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Exploring Determinants of Urban Form in China through an Empirical Study among 115 Cities

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Abstract: This study aims to analyze and explain the factors that influence the urban form of Chinese cities through an empirical analysis of a cross-sectional dataset of 115 cities in 2000 and 2010. Four spatial metrics, including population density, a contiguity index, a fractal dimension index, and a shape index, are used to quantify urban form. The paper compares urban form across four economic zones and across cities of different sizes. Ordinary least square and first-difference regression models are used to analyze the determinants of urban form. The results show that urban sprawl in China is characterized by decreased population density and greater irregularity and complexity of urban built-up areas. Metrics, such as Gross Domestic Product, population, transportation costs, and economical structure are associated with urban form in different ways, and urban expansion based on large-scale industrialization and real estate development is unsustainable in the new era.

Keywords: urban morphology; determinants; empirical study; China

1. Introduction

Over the last two decades, researchers from multiple disciplines, such as natural sciences, economics, transportation planning, land use planning, and urban design, have made substantial progress in studying urban form [1] Rising concerns over the negative effects of urban sprawl, including traffic congestion, loss of farmland and green space, increasing costs for public services, air and water pollution, physical health, and high energy consumption, have made urban form a popular topic [2–7]. A progress to smarter urban form can only be achieved with a thorough understanding of urban form [1], but there remains considerable ambiguity about determinants of urban form.

Urban form has dramatically changed in China over the past few decades. Between 2000 and 2010, urban built-up areas in China increased by 5.1% per year, a much higher level than the urban population growth rate of 1.5% [8]. Urban sprawl has also brought serious environmental problems to Chinese cities, including traffic congestion, air and water pollution, energy consumption, and farmland loss [9–11]. For example, our previous study indicates that cities with low-density forms are more likely to endure higher levels of air pollution in China [12]. Despite growing debates, comprehensive assessments of urban form on a national level in China are limited, and rigorous exploration of factors that shape urban form has remained scarce.

This study tries to fill the research gap about determinants of urban form with an empirical study among 115 Chinese cities. Four metrics, namely population density, contiguity index, fractal dimension index, and shape index, are used to assess urban form for 115 large cities in 2000 and 2010. We make an assumption that population, economic growth, transportation costs, and economic structure are the main determinants of urban form for Chinese cities. Spatial metrics are compared across cities in different economic zones and cities of different sizes to analyze the effect of economic growth and population on urban form. Moreover, Ordinary Least Square (OLS) regressions and first-difference models are further used to understand how these factors affect urban form when controlling for other variables.

2. Literature Review

Measuring urban form is important for urban planning and public policy, and a wide variety of metrics have been developed to quantify urban form. The most intuitive metric of urban form may be population density, and it is often considered as the indicator of urban sprawl [13,14]. Although it is not easy to determine who first used this simple metric to describe urban form, population density is still regularly analyzed worldwide. With the development of Geographical Information System, some studies began to use neighborhood-level metrics to measure urban form on a small scale. For example, Ewing, Pendall, and Chen [15] characterized urban form with four factors representing density, land-use mix, degree of centering, and street accessibility. Likewise, Song and Knaap [16] measured the urban form by analyzing density, land-use mixtures, accessibility, pedestrian access, street design, and circulation systems, and some studies used spatial network analysis and traffic data to detect the dynamics of urban form [17]. Neighborhood-level metrics are largely dependent on block-level spatial data, which makes these metrics confined to individual cities. Remote sensing technologies offer an opportunity to measure urban form on a national level, which helps to understand urban form across cities. These metrics, often referred to landscape metrics, could be calculated from satellite images, and they have long been used in landscape ecology [18,19]. For example, shape index and fractal dimension index are usually used to measure shape complexity of urban development, and contiguity index is often employed to quantify urban continuity [20–22]. Since remote sensing data (e.g., Landsat) are available worldwide, landscape metrics have also been used to describe urban form for Chinese cities [23,24].

Rising concerns over social, economic, and environmental outcomes from urban sprawl have been motivating scholars searching for determinants of urban sprawl or urban size. Brueckner [25] argued that urban spatial expansion is primarily caused by three powerful factors: a growing population, rising incomes, and falling commuting costs. Quantitative methods emerged as a means to more systematically analyze driving factors of urban sprawl. Through an empirical analysis of 448 cities in the United States, Song and Zenou [26] found that the spatial size of cities is an increasing function of population, income, and transportation expenditure, and higher property taxes can make cities smaller. By analyzing cross-sectional datasets of Chinese cities, Ke, Song, and He [27] and Deng et al. [28] also found that population, income, commuting costs, the price of agriculture land, and economic structure have played powerful roles in China's urban expansion. Another empirical study also suggested that these variables are associated with levels of urban fragmentation [29]. However, quantitative exploration of drivers of urban form metrics (e.g., population density, contiguity index, fractal dimension index, and shape index) has remained scarce. It could be assumed that factors determining urban sizes in past studies may be associated with these spatial metrics.

3. Data and Methodology

3.1. Study Area and Data

This study selected 115 cities at the prefecture level and above with urban populations greater than 1 million (according to the Sixth National Population Census in 2010) (Figure 1). The sample includes 4 autonomous municipalities, 26 provincial capitals, and 85 prefecture-level cities. According to the latest standard for urban size developed by the State Council of China in 2014, these cities are classified into four types based on urban populations: 5 "super cities" (populations > 10 million), 9 "megacities" (populations between 5 and 10 million), 20 Type I large cities (populations between 3 and 5 million), and 81 Type II large cities (population between 1 and 3 million). These cities are located in different economic regions, with 52 in the eastern region, 12 in the northeastern region, 27 in the central region, and 24 in the western region.

