multivariate Analysis (OLS)

The role of growth in the expansion of the urban core is clear as we implement our strategy to estimate the model in equation (1). Holding constant the area of the urban core in 1988, the importance of *GDP*, our measure of overall wealth (and growth), in explaining the expansion of the urban core in the late 1990s is seen by its positive and highly significant coefficient (when the GDP variable is included by itself; Table 3, columns 3 and 6). The magnitudes of the coefficients, 0.451 in 1995 and 0.416 in 2000, intuitively mean that as GDP grows by 10 per cent (for example), the urban core expands by more than 4 per cent. Even as we incrementally add *Population* and measures of the importance of industrialisation (*GDP2_share*), the rise of the service sector (*GDP3_share*) and *AgriInvest* in Table 4 (columns 1 and 3), the importance of GDP growth remains. The magnitude of the coefficient changes slightly, falling from 0.451 in Table 3 (column 3) to 0.398 in Table 4 (column 1) for 1995 and from 0.416 in Table 3 (column 6) to 0.336 in Table 4 (column 3) for 2000. The statistical significance remains high. The high adjusted R^2 values also illustrate that growth, by itself (that is, holding constant the size of the urban core in 1988) and in concert with the rest of the economic/demographic variables, can explain a large amount of the variability of the expansion of the urban core. If these results were to hold up throughout our analysis, it is clear that growth is an important force that is pushing out the boundaries of the urban core.

Our results also show that, holding GDP constant, demographic and other economic variables are positive and significant. When only considering economic factors (and not considering any geophysical factors), *Population* is significant (Table 4, columns 1 and 3). Interestingly, in this relatively parsimonious model (that is, without holding geographical variables constant), the coefficient on the industrialisation variable (*GDP2_share*), although positive, is not significantly different than zero (Table 4, columns 1 and 3). In contrast, the coefficient on the variable measuring the importance of the service sector (*GDP3_share*) is both positive and significant. While this may be somewhat surprising, given that industrialisation is typically thought to be more land using than the service sector, it could be that the service sector's fast growth (it increased its share of GDP by 5 percentage points in our sample compared with a rise in the service sector of only 3 percentage points for industrialisation; Table 2) is somewhat behind the expansion of the urban core. It could also be that industrialisation is occurring more in the development zones, in regions outside the urban core.

Table 3. Simple OLS estimation result with lagged urban core (urban core area of 1988), 1995 and 2000 (2063 observations; Dependent variable: Ln(*Urban core area*))

	(1) *1995*	*(2)* *1995*	*(3)* *1995*	*(4)* *2000*	*(5)* *2000*	*(6)* *2000*
Ln(*GDP*)	0.803		0.451	0.748		0.416
	(53.32)***		(34.00)***	(51.94)***		(33.12)***
Ln($UrbanCore_{1988}$)		0.686	0.474		0.676	0.473
		(64.49)***	(44.93)***		(64.22)***	(45.21)***
Constant	–2.705	2.239	–1.679	–2.350	2.358	–1.405
	(15.18)***	(31.23)***	(13.04)***	(13.27)***	(33.26)***	(11.04)***
R^2	0.58	0.67	0.79	0.57	0.67	0.78

Notes: Absolute values of t-statistics in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

The negative (and significant) sign on the coefficient of *AgriInvest* is consistent with the hypothesis that less urban land will be converted, other things equal, if the agricultural sector is more productive. Taken together, the signs and significance suggest that, although complex, the economy (and demography) of contemporary China are playing a role in the expansion of the urban core.

Even when geophysical factors are added to the model in Table 4 (columns 2 and 4) the economic variables mostly keep their same signs and degrees of significance. It should be noted, however, that, when all of the variables are added in columns 2 and 4, the magnitudes of some of the variables change somewhat. Most conspicuously, when all of the geophysical variables (distance, density, terrain and climate variables) are added, the coefficient of the GDP variable, while still positive and significant, falls by 0.06 percentage points (from 0.398 to 0.336—a fall of about 18 per cent for the observations in 1995; and from 0.365 to 0.306—a fall of about 19 per cent for the observations in 2000). At the same time, the coefficients on *Population*, *GDP2_share* and *GDP3_share* all become larger (and the t-ratio for the coefficient on the *GPD2_share* variable also rises). The lesson from this part of the analysis is that, when attempting to measure the effect of economic variables on urban core expansion, it is important to consider the effect of geophysical variables. Without accounting for them, the coefficients of the economic variables are subject to modest omitted variable bias.

While this analysis suggests that the inclusion/exclusion of geographical control variables affects the signs and levels of significance of the coefficients of interest somewhat, it could be that the nature of the relationship between GDP and urban core area might differ by geographical region. With the concern that the geographical regions might affect urban core area, we rerun one of our main equations (the ones originally reported in Table 4) by including the regional dummies to identify the location of counties in the regions of eastern, central and western China. The main question of interest is whether or not the impact of GDP growth on the expansion of the urban core differs in different parts of China. Importantly, after running the supplementary analysis, we do not find that the estimated coefficients (measuring the impact of GDP on the expansion of the urban core)

Table 4. Estimation results of OLS with lagged urban core (urban core area of 1988), 1995 and 2000 (2063 observations; dependent variable: Ln(*Urban core area*))

	(1) *1995*	*(2)* *1995*	*(3)* *2000*	*(4)* *2000*
Ln(*GDP*)	0.398	0.365	0.336	0.306
	(16.14)***	(14.25)***	(15.50)***	(13.48)***
Ln(*Population*)	0.091	0.149	0.143	0.185
	(3.05)***	(5.15)***	(5.23)***	(6.85)***
Ln(*AgriInvest*)	–0.024	–0.012	–0.020	–0.010
	(3.80)***	(2.06)**	(3.18)***	(1.59)
Ln(*HwyDensity*)		0.004		0.006
		(1.99)**		(3.32)***
GDP2_share	0.079	0.119	0.176	0.096
	(0.75)	(1.20)	(1.52)	(0.85)
GDP3_share	0.406	0.637	0.779	0.891
	(3.05)***	(4.96)***	(5.13)***	(6.01)***
Ln($UrbanCore_{1988}$)	0.470	0.419	0.465	0.420
	(44.71)***	(40.64)***	(44.48)***	(40.70)***
Ln(*DistPort*)		–0.011		–0.006
		(1.58)		(0.89)
Ln(*DistPvCapital*)		0.003		0.004
		(1.01)		(1.22)
SharePlain		0.224		0.213
		(4.24)***		(4.04)***
Ln(*Rainfall*)		–0.254		–0.240
		(6.71)***		(6.26)***
Ln(*Slope*)		–0.031		–0.025
		(2.86)***		(2.28)**
Ln(*Temperature*)		–0.043		–0.003
		(0.76)		(0.05)
Ln(*Elevation*)		0.016		0.011
		(1.81)*		(1.20)
Constant	–2.342	–0.426	–2.529	–0.820
	(10.29)***	(1.15)	(11.22)***	(2.17)**
R^2	0.79	0.82	0.79	0.81

Notes: Absolute values of t-statistics in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

differ when we use models with and without regional dummies (Appendix, Table A2).

