Contemporary Evolution and Scaling of 32 Major Cities in China

Article *in* Ecological Applications · June 2018

DOI: 10.1002/eap.1760

Shuqing Zhao
Peking University

Shuguang Liu
Central South University of Forestry and Technology

Chunxue Xu
Peking University

Wenping Yuan
Beijing Normal University

Article type : Articles

Contemporary Evolution and Scaling of 32 Major Cities in China

Shuqing Zhao[1,*], Shuguang Liu[2], Chunxue Xu[1], Wenping Yuan[3], Yan Sun[1], Wende Yan[2], Meifang Zhao[2], Geoffrey M. Henebry[4], Jingyun Fang[1]

1 College of Urban and Environmental Sciences and Key Laboratory for Earth Surface Processes of the Ministry of Education, Peking University, Beijing 100871, China

2 National Engineering Laboratory of Forest Ecology and Applied Technology for Southern China and College of Biological Science and Technology, Central South University of Forest and Technology, Changsha 410004, China

3 Zhuhai Joint Innovative Center for Climate-Environment-Ecosystem and Key Laboratory of Urban Climate and Ecodynamics, Beijing Normal University, Zhuhai 519087, China.

4 Geospatial Sciences Center of Excellence (GSCE), South Dakota State University, Brookings South Dakota 57007, United States of America

***Correspondence to: S.Q. Zhao (**sqzhao@urban.pku.edu.cn, Tel/Fax: 86-10-6276 7707**)**

Running Head: Urbanization and scaling in China

Abstract

Most of the planet's population currently lives in urban areas and urban land expansion is one of the most dramatic forms of land conversion. Understanding how cities evolve temporally, spatially, and organizationally in a rapidly urbanizing world is critical for sustainable development. However, few study has examined the co-evolution of urban attributes in time and space simultaneously and the adequacy of the power law scaling across cities and through time, particularly in countries that have experienced abrupt, widespread political and economic changes. Here we show the temporal co-evolution of multiple physical, demographic, socioeconomic, and environmental attributes in individual cities, and the cross-city scaling of urban attributes at six time points (i.e., 1978, 1990, 1995, 2000, 2005, and 2010) in 32 major Chinese cities. We found the power law scaling could adequately characterize both the cross-city scaling of urban attributes across cities and the longitudinal scaling describing the temporal co-evolution of urban attributes within individual cities. The cross-city scaling properties demonstrated substantial changes over time signifying evolved social and economic forces. A key finding was that the cross-city linear or superlinear scaling of

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/eap.1760

urban area with population contradicts the theoretical sublinear power law scaling proposed between infrastructure and population. Furthermore, the cross-city scaling between area and population transitioned from linear to superlinear over time, and the superlinear scaling in recent times suggests decreased infrastructure efficiency. Our results demonstrate a diseconomy of scale in urban areal expansion that indicates a significant waste of land resources in the urbanization process. Future planning efforts should focus on policies that increase urban land use efficiency before continuing expansion.

Key words: evolution of cities; urban attributes; scaling laws; power scaling; horizontal scaling; temporal scaling; urban sustainability; urban ecosystems

1 Introduction

We are entering an increasingly urbanized world with more people now living in cities than in rural areas and accelerating expansion of urban land (UN, 2015; Angel et al., 2011). Urbanization presents both opportunities (e.g., wealth creation, innovation, and efficient resource use) and challenges (e.g., crowding, traffic congestion, and environmental degradation) toward a sustainable future for human societies (Grimm et al. 2008; Seto et al., 2010). Studying how cities evolve temporally, spatially, and organizationally enables integration of natural and social sciences (Batty, 2008; Bettencourt and West, 2010), and findings and theories may greatly benefit urban and regional planning, land use optimization, and sustainable development (Batty, 2013).

Cities are characterized by the co-evolution of closely interwoven, deeply interdependent, and often locally-constrained physical, technological, socioeconomic, political, and environmental characteristics and processes (Pickett et al., 2005; Kaye et al., 2006). It is very challenging to understand how these diverse properties and processes interweave and co-evolve within and across cities (Batty, 2013). Considerable research has been devoted to the horizontal or spatial organization and/or scaling of cities. For example, case studies have demonstrated the fractality of cities (Batty, 2008; Batty and Longley, 1994), Zipf's law for city size distribution (Zipf, 1949; Jiang and Jia, 2011), and Gibrat's law for independence between city size and urban growth (Gibrat, 1931; Eeckhout, 2004). However, the universality of some of these laws is still under debate (Rozenfeld et al., 2008; Cristelli et al., 2012; Zhao et al., 2015a).