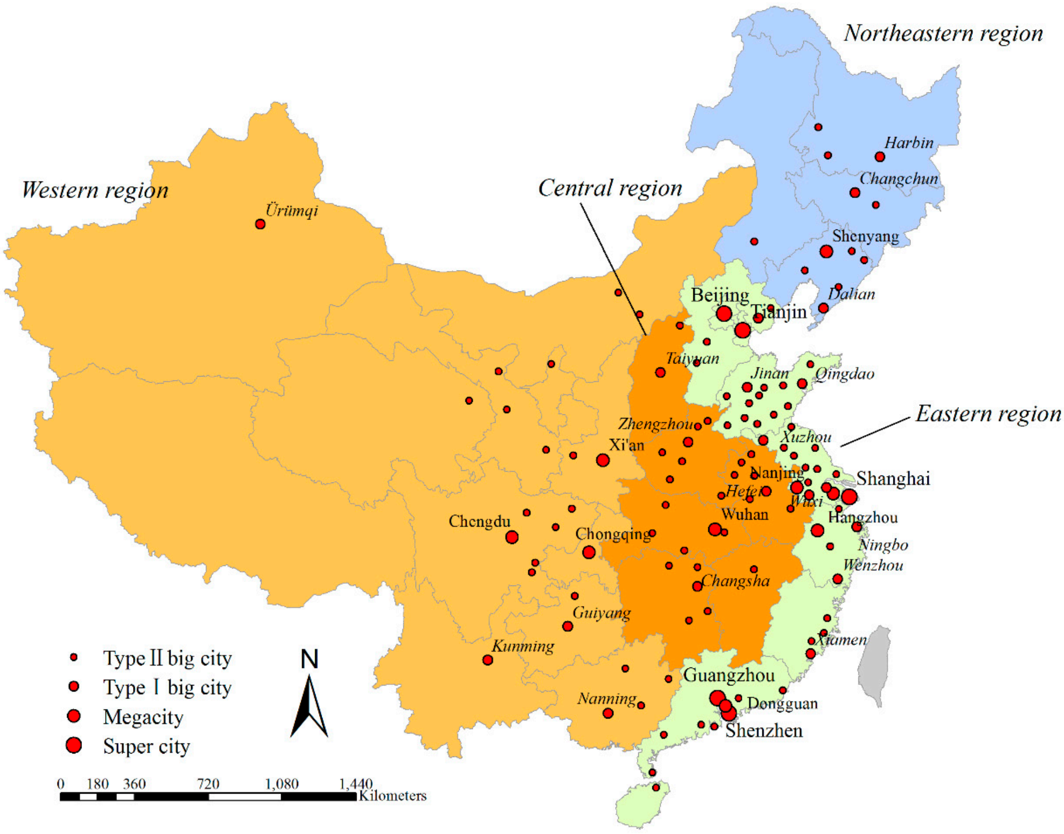


Figure 1. The 115 cities included in the study.

Data used in this study include the 2010 nighttime light data from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS), urban expansion areas across the East Asia region between 2000 and 2010 produced by the University of Wisconsin [30], 2000 and 2010 population distribution data from the Landscan database, socio-economic data (GDP and structure of the economy) from the 2000 and 2010 China City Statistical Yearbooks, topographic data (elevation and slopes, 1 km resolution) from the China Digital Elevation Model Database in Cold and Arid Regions Sciences Data Center, and data of water bodies (e.g., rivers, canals, and lakes) from the DIVA-GIS website (http://www.diva-gis.org/gdata).

Prior studies often utilized DMSP/OLS nighttime light data to delineate urban built-up boundaries [31]; therefore, we used 2010 DMSP/OLS nighttime light data, which has been validated by Jiang [32], to delineate urban built-up boundaries for the 115 cities. These boundaries were used to derive the spatial patterns of urban land and population distribution. Data of urban land in 2000 and 2010 are from satellite-based maps of urban expansion (250 m resolution) provided by the World Bank [30]. These maps were produced with MODIS data and Google Earth imagery, with map accuracies reaching 83% for urban extent and 71% for urban expansion [33]. Figure 2 provides examples of urban built-up boundaries and urban land for several cities.