5. Spatial Statistical Analysis and the GDP–Urban Core Relationship

Although we initially estimated the model in equation (1) using OLS as the benchmark (in the previous section), if data contain spatial relationships, they can violate the assumptions underlying OLS. Using OLS with data with spatial relationships can lead either to to inefficiency and invalid hypothesis-testing procedures, or to bias and inconsistent parameter estimates (Anselin, 1995).[6]

Spatial relationships can be modelled in a variety of ways. One way is to hypothesise that the value of the dependent variable (the urban core, in our study) observed at a particular location is partially determined by some function of the value of the dependent variable of its neighbours. The variable measuring these effects is typically formulated as a spatially weighted average of the neighbouring values of the dependent variable, where the neighbours are specified through the use of a so-called spatial weights matrix (Anselin, 1988). We generate the spatial weights matrix using the software of GeoDA, a free toolset capable of doing the spatial analyses.

Specifically, the spatial lag model in matrix form is given by

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \beta \qquad (2)$$

where, $\mathbf{y}$ is an $n\times1$ vector of the dependent variable; $\mathbf{W}$ is an $n\times n$ spatial weights matrix, which specifies the neighbours used in the averaging (resulting in the spatial lag term, $\mathbf{Wy}$); ρ is a scalar spatial autoregressive parameter; $\mathbf{X}$ is an $n\times k$ matrix of independent variables; β is a matching vector or parameters; and β an $n\times 1$ vector of error terms.

The inclusion of the spatial lag term on the right-hand side of the equation is motivated by theory as the equilibrium outcome of processes of social and spatial interaction. This model cannot be estimated by OLS due to simultaneity bias. According to Anselin (2002), it must be estimated by using either IV estimators or maximum likelihood (ML) techniques.

The other way of incorporating spatial relationships is by modelling the effects through the spatial dependence that enters the relationship through the error term. When accounting for spatial dependence through the error term, the model accounts for the situation in which the errors associated with any one observation are spatially weighted (or 'neighbourhood') averages of the errors, plus a random error component. Specifically, the spatial error model in matrix form is given by

$$\mathbf{y} = \mathbf{X}\beta + \beta \text{ where } \beta = \beta\mathbf{W}\beta + \mathbf{u} \qquad (3)$$

where, β is a vector of spatially autocorrelated error terms; $\mathbf{u}$ is a vector of *i.i.d.* errors; and β is a scalar parameter known as the spatial autoregressive coefficient.

5.1 Spatial Autocorrelation Tests

In order to reach a better understanding of the severity of the spatial associations in our data, we first must perform a series of diagnostics to test the extent of the spatial autocorrelation of the dependent variable (log of urban core area) using Moran's I statistic (Anselin, 1988). A Moran's I analysis is carried out by generating scatter plots with the log of the area of the urban core on the horizontal axis and the spatial lag of the log of the area of the urban core (that is, the log of the area of the urban core of each of an observation's neighbours weighted by the spatial weight matrix) on the vertical axis (Anselin, 1995, 2002). In essence, the scatter plots illustrate the global Moran's I, which is a commonly used test statistic for spatial autocorrelation. Values of Moran's I larger than 0 indicate positive spatial autocorrelation. *GeoDa* 0.9.5 was used to perform these tests as well as to estimate the spatial econometric models in the next section (Anselin *et al.*, 2006).

Based on the Moran's I test statistic, we find that the spatial autocorrelation, or spatial association, in China's urban land use data is high (Figure 2). The spatial associations are identified by a high Moran's I of 0.519 for the year 1995. The Moran's I is 0.506 for 2000, meaning that spatial associations are equally high in that year.

We next assess the statistical significance of the Moran's I (Figure 3). To do so, we randomise the data over space and calculate a single value of a Moran's I statistic. We then repeat this procedure 999 times, obtaining an empirical distribution of the Moran's I under the null hypothesis of no spatial autocorrelation. Finally, we compare this distribution with

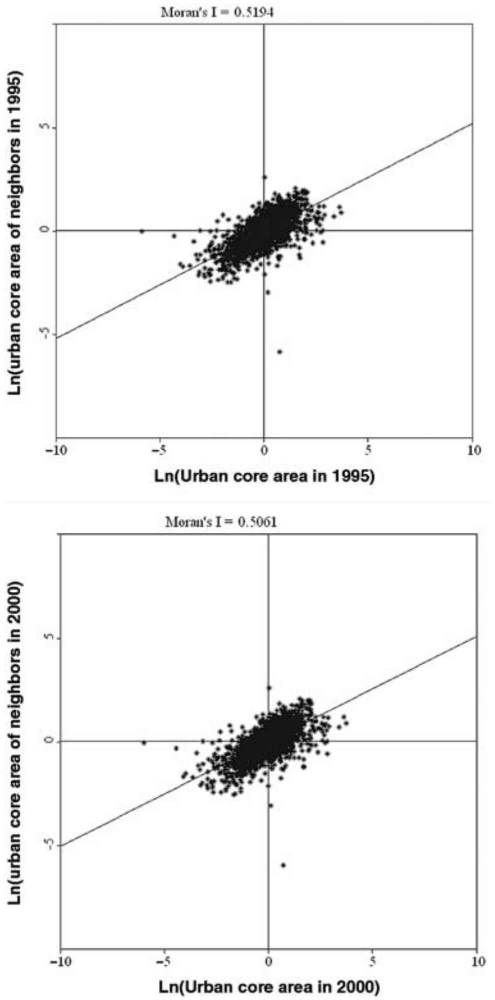

Figure 2. Spatial autocorrelation Moran scatter plot. *Above*: ln(*urban core area in 1995*) on ln(*urban core area of neighbours in 1995*); *below*: ln(*urban core area in 2000*) on ln(*urban core area of neighbours in 2000*).

the Moran's I calculated with the original data (that was not randomised over space). Figure 3 and the corresponding p-values show that the Moran's I values for both years are statistically significant. Therefore, we reject the null hypothesis that there is no spatial association in our data. This result suggests that we *should* attempt to control for the effects of spatial association in our analysis when we are interested in estimating the effect of economic growth on the size of the urban core of China's cities.

In fact, there are a number of reasons to believe that the spatial lag model might help us to reach a better explanation of the expansion of the urban core. For example, there may be geographical and economic forces that come into play in a region that could arise from the economic and other (such as political/social) activities of the agents in the urban areas in neighbouring counties. Specifically, if counties in adjacent areas are growing fast, this may attract builders (on the supply side) and those that demand land (on the demand side) for many economic activities also to begin to expand economic activity (that requires urban core expansion) in the county itself. Economists (for example, Brueckner and Fansler, 1983) have called these agglomeration effects and it has been shown empirically (for example, Burchfield *et al.*, 2006) that they are important determinants of urban land expansion.