The power scaling law, originally used to describe the allometric scaling of metabolic rate with animal body mass (Kleiber, 1947), has been adopted to scale many urban properties (Bettencourt et al., 2007; Bettencourt, 2013). We follow the tradition of using population size as an explanandum in urban scaling since human capitals play a vital role in urban metabolisms (Lucas, 1988; Eaton and Eckstein, 1997; Bettencourt et al., 2007):

$$y = aN^{\beta}$$

where y and N are the urban attribute and the city size, represented by the population of a city, at a given point in time, respectively, and α and β are parameters. The magnitude of the parameter coefficient for the scaling exponent β is the most interesting feature of the power law model as it indicates three regimes of scaling behavior: (1) sublinear (β<1), (2) linear (β≈1), and (3) superlinear (β>1). Bettencourt and colleagues (Bettencourt et al., 2007; Bettencourt, 2013) further articulated that each urban feature would fall into a specific scaling regime. For example, competition, creativity, and productivity grow with city size so that the scaling of such properties should be superlinear (β≈7/6, increasing returns to scale). On the other hand, infrastructure and services (e.g., per capita living space) tend to decrease with city size and, thus, their scaling falls into the sublinear regime (β≈5/6, economies of scale). Recent studies (e.g., Arcaute et al., 2015; Strano and Sood, 2016), however, have shown that the scaling of urban features with city size does not necessarily follow Bettencourt's scheme between the nature of urban properties and the scaling regime.

Temporal or longitudinal dynamics and co-evolution of urban attributes are important aspects of urbanization, but they have received less attention than the horizontal organization of cities because of the challenges in acquiring relevant data for multiple periods (Ramalho and Hobbs, 2012; Alberti, 2015; McPhearson et al., 2016). In a previous study we have shown that Gibrat's law characterizing the independency of city expansion rate and city size was adequate for some periods but not others in China due to shifts in socioeconomic policies (Zhao et al., 2015a). Nevertheless, temporal scaling studies are rare.

Urban scaling studies have predominantly used urban population to indicate city size (Bettencourt et al., 2007; Rozenfeld et al., 2008; Lobo et al., 2013). Yet, population is not the only measure that can be used to represent the size of a city. Alternative measures include the areal extent within administrative boundaries and the total impervious surface area. These alternative measures have become available because of increasing access to earth observation technologies and data. For example, city expansion has been mapped using remotely sensed imagery at local to global scales (Bagan and Yamagata, 2012; Zhao et al., 2015b; Schneider et al., 2009). An important emerging research need is the analysis of the co-evolution of city area expansion with other urban attributes, including population to understand the drivers and consequences of urbanization at national, regional, and global scales.

Along with its rapid economic growth, China has experienced unprecedented urban expansion during the past three decades. Although many studies have been conducted to examine urbanization in China (Zhao et al., 2015a, 2015b; Seto and Fragkias, 2005; Bai et al., 2012; Schneider and Mertes, 2014), few comprehensive studies exist at city and national levels that combine the socioeconomic dimensions with the physical processes to examine their co-evolution. Here we used a combination of remotely sensed city area expansion and corresponding demographic, socio-economic, and environmental data from census reports to depict how Chinese major cities, individually and as a whole, had evolved from 1978 to 2010. Our research aims included: (1) quantifying the temporal (or longitudinal) co-evolution of multiple urbanization attributes for individual cities; (2) analyzing the cross-city (or horizontal) organization of urban attributes and rates (i.e., the scaling of urban attributes with city size) in China at six points in time (1978, 1990, 1995, 2000, 2005, and 2010) using the power law model; and (3) examining the temporal change of the cross-city scaling (or horizontal organization) of Chinese cities. Key scientific questions include: (1)

How do the scaling coefficient values vary in time with urban attributes within individual cities and across all cities? (2) Do all the co-evolutionary scaling coefficient β values conform to Bettencourt's theoretical predictions? (3) Is power law scaling applicable to describe the horizontal organization of cities in China? (4) How did the cross-city scaling change in China as a result of recent socioeconomic reforms?