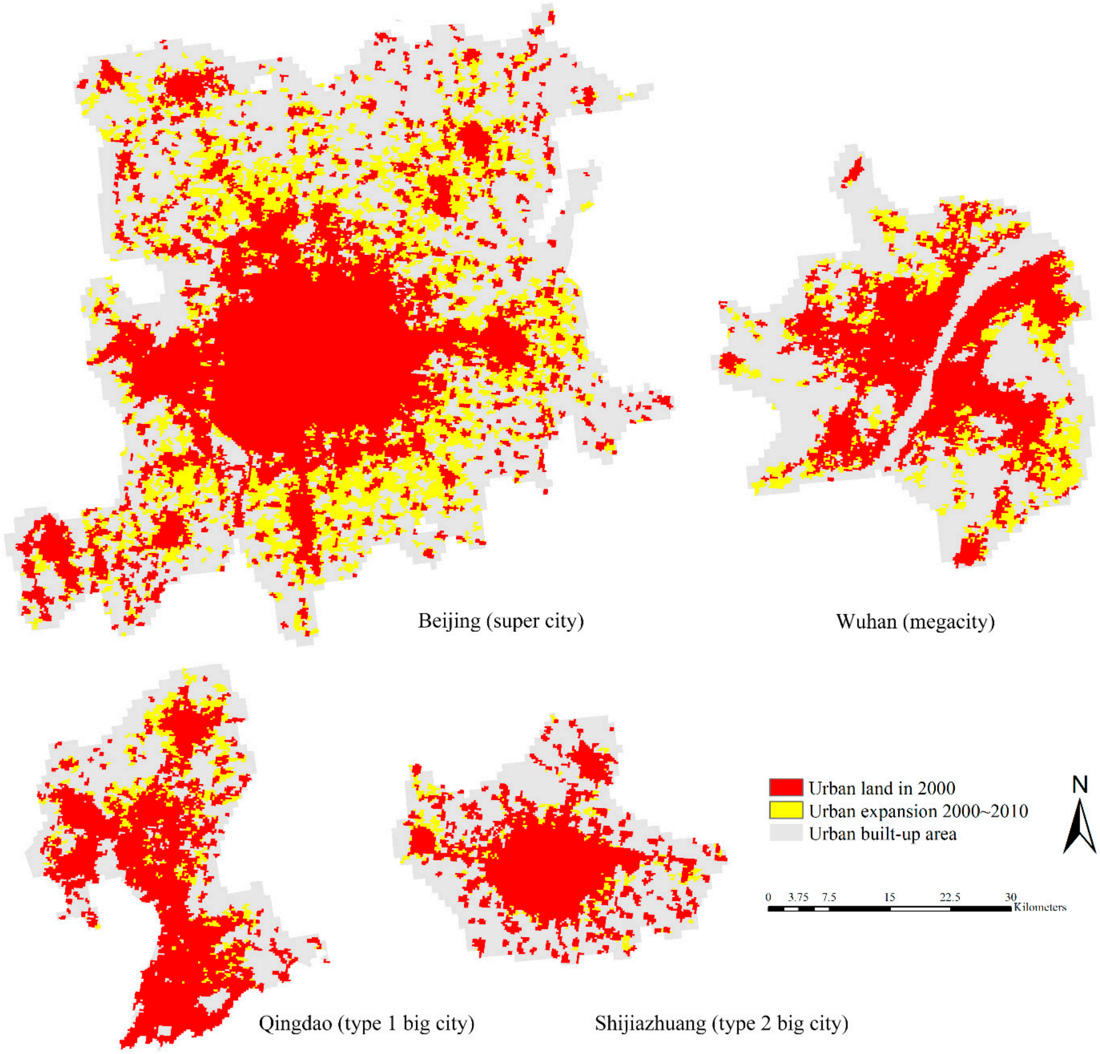


Figure 2. Examples of urban built-up areas and urban expansion in 2000 and 2010.

3.2. Urban Form Metrics

According to previous studies, population density, contiguity index, fractal dimension index, and shape index are usually used to quantify urban form, and data for these metrics are available at a national scale. Hence, the four metrics are selected to reflect different dimensions of urban form, namely density, spatially continuous level, shape irregularity, and spatial complexity.

Rather than using census-defined boundaries, we utilized urban built-up areas to calculate the population density, and population data are from LandScan Population Database (ORNL) with 1 km resolution. The contiguity index (*CONTIG*) is used to characterize the spatially continuous level of urban lands, and discontinuous urban growth, such as leapfrog development, may fragment farmland and wildlife habitat [34]. The lowest *CONTIG* value equals 0 for a most discontinuous urban form and increases to a limit of 1 as urban contiguity increases. The shape index (*SHAPE*) represents the shape irregularity of urban lands, and irregular boundaries among suburban areas are expected to increase automotive trips, tailpipe emissions, and energy consumption [10,23]. The higher the *SHAPE* value, the more irregular the urban form (value ranging from 0 to 100). The fractal dimension index (*FRAC*) evaluates the spatial complexity (value ranging from 1 to 2), and a higher value generally indicates that urban lands are more jagged [24]. We utilized Fragstats 4.2 to calculate *CONTIG*, *SHAPE*, and *FRAC* metrics for each city. Examples of urban form are shown in Figure 3.

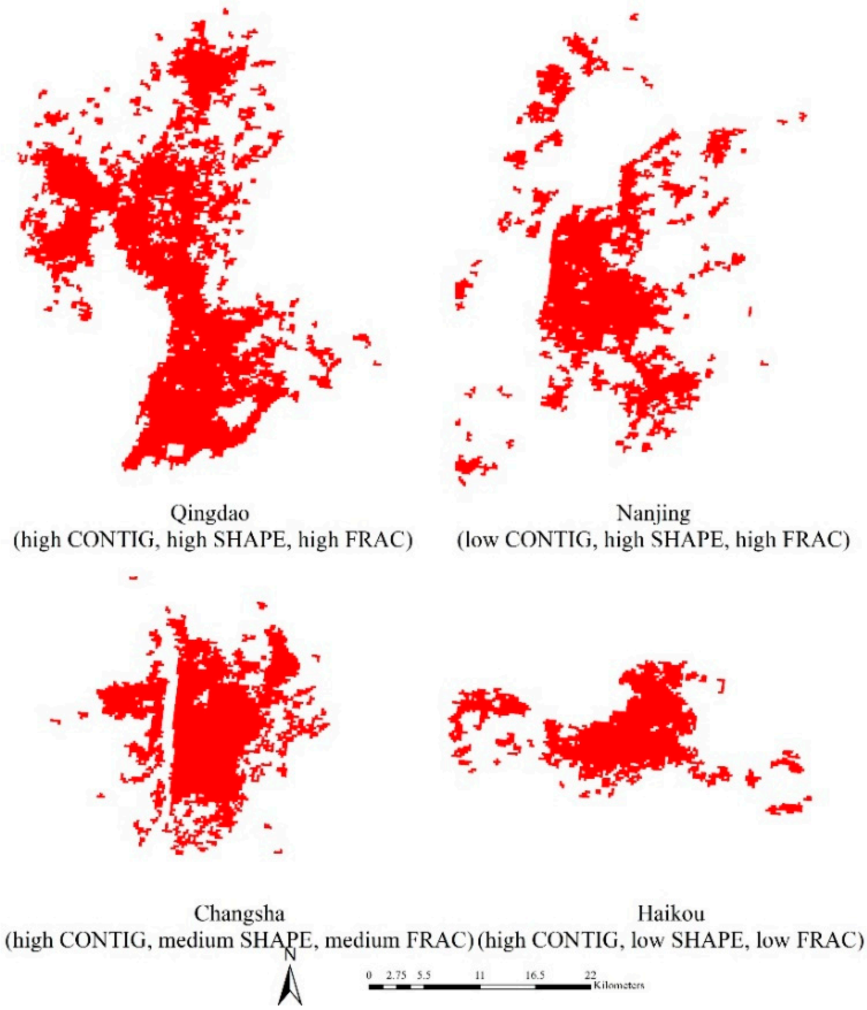


Figure 3. Examples of urban form metrics in 2010.