5.2 Specification Tests

From the Moran's I analysis already conducted, we now know that spatial associations among neighbouring counties in terms of the dependent variable—that is, the log of the size of the urban core (Figure 4) and/or spatial associations among the explanatory variables—such as the log of GDP (Figure 5) and log of county population size, county highway density, per capita agricultural investment, share of industrial GDP and tertiary GDP (Figures A1–A5 in the Appendix)—may be affecting the estimated relationship between GDP and the size of the urban core. Before modelling this, we first need to know the nature of the spatial dependency (is it the first type—embedded in the spatial lag of the dependent variable; or is it the second type—embedded in the error term). To determine this, we performed a set of specification tests to specify the structure of the spatial effects

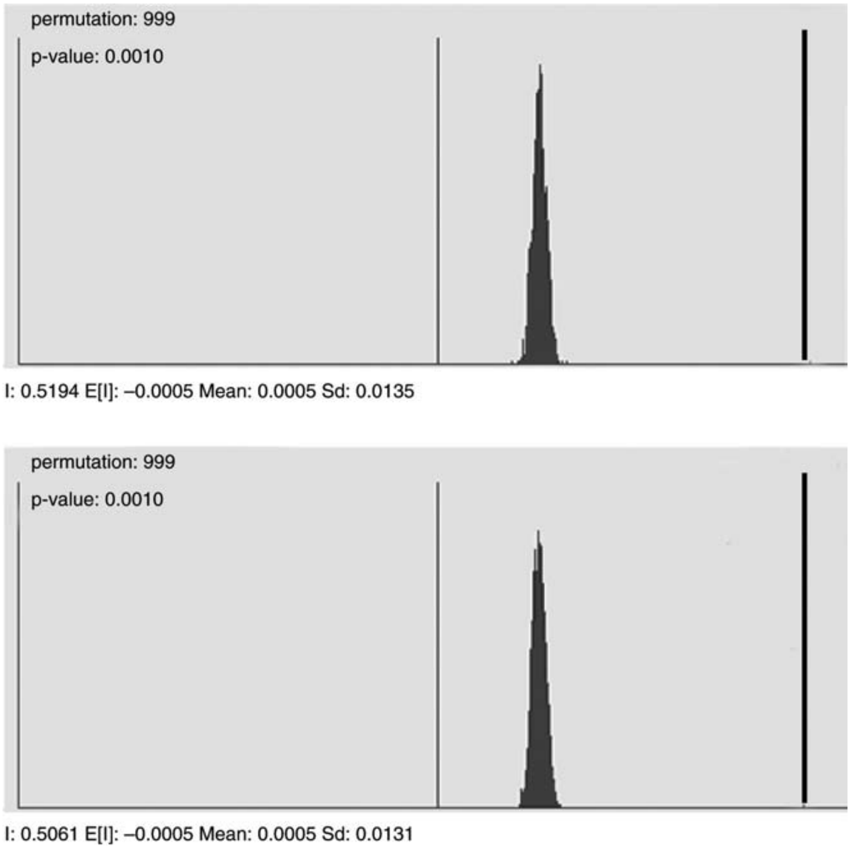

Figure 3. Permutation empirical distribution for Moran's I. *Above*: 1995; *below*: 2000. Note: In addition to the reference distribution, and the statistic (shown as a black bar), the graphs show the number of permutations and the pseudo significance level in the upper left corner, as well as the value of the statistic (0.5194), its theoretical mean (E[I] = -0.0005), and the mean and standard deviation of the empirical distribution. These values (-0.0003 and 0.0135 in 1995 and -0.0002 and 0.0131 in 2000) will typically differ slightly between permutations. We reassessed the sensitivity of the results to the particular random permutation by selecting different scheme of permutations and found that with 999 permutations the p-value is always significant at 1 per cent, which theoretically is the smallest p-value in our analysis.

in the regression model. Specifically, using the OLS residuals and spatial weights, we conduct the Lagrange Multiplier (LM) test for spatial error autocorrelation and spatial lag dependence (Anselin and Bera, 1998). The LM test suggests that the *mixed* spatial lag and spatial error model fits the data best (Table 5). The LM lag and LM error tests are both significant for models in 1995 and 2000 (Table 5, rows 1–4). For this reason, we use models that account for *both* of these effects. As an alternative, we estimate a spatial lag model and a spatial error model separately.

Specifically, the spatial lag model we employ is

$$\mathbf{y} = \rho_y \mathbf{W}\mathbf{y} + \rho_x \mathbf{W}\mathbf{x} + \mathbf{X}\beta + \beta \qquad (4)$$

Empirically, this model is estimated by extending the reduced-form model in (1) and including the spatially lagged variables of the

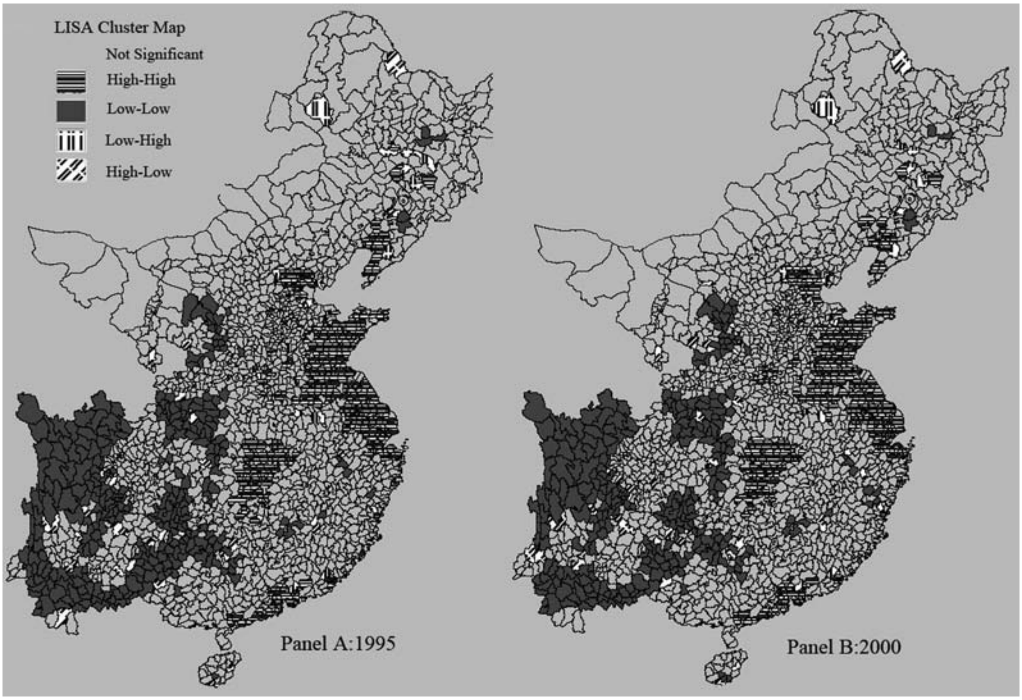

Figure 4. Local Moran's I of ln(*UrbanCore*).