2 Materials and Methods

2.1 Study areas

Our study areas included 32 major cities in mainland China, covering a broad range of geographical locations and city size (Zhou et al., 2014; Zhao et al., 2016). The boundaries of these 32 major cities follow China's official definition of the administrative areas (i.e., city, *shi*) (Figure S1). The use of administrative boundary enables us to couple urban land expansion with urban demographic, socioeconomic, and environmental attributes in China since most of these data were collected and reported by administrative unit.

Our definition of cities is based on urban administrative boundaries. It corresponds to metropolitan statistical areas in the U.S. and larger urban zones or functional urban areas in the European countries as they are all defined as integrated economic and social units, comprising urban cores and administrative subdivisions with substantial fractions of their working forces commuting within city boundaries (Bettencourt et al., 2007). The consistent scaling relationships relating urbanization to economic development and knowledge creation found in USA, China, and European countries by Bettencourt et al. (2007) also indicate that the definitions of cities across these countries are fundamentally similar, making our results from this study comparable to previous studies (e.g., Bettencourt et al., 2007).

2.2 Data Sources

Within the administrative boundary of each city, the urban land was defined as all non-vegetative areas dominated by human-made surfaces, including residential, commercial, industrial, and transportation space, was characterized using remotely sensed data. Cloud-free Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+) remote sensing data were used to obtain the information on urban land expansion for those 32 cities over the past three decades. Details about processing to derive the extents of urban area for the six periods (1978, 1990, 1995, 2000, 2005, and 2010) are described in our previous work (viz., Zhao et al., 2015a, 2015b).

Other data about the 32 cities, including urban population, urban GDP, total wage, number of automobiles, and concentration of air pollutants (i.e., PM_{10}, NO_x, and SO_2), were primarily obtained from Chinese statistical yearbooks between 1978 and 2010. Table S1 lists the socioeconomic and environmental variables used in this study and data sources.

2.3 Temporal scaling of urban attributes within each city

The temporal scaling or the co-evolution of two urban attributes within each city was analyzed and quantified using the following power law:

$$y_t = a_t x_t^{\beta_t} + e_t \qquad (1)$$

Where x_t and y_t are two attributes of interest in a given city, α_t and β_t are coefficients determined using an orthogonal or total least squared regression procedure (ORTH), e_t is the error term. There were two reasons for us to use an ORTH instead of the ordinary least square (OLS) regression. First, all measurements of urban attributes contained errors, and thus the errors in both the x and y directions should be minimized in the analysis of co-evolving urban attributes. OLS only minimizes the squared differences of fitted values and measurements of the dependent attribute and ignores the errors in the independent attribute. In contrast, ORTH considers errors in x and y by minimizing the total squared differences between fitted values and measurements in both attributes. Second, it is often difficult to determine which urban attribute is dependent and which is independent in a co-evolutionary relationship (e.g., urban area and urban population). It is therefore prudent for the scaling relationship to be reversible between x and y, meaning the regression of x (dependent) and y (independent) can be derived from the regression result of y (dependent) and x (independent). OLS is asymmetric and usually cannot meet the reversibility requirement while ORTH does.

The β_t values were derived from temporal observations of paired attributes in a given city from 1978 to 2010 using bootstrapped orthogonal regression in R (R Development Core Team, 2013). The 95% confidence range of the scaling exponent (β_t) was quantified using the predictive intervals of β_t (i.e., the β_t at 2.5^{th} and 97.5^{th} percentiles) from orthogonal regressions of 2000 bootstrapped samples. Sometimes the number of observations was not enough to perform bootstrapped regression, and therefore β_t could not be derived. The type of scaling can be determined according to the confidence interval of β_t:

- Sublinear: the upper bound of the 95% confidence interval < 1
- Superlinear: the lower bound of the confidence interval > 1
- Linear: the confidence interval contains 1

2.4 Horizontal organization and scaling of urban attributes across cities

The horizontal organization and metabolisms of cities follow power scaling laws (Bettencourt et al., 2007; Bettencourt, 2013). We explored such scaling laws in China:

$$y_s = a_s x_s^{\beta_s} + e_s \qquad (2)$$

Where x_s and y_s are two attributes of interest from various cities at a given point in time, α_s and β_s are coefficients determined using ORTH, and e_s is the error term. We used β_s to represent the exponent of cross-city scaling to differentiate the exponent of temporal co-evolution or scaling (β_t) within each city. The β_s value, its confidence limits, and the type of scaling were derived similarly to that of β_t as described in previous section.