3.3. Determinants

Four main factors, including economic growth, population, transportation costs, and economic structure, are assumed to be associated with urban form metrics in the following model:

$$\begin{aligned} UrbanFormMetric_{it} & \\ &= a_1 GDP_{it} + a_2 Populaition_{it} + a_3 Bus_{it} + a_4 GDP2Share_{it} + a_5 GDP3Share_{it} \\ &+ a_6 UrbanArea_{it} + a_7 Elevation_i + a_8 Slope_i + a_9 WaterShare_i + b \end{aligned} \quad (1)$$

The variable $UrbanFormMetric_{it}$ is one of the three metrics of urban form (*CONTIG*, *SHAPE*, and *FRAC*) for the *i*th city in the year *t* (2000 or 2010). The explanatory variables are as followings. Gross Domestic Production (GDP_{it}) is the indicator for economic development, and $Population_{it}$ is calculated from LandScan data within the urban land boundaries. Because there is no direct way to measure commuting cost across Chinese cities over time, we included the number of buses per 10,000 people (Bus_{it}) to represent transportation costs. The underlying assumption is that an increase in buses makes travel more convenient and cheap, thus enabling people to live in cheaper housing further from downtowns while paying lower commuting costs. The change of economic structure has an impact on urbanization in developing countries [35], so it was included in our model. $GDP2Share_{it}$ represents the share of the industrial sector in local GDPs, and $GDP3Share_{it}$ represents the share of the service sector in local GDPs. Urban land area ($UrbanArea_{it}$) is also included to control for the impact of urban expansion on urban form at different sizes and scales. All of the above variables vary over time from 2000 to 2010. To make administrative regions consistent within urban built-up areas, we used the value of GDP_{it}, Bus_{it}, $GDP2Share_{it}$, and $GDP3Share_{it}$ in urban districts for each of the 115 cities in the China City Statistical Yearbooks, thus excluding data from counties and county-level cities also governed by the 115 cities. Because high agricultural rents may hinder urban expansion [28], prior studies on the econometric model often account for the value of agricultural land. We initially attempted to use the share of the primary sector in the GDP as a proxy for agricultural land rent because data on agricultural rent during our sample time is unavailable. However, given its multicollinearity with $GDP2Share_{it}$ and $GDP3Share_{it}$, this factor was not included in our final model.

Several topographic variables [29] are controlled in the model, and they did not vary over time. For each city, average elevation ($Elevation_i$), average slope ($Slope_i$), and ratio of water bodies ($WaterShare_i$) within the urban built-up area were measured. Because these three variables can be correlated with difficulties related to constructing buildings and infrastructure, these factors provide a control for the ruggedness of each city's terrain. Population density is not used as a dependent variable, for $Population_{it}$ and $UrbanArea_{it}$ are independent variables in the regression models. Table 1 summarizes the list of variables.

Table 1. Description and Data source of variables.

Variables	Description	Data Source	Unit
PD	Ratio of population to area (km^2)	2000/2010 LandScan population data	Persons/km^2
CONTIG	Average contiguity value minus 1, divided by the sum of the template values minus 1	Urban expansion data between 2000 and 2010 from WorldBank	
SHAPE	Patch perimeter divided by the square root of patch area, adjusted by a constant to adjust for a square standard		
FRAC	Two times the logarithm of patch perimeter divided by the logarithm of patch area		
GDP	Gross Domestic Production	China City Statistical Yearbook 2000 and 2010	10,000 yuan
Population	Population	2000/2010 LandScan population data	Persons
Bus	Number of buses per 10,000 people	China City Statistic Yearbook 2000 and 2010	Vehicles
GDP2Share	Share of industrial sector in GDP		%
GDP3Share	Share of service sector in GDP		%
UrbanArea	Area of urban land	Urban expansion data between 2000 and 2010 from WorldBank	km^2
Elevation	Average elevation in the urban built-up area	Cold and Arid Regions Sciences Data Center	m
Slope	Average slope in the urban built-up area		Degree
WaterShare	Ratio of inland water to overall urban built-up area	DIVA-GIS	%

It is possible that additional unobserved or unmeasured variables, which are correlated with urban form, are not included in the model. For example, urban form may be affected by historical and cultural differences between northern and southern China; the power of a political center may also impact urban expansion. When time-series data are available, a first-difference model may help to reduce the impacts of unmeasured factors [28]. Therefore, a first-difference model was also used in this paper, and six time-variant factors in Equation 1 were redefined by calculating the difference values between 2000 and 2010. The redefined model (Equation (2)) is as follows:

$$\begin{aligned} \Delta UrbanFormMetric_i & \\ &= a_1\Delta GDP_i + a_2\Delta Populaition_i + a_3\Delta Bus_i + a_4\Delta GDP2Share_i \\ &+ a_5\Delta GDP3Share_i + a_6\Delta UrbanArea_i + b \end{aligned} \tag{2}$$

4. Results

4.1. Comparison of Urban Form

Descriptive statistics for the measured variables are shown in Table 2. Comparison of urban form among different regions (Figure 4) show that urban form was different between the developed region (the eastern region) and developing regions (the western, central, and northeastern regions). Eastern cities showed the lowest population density in both 2000 and 2010, followed by central cities. The mean differences in population densities between the eastern region and other regions, except for the central region, grew from 2000 to 2010. Western cities exhibited the densest population in 2000, but they were surpassed by northeastern cities in 2010, although the difference was not significant. From the paired sample test (Table 3), we found that population density in 2000 was significantly different from 2010. Population density decreased in 70 cities (61%), whereas it increased in the other 45 cites (39%). The mean population density decreased by 11.73% from 2010, which resulted from the fast expansion of urban land when compared to the lower increase in urban populations. Population density decreased in 34 eastern cities (65%), 16 central cities (59%), 13 western cities (54%), and 7 northeastern cities (58%), which indicates that decreasing density was most prevalent in the eastern region.