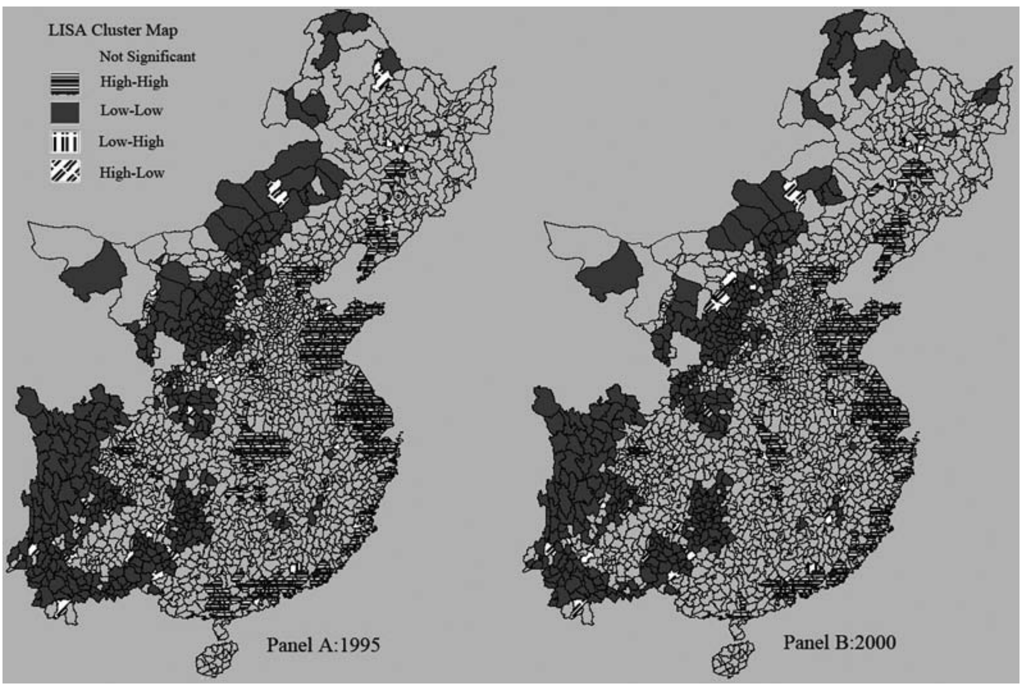

Figure 5. LISA cluster map of ln(*GDP*).

Table 5. Diagnoses of spatial lag and/or error problems (N = 2063; dependent variable: Ln(*Urban core area*) in hectares)

	1995	*2000*
LM (lag)	117.08	115.67
	(0.00)	(0.00)
Robust LM (lag)	33.56	40.07
	(0.00)	(0.00)
LM (error)	170.45	137.46
	(0.00)	(0.00)
Robust LM (error)	86.94	61.85
	(0.00)	(0.00)
Adjusted R^2	0.82	0.81

dependent variable (urban core) as well as those of the key explanatory variables, including GDP and the other economic variables

$$UrbanCore_{it} = f(GDPit, GDP2\_share_{it}, GDP3\_share_{it}, AgriInvest_{it}, Population_{it}, DistPort_{i}, DistPvCapital_{i}, HwyDensity_{i}, SharePlain_{i}, Rainfall_{i}, Slope_{i}, Temperature_{i}, Elevation_{i}, UrbanCore_{i1988}, WUrbanCore_{it}, WGDP_{it}, WGDP2\_share_{it}, WGDP3\_share_{it}, WAgriInvest_{it}, WPopulation_{it}) \quad (5)$$

5.3 Results from the Spatial Econometrics Model

The estimates of the coefficients produced by the spatial econometric model and the measures of the fit are presented in Table 6. The spatial autoregressive coefficient (the coefficient on the spatial lag of the dependent variable) is positive (0.148) and is highly significant (z = 10.25) for the observations in 1995 (Table 6, row 15, column 2). Similarly, the coefficient is positive (0.148) and highly significant (z = 10.18) for the observations in 2000 (Table 6, row 15, column 4). There are some minor differences in the coefficients of the other regression coefficients between the spatial lag model (Table 6, column 2) and the classical OLS (Table 4, column 2). However, most importantly, although the sign and level of significance of the coefficients estimated from the spatial econometric models are mostly the same, their magnitudes show systematically a decreasing trend in absolute value. To some extent, some of the explanatory power of these variables is attributed to the spatial lag of the dependent variable (*W*_ln(*Urban core area*)). Moreover, the effect due to the spatial dependence is now picked up by the coefficients of the spatially lagged variables. This means, of course, that by using spatial statistical analysis we can more precisely estimate the coefficients in the model.

Most importantly from the perspective of this paper, the coefficient on the GDP variable has decreased. In 1995, after using our spatial statistical model, the coefficient measuring the effect of GDP on the urban core falls from 0.365 (Table 4, column 2) to 0.316 (Table 6, column 2). In 2000, the coefficient falls from 0.306 (Table 4, column 4) to 0.279 (Table 6, column 4).

The spatial autoregressive coefficients (i.e. those associated with the error term) are estimated by the spatial error model. As in the spatial lag model, the coefficients of the GDP variable are positive and highly significant for both years (Table 6, row 16, columns 1 and 3). Importantly, the regression coefficients are slightly smaller in absolute values relative to our OLS model (Table 4, columns 2 and 4). As a result of these findings, we can conclude that such analyses need to consider the effects of spatial lag and/or error effects.