We realized that the relationship between urban attributes can be analyzed using other methods such as direct comparison or statistic regression (e.g., Bloom et al., 2008; Leitao et al., 2016). The use of the power scaling relationship in this study was based on the following considerations: (1) our observations fit the power scaling relationship well (see supplemental materials); (2) as described earlier, the power scaling has been successfully adopted to scale many urban properties (Bettencourt et al., 2007; Bettencourt, 2013); using a consistent approach can facilitate comparison with previous studies.

We did not consider the impacts of inflation on the economic attributes such as GDP and wage, which introduce artefacts into the economic measures. However, we believe the effect on our results is minimal for two reasons. First, the values of the exponent βs and βt for all cities are subjected to the same bias, and hence can be compared between them in principle. Second, our focus is on the trend and co-evolution of the urban attributes only with respect to whether β is >1 or <1, and not on the value.

3 Results

3.1 Evolution of Urban Attributes over Time

The expansion of urban area (y) over time (t) in individual cities follows the power curve in general (i.e., $y = at^{\gamma} + b$) (Fig S2). Other urban attributes such as population are also a power function of time (Fig S3). The power relationship is strong as indicated by the small p values of the exponent γ in these figures. Figure 1 summarizes the significant values of the exponent γ ($p<0.05$) for each urban attribute in the form of density distribution. For example, the density function of the exponent γ for area (Figure 1A) reflects the distribution of all the exponent values for all 32 cities (i.e., Fig S2). Three phenomena in the temporal evolution of city attributes can be seen (Figure 1). First, all cities have been expanding in area and population (positive exponents), so are their GDP, total wage, the number of automobiles, and GDP density. This signifies wealth accumulation over time. Second, air pollutants have been decreasing in most of the 32 cities as suggested by more negative exponents (red) than positive ones (black). Third, population density (persons per unit urban area) has been decreasing, implying the living space per capita has been improving, in most cities (more negative than positive exponents).

3.2 Co-evolution of Urban Attributes in Individual Cities

3.2.1 Area-based scaling

When urban area was the independent attribute (i.e., x) to scale other urban attributes, we found the following phenomena (Figure 2A-2D, Figure 3A-3C, and Table 1):

(1) The population ~ area co-evolution in Chinese cities varied greatly as shown by the coexistence of all three types of scaling. That population growth increasingly lagged urban land expansion (i.e., $\beta_t < 1$) was the dominant scaling as it occurred in 19 of the 32 cities. Shenzhen, the most successful Special Economic Zone setup by the central government in the late 1970s to experiment the Open-up and Reform policy, was the only city showing a superlinear scaling ($\beta_t > 1$) with its population growth increasingly exceeded urban area expansion. The linear scaling ($\beta_t \approx 1$) in the remaining 12 cities suggests that the average urban space for each urban dweller expanded at the same rate as population.

(2) GDP increase progressively outpaced area expansion in every city from 1978 to 2010 because total GDP scaled superlinearly with area in all cities ($\beta_t > 1$).

(3) Increase of GDP density (i.e., GDP per unit area) progressively outpaced urban expansion in half of the cities as evidenced by the significantly superlinear scaling relationship between GDP density and urban area. Only one city (Hangzhou) showed a sublinear scaling relationship between GDP density growth and area expansion. In Hangzhou, the GDP density increase was progressively outpaced by city expansion. The expansion of the remaining 14 cities linearly matched the pace of GDP density change.

(4) The increase of wage progressively outpaced area expansion over time (i.e., superlinear scaling) for all individual cities.

(5) Of the 16 cities with automobile records, 3 and 13 cities demonstrated linear and superlinear scaling between automobile and area, respectively, signifying the increase of automobiles progressively outpaced urban area expansion over time in most cities.