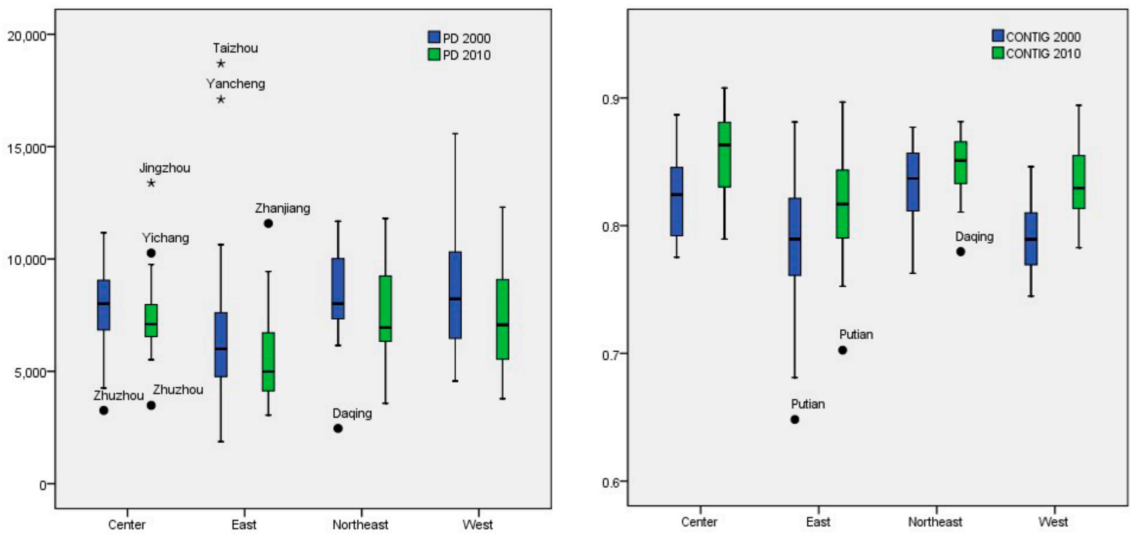
In 2000, eastern cities had the lowest contiguity index value among the four regions. On one hand, the policy of opening up brings new economic and technological development zones to the eastern area, which may have resulted in leapfrog-style development patterns. On the other hand, the separation of dense water networks, such as lakes and rivers, may have decreased *CONTIG* values in the eastern region. The *SHAPE* and *FRAC* values show that eastern and western cities showed greater irregularity and complexity on average than central cities. This phenomenon was much more apparent in 2010, which exhibited larger mean differences and greater significance than in 2000. For example, although the *SHAPE* values for eastern cities were not significantly higher than western and northeastern cities in 2010, the outliers in Figure 4 (e.g., Dongguan, Tianjin, Beijing) had much higher values. As measured by *SHAPE* and *FRAC* values, cities in the central region were the most compact. From 2000 to 2010, the increase of *SHAPE* and *FRAC* values displayed a higher level of irregularity and complexity in the urban form of Chinese cities. Both *SHAPE* and *FRAC* values increased for 55 cities (48%), with more than half of the eastern cities (28 cities, 54%), 11 central cities (41%), 12 western cities (50%), and 4 northeastern cities (33%).

In general, cities in the eastern region exhibited the most complex and irregular shapes, the lowest population density, and the least continuous urban form. Western and northeastern cities showed moderate metrics for urban form when compared with results for the central region. Developed cities in the eastern region showed differences in urban form from cities in developing regions, which may have been due to the difference in urban expansion between the eastern region and the other regions. Export-led industrialization, foreign investment, and provincial-led infrastructure investment has made the eastern region a growth hub for urban development in China [36].

Table 2. Descriptive statistics for the measured variables.

Variables (Year)	Minimum	Maximum	Mean	Std. Deviation	N
PD (2000)	1870	18,700	7460	2991	115
PD (2010)	3050	13,384	6586	2198	115
CONTIG (2000)	0.65	0.89	0.80	0.04	115
CONTIG (2010)	0.70	0.91	0.83	0.04	115
SHAPE (2000)	2.00	10.78	4.29	1.57	115
SHAPE (2010)	1.85	21.85	5.51	3.31	115
FRAC (2000)	1.08	1.23	1.15	0.03	115
FRAC (2010)	1.08	1.29	1.17	0.04	115
GDP (2000)	199,586	40,986,400	3,354,693	5,270,149	113
GDP (2010)	1,054,562	169,715,503	17,151,345	25,420,000	115
Population (2000)	74,120	10,336,932	1,173,041	1,487,203	115
Population (2010)	93,231	13,489,355	1,638,764	2,010,851	115
Bus (2000)	0.36	91.97	7.31	9.00	112
Bus (2010)	0.43	103.11	9.60	10.20	115
GDP2Share (2000)	15.90	92.30	49.46	10.65	113
GDP2Share (2010)	19.61	85.45	51.15	10.69	115
GDP3Share (2000)	7.30	71.70	43.48	9.37	113
GDP3Share (2010)	14.01	78.66	43.87	11.20	115
UrbanArea (2000)	11.56	1419.00	174.45	204.96	115
UrbanArea (2010)	12.00	2159.25	270.61	343.12	115
Elevation	2.00	2328.00	227.35	424.80	115
Slope	0.03	4.12	0.72	0.73	115
WaterShare	0.00	27.67	3.62	5.37	115

Note: Hezhou, Guangxi and Wuwei, Gansu became prefecture cities in 2002 and 2000, so there is no statistical data for these two cities in 2000. There is no data for buses per 10,000 people for Bazhong, Sichuan from 2000.