There is one additional important finding of our analysis of the determinants of the spatial size of cities. In addition to the direct effect of GDP on the urban core (which is embodied in the value of the coefficient on the *GDP* variable, discussed earlier), there also appears to be an indirect effect of growth that is an important determinant of the spatial size of the urban core. The coefficient on the *GDP3_share* variable is positive, significant and the magnitude of the coefficient rises over time. This means that across space as the

Table 6. Comparisons on the maximal likelihood estimation results between spatial lag and spatial error models (N = 2063; dependent variable: Ln(*Urban core area*) in hectares)

	1995		*2000*	
	Error	*Lag*	*Error*	*Lag*
Ln(*GDP*)	0.344	0.316	0.299	0.279
	(12.50)***	(12.54)***	(12.49)***	(12.57)***
Ln(*Population*)	0.205	0.163	0.218	0.181
	(6.52)***	(5.82)***	(7.53)***	(6.91)***
Ln(*AgriInvest*)	−0.007	−0.008	−0.006	−0.006
	(1.12)	(1.38)	(0.94)	(0.97)
Ln(*HwyDensity*)	0.005	0.003	0.007	0.006
	(2.47)**	(2.03)**	(3.35)***	(3.24)***
GDP2_share	0.312	0.139	0.261	0.078
	(2.96)***	(1.44)	(2.18)**	(0.72)
GDP3_share	0.775	0.735	0.916	0.942
	(6.01)***	(5.90)***	(6.20)***	(6.55)***
Ln($UrbanCore_{1988}$)	0.371	0.399	0.379	0.400
	(36.75)***	(39.78)***	(37.11)***	(39.68)***
Ln(*DistPort*)	−0.002	−0.007	−0.007	−0.002
	(1.58)	(1.00)	(1.02)	(0.28)
Ln(*DistPvCapital*)	0.002	0.002	0.003	0.003
	(0.56)	(0.70)	(0.92)	(0.92)
SharePlain	0.274	0.117	0.264	0.103
	(4.50)***	(2.23)*	(4.39)***	(1.97)**
Ln(*Rainfall*)	−0.260	−0.240	−0.242	−0.230
	(5.32)***	(6.56)***	(5.03)***	(6.18)***
Ln(*Slope*)	−0.028	−0.011	−0.022	−0.006
	(2.45)**	(1.11)	(1.93)**	(0.56)
Ln(*Temperature*)	−0.073	−0.063	−0.023	−0.026
	(1.00)	(1.16)	(0.33)	(0.47)
Ln(*Elevation*)	0.015	0.001	0.012	0.006
	(1.72)*	(0.12)	(1.37)	(0.65)
*W*_Ln(*Urban core area*)		0.148		0.148
		(10.25)***		(10.18)***
Lambda	0.326		0.294	
	(10.69)***		(9.42)***	
Constant	−0.820	−0.755	−0.787	−1.086
	(2.17)**	(2.09)**	(1.68)*	(2.96)***
Adjusted R^2	0.81	0.82	0.82	0.81

Notes: Absolute values of t-statistics in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

service sector expands, more land is needed in the urban core. Over time, this effect is rising. If the structure of the economy—in particular, the rise of the tertiary sector—is connected with growth as suggested by Kuznets (1966), then the falling direct effect of GDP growth appears to be pulled back up, at least in part, by the rising indirect effect.

The effects of the five spatial lag terms of the explanatory variables, *GDP*, *GDP2_share*, *GDP3_share*, *AgriInvest* and *Population*, incorporated in the estimation models (equation

(5)) have been included in the Appendix (Table A3). The results demonstrate that the incorporation of these spatial lag terms does not affect the sign of the coefficients for *GDP*, although the magnitude of the coefficient decreases by 3.9 percentage points (Table A2, row 1, column 2 and Table 6, row 1 column 4).

6. Conclusions and Discussion

This paper demonstrates the close relationship between economic growth and the size of the area of the urban core. We show that the spatial size of China's urban core has risen during the late 1990s. We also used descriptive statistics and multivariate analysis to identify the determinants of urban land use. Our analysis shows the overwhelming importance of growth on the area of urban core. The results show that the size of the urban core expanded with the economic growth: when the economy rose by 10 per cent, the size of the urban core rose by 3 per cent. Our results also demonstrated that there are important indirect effects associated with growth; changes in the structure of the economy (which almost always accompanies growth) also are shown to be important determinants of the spatial sizes of China's cities. If urban planners want to predict the future expansion of the urban cores of their cities, they should consider both the direct and indirect consequences of growth.

Our analysis also has shown that, by employing spatial statistical analysis, we were able to estimate the elasticity of economic growth on urban land expansion in China more consistently and with increased efficiency. In doing so, the value of our coefficient fell. This means that if this is true more generally, when analysts do not account for spatial effects, they may be overestimating the effects of GDP growth on the expansion of the spatial size of the urban core. In essence, spatial statistical techniques allow us explicitly to include or filter out the effects (those associated with spatial dependencies) that were obscuring the true relationship between GDP growth and the size of the urban core.

Although we explore and estimate the relationship between economic growth and the urban core area by doing an empirical study in China in this paper, there are some limits to be acknowledged here. One of the limits is that it is almost impossible for us (because of an absence of good proxies) to include measures for a number of the political and institutional factors that might also affect the expansion of the urban core. These issues, however, are addressed in a number of other papers in the literature (Wu and Yeh, 1997; Yeh and Wu, 1999; Wu, 2001; Ma, 2002; Lin and Ho, 2005). Space restrictions also limit our ability to explore deeply the differences in the nature of the relationship between growth and the expansion of the urban core across cities that are in different geographical areas of China. It is certainly possible that there are complex interactions between certain geographical features and the growth/core expansion relationship. Because of the potential importance of this issue, however, we do not ignore it completely. In the paper, we did several exercises to test (in brief terms) for differences in the growth/core expansion relationship in coastal, central and western regions of China.

Notes

1. This is a familiar story in China. Many researchers (for example, Wu and Yeh, 1997; Yeh and Wu, 1999; Wu, 2001; Ma, 2002; Lin and Ho, 2005) have documented the propensity for local governments to increase their fiscal earnings from land conversion. It is also true that the national government is concerned about excess conversions. Therefore, in response, in 1997 the central government introduced a rigorous inspection system that is trying to control out-of-plan rural–urban land conversion (Zhang and Jia, 2001). More recently, in an attempt to control rural–urban land conversion, the State Council and the Ministry of Land and Resource (MLR) began jointly to implement the second

round of a detailed survey on land use which was supposed to serve as the basis of a regional development planning effort (MLR, 2008).

2. In China it is clear that urban planners need to understand the relationship between economic growth and urban land conversion. The State Council has issued no fewer than three major directives that seek to force urban planners to consider economic growth in their urban planning designs (State Council of China, 2004, 2006, 2008).
3. The county units cover the entire area of mainland China's 31 provinces and province-level municipalities. Due to inherent differences in the nature of land use and other data, we did not include counties in Taiwan, Hong Kong and Macao.
4. Fortunately, there are only slight differences between the results when we use the OLS estimator using the entire dataset ($N = 2348$) and when we use the dataset that is constructed after dropping the four western provinces ($n = 2063$). (See the Appendix, Table 1.)
5. Remote sensing, particularly photo-interpretation, relies on a human cognitive system to extract information from images. This process is often broken down to various kinds of attributes that are considered when interpreting images, among which colour, tone and texture are always the most commonly used attributes to decode the digital images (Rajeshwari, 2006). By examining the changes in colour, texture and tone in the Landsat Images, we identify both different types of built-up area and the changes in urban land use.
6. For recent reviews of the spatial econometrics literature, see Anselin (2002) and Florax and van der Vlist (2003).