(6) Three types of scaling coexisted for the scaling of air pollutants (PM_{10}, NO_x, and SO_2) with area, and most of the scaling were sublinear or linear. Specifically, most cities showed sublinear scaling on PM_{10}, and linear scaling on NO_x and SO_2.

3.2.2 Population-based Scaling

When population was the independent attribute (i.e., x) to scale other urban attributes, we found (Figure 2E-2G, Figure 3D-3F, and Table 1):

(1) GDP growth increasingly outpaced population growth over time for all individual cities as indicated by the superlinear scaling between GDP and population.
(2) The growth of total wage increasingly exceeded population growth in each individual city.
(3) Of the 16 cities with proper data, automobiles increased progressively with population (i.e., superlinear scaling) in 14 of the cities, and increased proportionally with population (i.e., linear scaling) in 2 other cities.
(4) All three types of scaling existed for air pollutants with most being linear scaling.

3.2.3 GDP-based Scaling

When GDP was the independent attribute (i.e., x) to scale other urban attributes, we found (Figure 2H and 2I, Figure 3G-3I, and Table 1):

(1) Wage increase progressively exceeded GDP growth (i.e., superlinear co-evolution) in 16 cities, matched with GDP growth (i.e., linear co-evolution) in 14 cities, increasingly lagged GDP growth (i.e., sublinear co-evolution) in only one city (i.e., Hohhot).
(2) Automobile increase matched the pace of GDP growth in 11 of the 16 cities (i.e., linear scaling), and progressively outpaced by GDP growth the remaining 5 cities (i.e., sublinear scaling).
(3) Pollutant scaling with GDP was mostly sublinear (i.e., pollution progressively outpaced by GDP growth) with only a few linear and none superlinear.

3.3 Horizontal Organization or Scaling of Urban Attributes across Cities

To better visualize the various results of horizontal scaling of urban attributes and their temporal evolution, we translate the results into the personal impressions of a traveler moving through chains of cities: (1) from smaller to larger cities in terms of areal extent; (2) from less to more populated cities; and (3) from past to more recent periods.

3.3.1 Area-based Scaling

When urban area was the independent attribute of cities, it scaled with other urban attributes the following ways (Figure 4A-4F and Table 2):

(1) GDP scaling with urban area was sublinear in 1978 and 1990. A person traveling through a chain of small-to-large cities would have felt that the GDP growth increasingly lagged urban area change in these two periods. GDP scaling changed to linear since 1995.
(2) Total wage scaling with area was sublinear during the early two periods (i.e., 1978 and 1990). A person traveling from small to large cities within these periods would have felt that the rate of wage increase increasingly lagged the pace of urban area expansion. This situation changed

since 1995 when the total wage scaling with area became linear.

(3) Automobile scaling with area was sublinear in 1990. A traveler in 1990 would have felt the rate of automobile increase progressively lagged the rate of urban area expansion from small to large cities. The automobile scaling became linear since 1995 although the 95% confidence intervals of the β_s values were strongly tilted toward the sublinear scaling.

(4) The scaling of pollutants with area was superlinear or linear but the 95% confidence intervals of β_s value were heavily tilted toward superlinear, and there were no apparent temporal trends. The traveler would have felt the rate of air quality deterioration have increasingly outpaced the rate of city area change as the person traveled from small to large cities.

3.3.2 Population-based Scaling

When population was the independent urban attribute, the following horizontal scaling relationships were found (Figure 4G-4L, Figure 5, and Table 2):

(1) Area showed superlinear scaling with population before 2000 across the 32 major cities in China. Although the 95% confidence intervals of the exponent β_s were largely skewed to superlinear scaling since 2000, the scaling was not significantly different from linear scaling. The magnitude and the temporal change of β_s suggest two phenomena. First, a person traveling through a chain of cities from less to more populated cities would have felt that the rate of urban area increase was increasingly faster than the rate of population growth. In other words, the larger the city in population, the increasingly larger the area. Second, after moving through the sequence of cities repeatedly since 1978, a traveler would have felt that the difference between the rates of population growth and area expansion have decreased over time resulted from the temporal change of β_s from superlinear to linear.