(**a**) (**b**)

Figure 4. *Cont.*

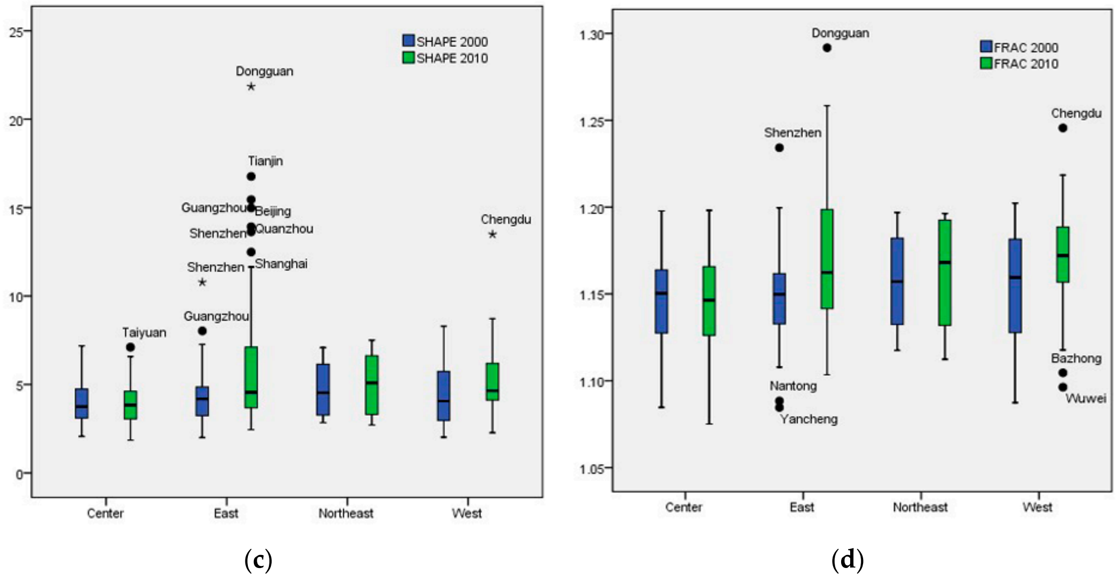


Figure 4. Comparison of metrics across four economic regions: (**a**) *PD*, (**b**) *CONTIG*, (**c**) *SHAPE*, and (**d**) *FRAC*.

Table 3. Paired sample test between 2000 and 2010.

Metric	Mean	S.D.	t	Sig.	Smallest Five	Largest Five
PD	−875	2421	−3.874	0.000	Taizhou, Yancheng, Tianshui, Zigong, Wuwei	Jingzhou, Shenzhen, Zhuhai, Dongguan, Wenzhou
CONTIG	0.033	0.026	13.678	0.000	Yangzhou, Zhuzhou, Jiaxing, Taizhou, Qiqihar	Dongguan, Changde, Ningbo, Kunming, Changsha
SHAPE	1.213	2.402	5.413	0.000	Yueyang, Wuhan, Changsha, Nanyang, Haikou	Dongguan, Tianjin, Beijing, Suzhou, Quanzhou
FRAC	0.015	0.027	6.219	0.000	Yueyang, Nanyang, Changsha, Haikou, Ezhou	Dongguan, Suzhou, Ningbo, Hangzhou, Beijing

Comparing results for super cities, megacities, type I big cities, and type II big cities shows the association between urban form and city size (Figure 5). Super cities exhibited the lowest population density in 2000, even though they had the largest populations. From 2000 to 2010, urban sprawl was quite common in megacities, where the density decreased in 8 of 9 megacities. Most super cities (4 of 5) and type I big cities (11 of 20 cities) became more irregular and complex, whereas only 2 of 7 megacities followed this trend. Increases of *CONTIG* values show that urban form became more continuous than before. This may have been the result of new developments between urban cores and fringe areas [11]. The *CONTIG* values for 9 cities decreased, all of which were type II big cities. In 2010, the mean population densities of super cities and megacities were lower than those in type I and type II big cities. The boxplots for *SHAPE* and *FRAC* values show stair step-like shapes that increased with city size, and the value of these metrics for a high-level city was bigger than a low-level city. For example, the *FRAC* value for super cities was significantly higher than that of megacities, and the latter was significantly higher than that of type I big cities. In all, the results show that the level of complexity and irregularity increased as city sizes increased. During this period, many cities grew rapidly, along with the development of the urban economy and population [37]. Medium and large cities have accommodated most of the urban population growth, which makes super cities and megacities possible [38]. In addition, some big cities expanded their administrative areas by merging their suburban counties, thus accelerating urban sprawl.