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Appendix

Table A1. Estimation results of OLS using full observations and subset of the observations (dependent variable: Ln(*Urban core area*) in hectares)

	1995	*1995*	*2000*	*2000*
Ln(*GDP*)	0.384	0.364	0.325	0.306
	(14.75)***	(14.24)***	(13.71)***	(13.48)***
Ln(*Population*)	0.137	0.149	0.165	0.184
	(4.78)***	(5.14)***	(6.12)***	(6.84)***
Ln(*AgriInvest*)	−0.015	−0.012	−0.010	−0.010
	(2.49)**	(2.05)**	(1.50)	(1.59)*
Ln(*HwyDensity*)	0.002	0.003	0.005	0.006
	(1.00)	(1.99)**	(2.47)**	(3.31)***
GDP2_share	0.139	0.119	0.102	0.095
	(1.37)	(1.19)	(0.91)	(0.85)
GDP3_share	0.607	0.637	0.760	0.890
	(4.65)***	(4.96)***	(5.11)***	(6.01)***
Ln($UrbanCore_{1988}$)	0.425	0.418	0.431	0.420
	(40.02)***	(40.63)***	(40.49)***	(40.70)***
Ln(*DistPort*)	−0.013	−0.011	−0.008	−0.006
	(1.80)*	(1.57)	(1.09)	(0.89)
Ln(DistPvCapital)	0.001	0.003	0.002	0.004
	(0.31)	(1.01)	(0.54)	(1.22)
SharePlain	0.232	0.223	0.218	0.213
	(4.28)***	(4.23)***	(3.88)***	(4.04)***
Ln(*Rainfall*)	−0.146	−0.253	−0.153	−0.239
	(5.26)***	(6.71)***	(5.53)***	(6.25)***
Ln(*Slope*)	−0.043	−0.030	−0.038	−0.024
	(3.95)***	(2.86)***	(3.38)***	(2.28)**
Ln(*Temperature*)	−0.081	−0.042	−0.028	−0.003
	(1.85)*	(0.75)	(0.66)	(0.05)
Ln(*Elevation*)	0.029	0.015	0.021	0.011
	(3.15)***	(1.80)*	(2.08)**	(1.20)
Constant	−1.042	−0.426	−1.272	−0.820
	(3.14)***	(1.14)	(3.82)***	(2.17)**
Adjusted R^2	0.82	0.82	0.81	0.81

Notes: Absolute values of t-statistics in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

Table A2. Comparison table for the difference of OLS estimation between excluding and including the regional dummy variables, with lagged urban core (urban core area of 1988) (2063 observations; dependent variable: Ln(*Urban core area*))

	(1) *No region dummy*	*(2)* *With region dummy*	*(3)* *No region dummy*	*(4)* *With region dummy*
Panel (a): 1995				
Ln(*GDP*)	0.398	0.405	0.365	0.382
	(16.14)***	(15.10)***	(14.25)***	(14.68)***
Ln(*Population*)	0.091	0.075	0.149	0.128
	(3.05)***	(2.46)**	(5.15)***	(4.34)***
Ln(*AgriInvest*)	−0.024	−0.021	−0.012	−0.010
	(3.80)***	(3.28)***	(2.06)**	(1.66)*
GDP2_share	0.079	0.021	0.119	0.029
	(0.75)	(0.21)	(1.20)	(0.29)
GDP3_share	0.406	0.405	0.637	0.593
	(3.05)***	(3.05)***	(4.96)***	(4.66)***
Ln($UrbanCore_{1988}$)	0.470	0.460	0.419	0.408
	(44.71)***	(43.58)***	(40.64)***	(39.61)***
Region dummy: central		0.123		0.141
		(3.97)***		(4.47)***
Region dummy: west		−0.078		−0.072
		(2.17)**		(1.83)*
Ln(*HwyDensity*)			0.004	0.005
			(1.99)**	(2.96)***
Ln(*DistPort*)			−0.011	−0.016
			(1.58)	(2.13)**
Ln(*DistProvCapital*)			0.003	0.003
			(1.01)	(0.86)
SharePlain			0.224	0.163
			(4.24)***	(3.02)***
Ln(*Rainfall*)			−0.254	−0.290
			(6.71)***	(7.69)***
Ln(*Slope*)			−0.031	−0.033
			(2.86)***	(3.06)***
Ln(*Temperature*)			−0.043	−0.016
			(0.76)	(0.28)
Ln(*Elevation*)			0.016	0.019
			(1.81)*	(2.15)**
Constant	−2.342	−2.147	−0.426	−0.198
	(10.29)***	(9.26)***	(1.15)	(0.53)
R^2	0.79	0.79	0.82	0.82
Panel (b): 2000				
Ln(GDP)	0.336	0.347	0.306	0.325
	(15.50)***	(14.90)***	(13.48)***	(14.11)***
Ln(*Population*)	0.143	0.126	0.185	0.163
	(5.23)***	(4.51)***	(6.85)***	(5.92)***
Ln(*AgriInvest*)	−0.020	−0.018	−0.010	−0.008

(Continued)

Table A2. (Continued)

	(1) *No region dummy*	*(2)* *With region dummy*	*(3)* *No region dummy*	*(4)* *With region dummy*
	(3.18)***	(2.81)***	(1.59)	(1.37)
GDP2_share	0.176	0.124	0.096	0.013
	(1.52)	(1.08)	(0.85)	(0.11)
GDP3_share	0.779	0.743	0.891	0.823
	(5.13)***	(4.90)***	(6.01)***	(5.56)***
Ln($UrbanCore_{1988}$)	0.465	0.456	0.420	0.411
	(44.48)***	(43.21)***	(40.70)***	(39.57)***
Region dummy: central		0.095		0.117
		(3.10)***		(3.68)***
Region dummy: west		-0.053		-0.037
		(1.52)		(0.93)
Ln(*HwyDensity*)			0.006	0.007
			(3.32)***	(4.00)***
Ln(*DistPort*)			-0.006	-0.011
			(0.89)	(1.40)
Ln(*DistProvCapital*)			0.004	0.004
			(1.22)	(1.10)
SharePlain			0.213	0.172
			(4.04)***	(3.13)***
Ln(*Rainfall*)			-0.240	-0.268
			(6.26)***	(6.97)***
Ln(*Slope*)			-0.025	-0.026
			(2.28)**	(2.38)**
Ln(*Temperature*)			-0.003	0.021
			(0.05)	(0.36)
Ln(*Elevation*)			0.011	0.012
			(1.20)	(1.40)
Constant	-2.529	-2.367	-0.820	-0.659
	(11.22)***	(10.20)***	(2.17)**	(1.71)*
R^2	0.79	0.79	0.81	0.81

Notes: Absolute values of t-statistics in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