(2) GDP scaling with population was linear in 1978, and it became superlinear for the rest of the time periods. This superlinear scaling relationship between GDP and population indicates that the larger the population, the increasingly higher the GDP. The superlinear scaling was the strongest in 2000 when Chinese economic reform was at its full swing.

(3) The scaling of total wage with population transitioned from linear (1978 and 1990) to superlinear (since 1995). A traveler in 1978 and 1990 would have noticed the average salary (not the total wage) remained roughly the same. This person would have noticed that the average salary increased progressively since 1995 when traveling from less to more populated cities.

(4) Automobile scaling with population was linear for all periods. However, although not significant statistically, the scaling coefficient increased from 1990 to 2000 and then leveled off.

(5) All pollutants (PM_{10}, NO_x, and SO_2) scaling with population was superlinear throughout the study period, suggesting the larger the population, the progressively higher the air pollutants. A traveler would have noticed that air pollution had become progressively worse from less to more populated cities. The data also showed that the degree of superlinearity decreased over time shown by the decrease of the β_s values, probably reflecting the reduction of pollution over time, at least on a per capita basis.

4 Discussion

4.1 Temporal evolution of urban attributes

We have used the power function to quantify the temporal change of urban attributes (see Fig S2 and S3). This approach works in most cases as the urban expansion processes in these cities do follow the power curve up to present. As urbanization gradually reaches its limits and the speed of expansion slows down, a different function such as logistic growth curve might be more suitable than the power curve as cities cannot expand as a power function of time forever. We have already witnessed the limitation of the power curve in mature cities such as Shenzhen where urbanization has been approaching to their physical limits (see Figure S2).

Chinese urbanization, characterized mainly by population migration from rural to urban areas, has been accelerating over the past three decades, and the urban population in China has increased from 17.9% in 1978 to 56.1% in 2015 (SSB, 2015). Associated with the population shift is a concurrent change in urban attributes including urban areal extent, GDP, number of automobiles, and air pollution levels (Liu and Diamond, 2005; Zhao et al., 2015b; Bai et al., 2014). Individually each city has been effective in accumulating wealth such as GDP and wage in addition to expansion in area and population (see Figure 1). However, differences exist across cities, and the effectiveness of urban expansion must be evaluated by examining the coevolution of multiple urban attributes and the horizontal organization of attributes across cities, which will be discussed below.

4.2 Temporal co-evolution of urban attributes within individual cities

The results of temporal scaling among paired urban attributes have revealed some interesting features about the characteristics of urbanization processes in these cities (Figures 2 and 3, and Table 1). First, we have found for the first time that the population and urban area co-evolved in these cities with all three types of scaling (i.e., superlinear, linear, and sublinear). Urban areal expansion progressively exceeded population growth in most cities. Only one city (Shenzhen) showed that areal expansion increasingly lagged population growth. The diversity of population ~ area scaling in these cities is the complex product of geographic factors, economic growth and development, policy shifts and institutional changes, among other driving forces. For example, the sublinear expansion of area in respect to population growth in Shenzhen was probably resulted from the interaction between its fast population growth, attracted by its tremendous business opportunities after being designated as China's first special economic zone in the late 1970s, and the limited physical area for expansion. Many cities, especially those where expansion was not physically constrained, have witnessed progressively faster areal expansion than population growth, because urban expansion has been considered as a practical vehicle for economic development at the city to national levels (Lin, 2007; Xu, 2008; Lin and Yi, 2011). That areal expansion progressively exceeded population growth in most cities has two important implications. On the positive side, it suggests the living space for average urbanites in China has largely been improving over time in most cities.

However, excessive areal expansion can lead to unintended outcomes, such as "ghost towns", if the expansion is not driven by demands (Shepard, 2015).

Second, given the impressive economic growth in China during the past three decades, it is not surprising to see rapid growth of GDP and wages accompanied by an increase in automobiles and a deterioration of air quality (Liu and Diamond, 2005; Zhao et al., 2006; Bai et al., 2014). This study further revealed details of their interwoven co-evolutions with other urban attributes. For example, GDP and wage increases have progressively outpaced both areal expansion and population growth in every city from 1978 to 2010. In addition, wage increase increasingly exceeded or matched GDP growth in most cities, and rarely lagged GDP growth. Along with increased income, automobiles increased progressively with population growth and areal expansion or matched the pace of GDP growth in most cities.