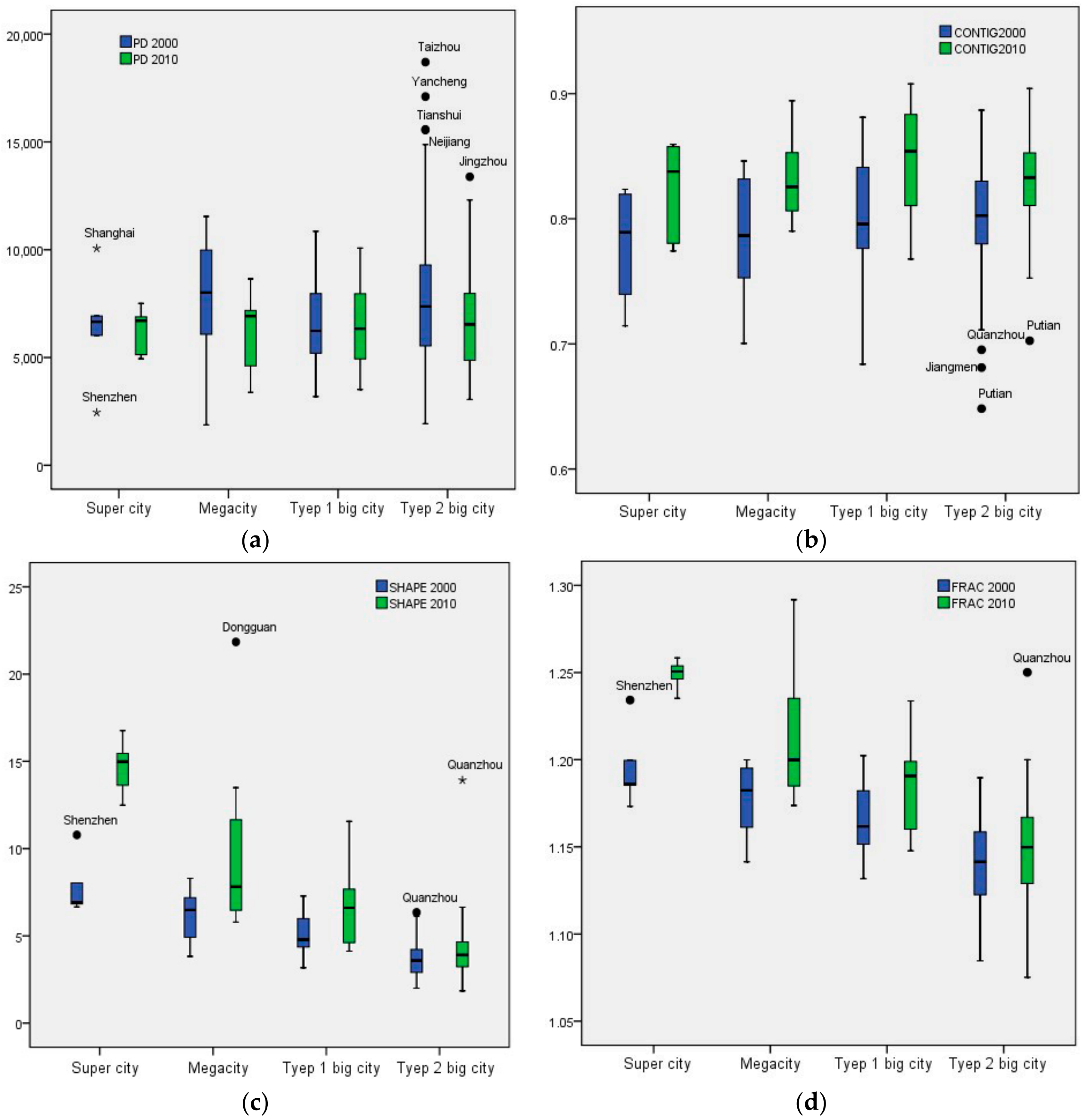


Figure 5. Comparison of metrics among cities of various sizes: (**a**) *PD*, (**b**) *CONTIG*, (**c**) *SHAPE*, and (**d**) *FRAC*.

4.2. Analysis of Determinants

As Tables 4 and 5 shows, OLS models and first-difference models were highly significant in illustrating patterns of *SHAPE* and *FRAC* across Chinese cities, with adjusted R^2 values ranging from 0.4 to 0.75. When comparing Tables 4 and 5, we found that some coefficients of all-time varying variables of the first-difference model were different. Although eastern cities showed greater *SHAPE* and *FRAC* values than cities in other regions, regression results indicated that *GDP* exhibited a negative relationship with the levels of irregularity and complexity when holding other socio-economic factors constant. This issue is discussed in the next section. The association between population and *SHAPE* or *FRAC* values was not statistically significant in the OLS regression models, but the coefficient for *SHAPE* became significantly positive in the first-difference model. New towns or real estate developments in suburban areas may have caused the increasing values of *SHAPE*. The positive relationship between population and *CONTIG* values implies population expansion of urban infill developments, which may have decreased green lands and open spaces. The negative and statistically significant relationship between *GDP* and *CONTIG* reflected fragmented urban land patterns caused by the development of industrial parks far away from urban cores [39].

The variable accounting for the number of buses per 10,000 people, a proxy for transportation costs, was statistically significant with the expected sign for *SHAPE* and *FRAC* values. When bus networks are dense or well developed, the cost of transportation on travelling time and money (transfer fees) is low. Residents are able to work or live in places far away from the city center, which allows cities to expand more freely with irregular and complex shapes.

The share of the industrial sector, *GDP2Share*, was positive and significant on the *FRAC* value in 2010, which indicates that industrialization may have increased the complexity of urban form. Industrial parks or economic development zones played an important role in Chinese industrialization and its growing economy, and these industrial zones are often scattered on urban fringes and occupy large areas of land with low densities, making urban land fragmented and increasing the complexity of city shapes [40]. Likewise, increases to the service sector, *GDP3Share*, exhibited a positive and significant relationship with *FRAC* values in 2010. The urbanization level rose from 36% in 2000 to 50% in 2010, and the share of the tertiary industry increased from 39% to 43.2% (National Bureau of Statistics). The land development of service sectors on urban fringes (e.g., college towns, research centers, and logistic districts) may have increased the complexity of urban form [39]. The coefficient for the industrial sector variable was larger than that of the service sector variable; this could be because industrial growth required greater areas of land, leading to more complex urban form.