Table A3. Maximal estimation on the determinants of urban land expansion including the spatial lag terms of independent variables, dependent variable, Ln(*urban core area*) in hectares, 1995 and 2000 (N = 2063)

	1995	*2000*
Ln(*GDP*)	0.297	0.268
	(9.95)***	(10.59)***
Ln(*Population*)	0.211	0.219
	(6.53)***	(7.50)***
Ln(*AgriInvest*)	−0.001	−0.001
	(0.09)	(0.08)
Ln(*HwyDensity*)	0.004	0.006
	(2.51)**	(3.51)***
GDP2_share	0.478	0.445
	(4.35)***	(3.48)***
GDP3_share	0.937	1.033
	(7.23)***	(7.01)***
Ln(*DistPort*)	−0.009	−0.006
	(1.32)	(0.81)
Ln(*DistPvCapital*)	0.001	0.001
	(0.34)	(0.42)
SharePlain	0.100	0.092
	(1.94)**	(1.78)*
Ln(*Rainfall*)	−0.151	−0.172
	(4.12)***	(4.54)***
Ln(*Slope*)	−0.032	−0.025
	(3.03)***	(2.43)**
Ln(*Temperature*)	0.012	0.042
	(0.23)	(0.75)
Ln(*Elevation*)	0.029	0.022
	(3.08)***	(2.34)**
*W*_ln(*Urban core area*)	0.299	0.282
	(13.93)***	(13.08)***
*W*_Ln(*GDP*)	−0.045	−0.054
	(1.03)	(1.40)
Ln(*UrbanCore*$_{1988}$)	0.375	0.380
	(37.87)***	(38.09)***
*W*_Ln(*Population*)	−0.103	−0.082
	(2.68)**	(2.36)***
*W*_Ln(*AgriInvest*)	−0.027	−0.018
	(2.51)**	(1.72)*
W_GDP2_share	−0.69	−0.688
	(4.14)***	(3.62)***
W_SGDP3_share	−0.431	−0.076
	(1.88)*	(0.28)
Constant	−1.121	−1.493
	(3.038)***	(3.82)***
R^2	0.84	0.83

Notes: Absolute values of t-statistics in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

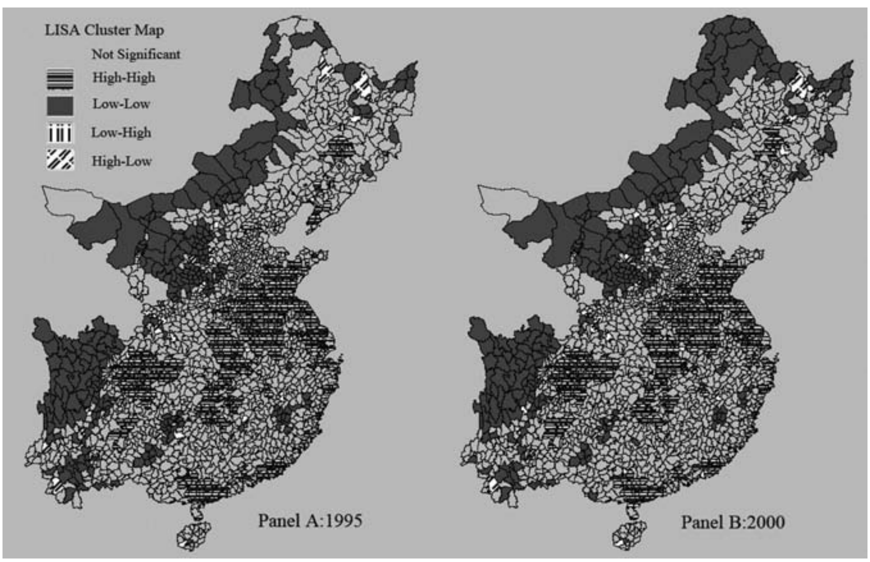

Figure A1. LISA cluster map of county population size.

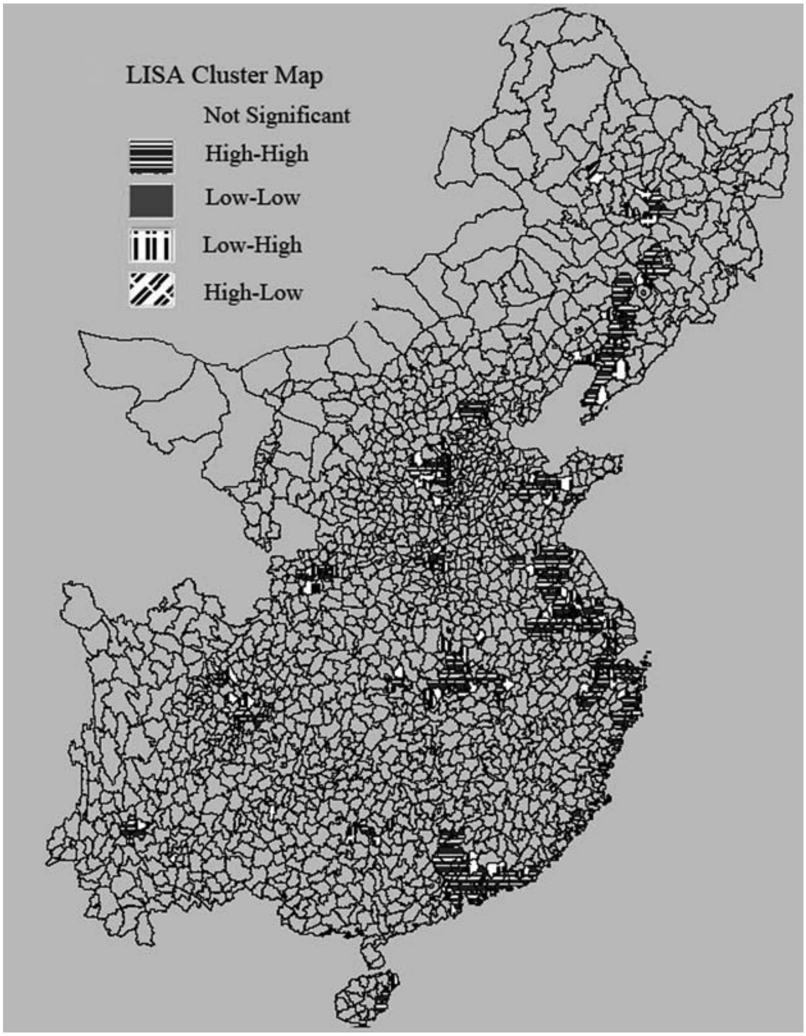

Figure A2. LISA cluster map of highway density.