It may be somewhat surprising that the coefficients for topographic variables (*Elevation*, *Slope*, and *WaterShare*) were not significant. Most cities in our sample were located in plain areas with low mean values for slopes (0.72 degree), elevation (227 m), and ratio of water areas (3.62%), which may explain their insignificance in the models. Nevertheless, the signs of their coefficients were consistent with our expectation that increases in slope, elevation, and ratio of water areas made cities more complex and irregular.

Table 4. Standardized B coefficients of the OLS model in 2000 and 2010.

Variable	*CONTIG*		*SHAPE*		*FRAC*	
	2000	**2010**	**2000**	**2010**	**2000**	**2010**
GDP	−0.493	−0.326	−0.374	−0.670	−0.407	−0.626
	(0.067)	(0.352)	**(0.034)**	**(0.000)**	(0.063)	**(0.006)**
Population	1.249	1.191	0.282	−0.112	0.331	0.091
	(0.000)	**(0.006)**	(0.197)	(0.613)	(0.224)	(0.738)
Bus	0.242	0.050	0.395	0.198	0.318	0.174
	(0.055)	(0.647)	**(0.000)**	**(0.001)**	**(0.002)**	(0.015)
GDP2Share	−0.174	−0.051	0.058	0.076	0.122	0.451
	(0.219)	(0.810)	(0.529)	(0.494)	(0.288)	**(0.001)**
GDP3Share	−0.141	0.168	0.106	−0.051	0.163	0.354
	(0.365)	(0.489)	(0.299)	(0.686)	(0.201)	**(0.025)**
UrbanArea	−0.869	−0.974	0.618	1.550	0.467	1.138
	(0.000)	**(0.006)**	**(0.000)**	**(0.000)**	**(0.018)**	**(0.000)**
Elevation	−0.003	0.106	0.042	0.013	0.045	0.019
	(0.983)	(0.376)	(0.596)	(0.831)	(0.645)	(0.805)
Slope	−0.055	−0.108	0.071	0.058	0.118	0.112
	(0.643)	(0.343)	(0.359)	(0.328)	(0.224)	(0.126)
WaterShare	−0.092	−0.050	0.009	0.034	0.070	0.013
	(0.315)	(0.586)	(0.876)	(0.479)	(0.351)	(0.821)
Ajusted R^2	0.101	0.104	0.616	0.755	0.404	0.632
	(0.017)	**(0.013)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

Note: bold value is at a 95% significance level.

Table 5. Standardized B coefficients of the first-difference model.

Variable	Standardized B, Sig.					
	CONTIG		*SHAPE*		*FRAC*	
GDP	−0.564	**(0.005)**	−0.467	**(0.001)**	−0.589	**(0.001)**
Population	0.543	**(0.000)**	0.244	**(0.012)**	−0.019	(0.874)
Bus	−0.010	(0.916)	0.030	(0.634)	0.110	(0.168)
GDP2Share	0.044	(0.644)	0.023	(0.853)	−0.198	(0.205)
GDP3Share	0.086	(0.353)	−0.035	(0.782)	−0.221	(0.157)
UrbanArea	0.382	(0.054)	1.008	**(0.000)**	1.117	**(0.000)**
Ajusted R^2	0.194	**(0.000)**	0.624	**(0.000)**	0.398	**(0.000)**

Note: bold values are at a 95% significance level.

5. Discussion

The results show that the expansion of the economy and population was associated with decreased population density and greater irregularity and complexity of urban lands in Chinese cities from 2000 to 2010. After the 1994 tax reform, local governments had to sell land through rapid urban expansion to meet their financial demands, and land economy had become a main driving force of urbanization in this period. Local governments were obsessed with irrational city construction of various forms, with decreasing population density [36]. Local governments often attracted large national or international companies with depressed industrial land price and tax relief, which was subsidized by soaring housing prices [41]. Land finance stimulated local governments to sell lands in newly-developed areas, and new towns and development zones had become a tool for land acquisition [36]. New towns and development zones with excessive land supplies not only caused decreasing population density and complexity of urban form, but also led to many problems, such as ghost cities and sleeping towns. China is estimated to increase in its urban population by nearly 300 million over the upcoming decades, and the urbanization level is projected to reach 76% by 2050 [42]. In the new era, the economic growth based on large-scale industrialization and real estate development is unsustainable. The transformation of national development goals in the new era calls for the transformation of the city development pattern, and Chinese cities have entered a new era of innovation-driven development. Economic growth guided by the five development concepts of innovation, coordination, green, openness, and sharing may help to shape sustainable urban form in Chinese cities. The Ministry of Natural Resources was established after the 19th CPC National Congress in 2018, and past urban planning for city growth will give way to resource management planning. There are still some limitations in this study. Only metrics like the shape index and the fractal dimension index were quantified, and metrics, such as polycentric structure, should be explored. National and local policies are not explicitly included in the model, and they may be responsible for unexplained residuals.

6. Conclusions

This paper analyzed urban form metrics, including population density, contiguity index, fractal dimension index, and shape index for 115 Chinese cities. Four spatial metrics were compared across cities in different economic zones and cities of different sizes. Population, economic growth, transportation costs, and economic structure were assumed to mainly determine urban form for Chinese cities, and OLS models and first-difference models were utilized to explore the associations between the factors and spatial metrics. Cities in the developed region appear to be the most discontinuous, complex, irregular, and least dense, and larger cities show a higher level of complexity and irregularity. By analyzing changes in urban form from 2000 to 2010, we found that urban sprawl continued to grow in most Chinese cities. On average, population densities were decreasing, and the shapes of cities were becoming more complex and irregular, but more continuous. GDP, population, transportation costs, and economical structure affected urban form in different ways, and land finance led to decreasing population density and complexity of urban form. City growth based on large-scale industrialization and real estate development would be weakened, and the innovation-driven development is required to make urban form more sustainable. Overall, this study presented a panoramic view on the urban form of Chinese cities from 2000–2010, and we contributed towards filling the research gap about the quantitative association between urban form and determinants.

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