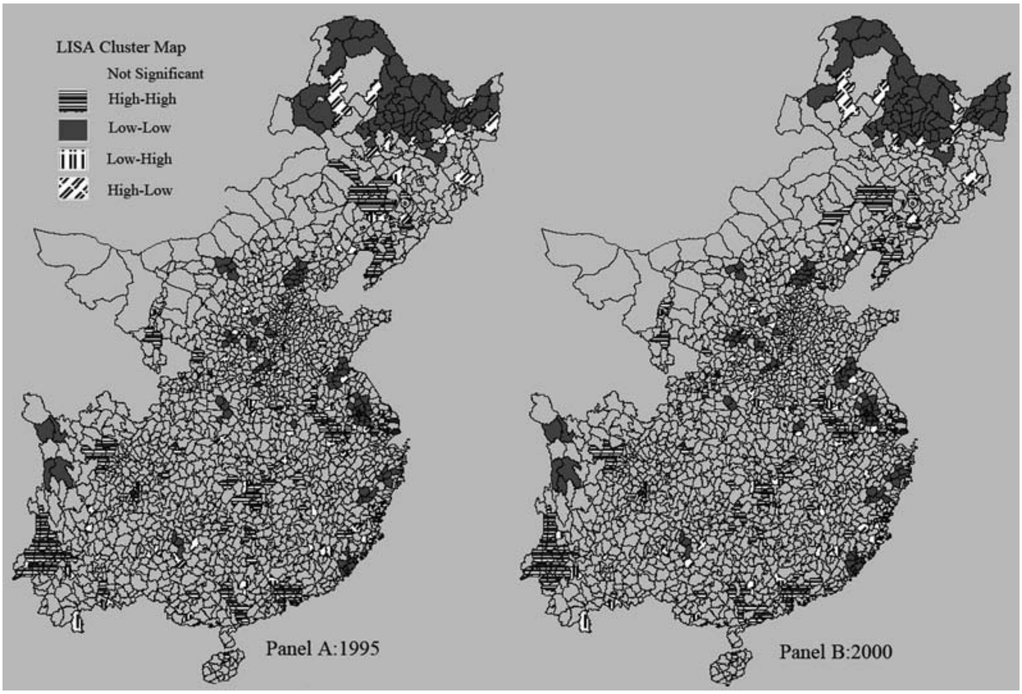

Figure A3. LISA cluster map of per capita agricultural investment.

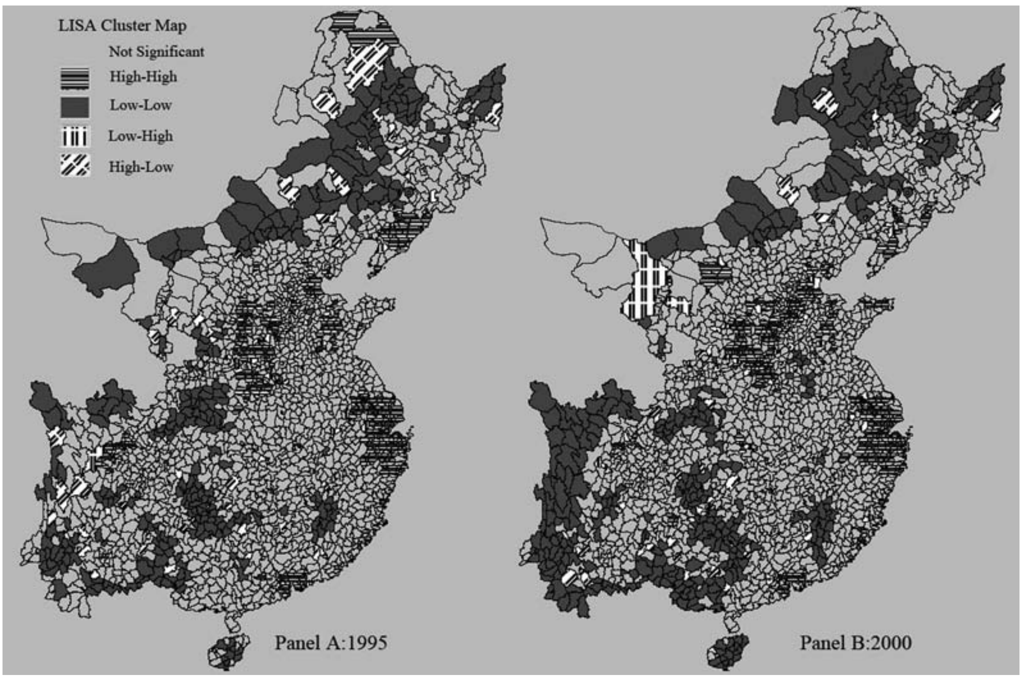

Figure A4. LISA cluster map of *GDP2_share*.

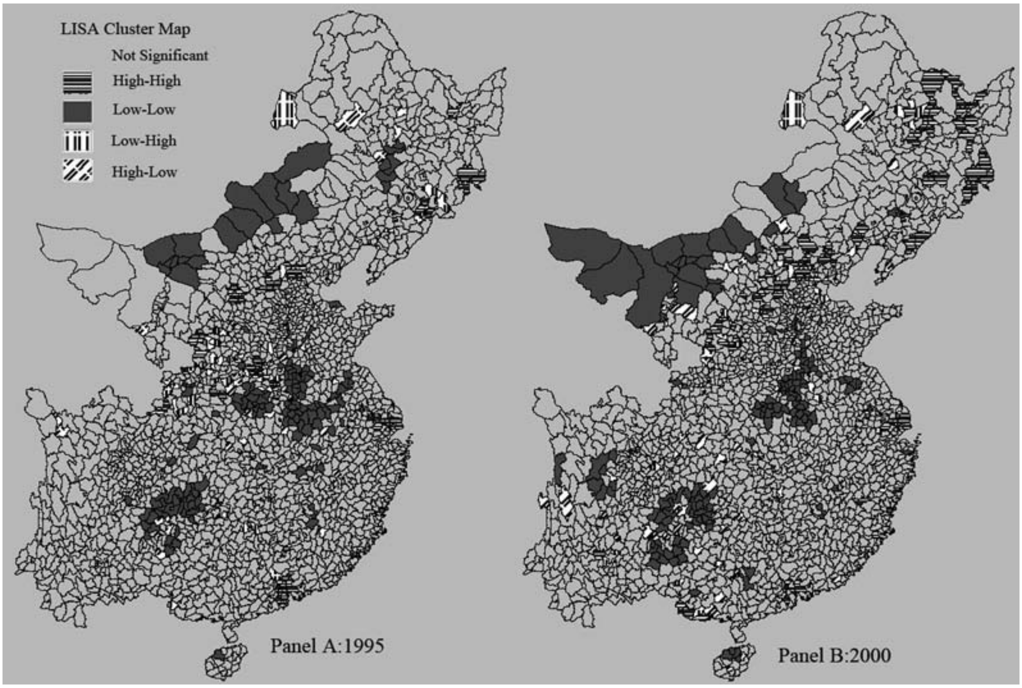

Figure A5. LISA cluster map of *GDP3_share* 2000.