Finally, different from the scaling of the economic growth and infrastructural expansion, air pollutants (e.g., PM_{10}, NO_x and SO_2) showed in most cities linear or sublinear scaling relationship with either urban area or population. This discrepancy suggests that these urban air pollutants were comparable to or progressively lagged the pace of urban expansion or population growth. More importantly, the scaling coefficients of these pollutants versus GDP were sublinear in most every city, suggesting pollution reduction from the perspective of GDP growth has been effective in these cities (Figure 3).

4.3 Area- and population-based cross-city scaling

Urbanization is an integrative process that involves changes in multiple interwoven dimensions involving area, population, economy, and environment. Previous urban scaling studies have focused mostly on demographic scaling, i.e., how urban attributes change with the increase or decrease of population. In contrast, studies of area-based scaling relationships are rare. Although theoretical considerations for area-based scaling have not yet been fully developed due to limited research, the theoretical scaling exponents for areal scaling can be readily derived from the theoretical sublinear scaling for land area (A) and population (N) (i.e., $A \propto N^{2/3}$, see Table 1 in Bettencourt, 2013). For example, the theoretical areal scaling relationship for socioeconomic factors (Y) should be $Y \propto A^{7/4}$ because $Y \propto N^{7/6}$ and $A \propto N^{2/3}$ according to Bettencourt (2013). This study shows that all area-based cross-city scaling exponents for socioeconomic factors across these cities were significantly lower than the theoretical value of 7/4 (Table 2). Furthermore, all the area-based scaling relationships were linear or sublinear, contradicting the theoretical prediction of superlinear scaling (Figure 4A-4F). This discrepancy suggests a tremendous waste of land resources in the expansion of these cities: the increase of socioeconomic efficiency as cities scale from small to large in area, seen from other regions and economic theory (Bettencourt et al., 2007; Rosenthal and Strange, 2004), is not observed in this study. In addition, the temporal transition from linear to sublinear scaling demonstrated the increasing waste of land resources over time. Our results from area-based scaling revealed important new characteristics of the urbanization processes that could not be obtained using the traditional demographic scaling (Figure 4 and Table 2), which supports previous observations that demographic attributes alone cannot untangle diverse drivers and outcomes in urbanization (Bai et al., 2012; Arcaute et al., 2015).

4.4 Cross-city area ~ population scaling: theoretical challenges?

According to urban scaling theory (Bettencourt, 2013), the relationship between urban area and total population across cities should be sublinear with an exponent β_s value of 2/3. This theoretical sublinear scaling signifies a population densification process and economies of scale: impervious surface area per capita decreases as city population increases. The cross-city scaling of area and population in this study did not conform to the existing theory. The scaling coefficient β_s values from our study varied from 1.36 to 1.67 during the six periods (Figure 5A-5F), which were all significantly greater than the theoretical sublinear scaling coefficient (β_s = 2/3). Superlinear cross-city scaling of urban area with population indicates that intercity areal differences were progressively larger than their corresponding population differences as one travels from less to more populated cities. The nonconformity of the scaling relationship between area and population observed in these cities to the scaling theory suggests that the theory might not be universal, the scaling of these cities might be abnormal, or both.

4.5 Cross-city scaling of GDP and population

Horizontally, many attributes associated with the intrinsic social aspects of cities such as information and wealth creation and productivity demonstrated superlinear scaling (β_s > 1). For example, cities with larger populations generally have higher levels of productivity than smaller ones (Sveikauskas, 1975; Segal, 1976; Bettencourt, 2013) resulted from increasing returns from population size due to knowledge spillover (i.e., the exchange of ideas among networks of individuals that promotes creativity and innovation) (Romer, 1986; Lucas, 1988; Florida, 2005). Data from this study agreed well with this generalized superlinear scaling of GDP versus population (Figure 5G-5L). Another significant finding of this study is that the scaling exponent β_s for GDP versus population increased from about 1 (linear scaling) in the late 1970s to the theoretical superlinear value 7/6 since 2000. This major temporal shift in exponent value tracked the trajectory of China's social and economic vitality brought about by various local to national economic reform policies. The linear scaling, an indicator of stable and stagnant economy (Strano and Sood, 2016), in the earlier periods reflected the ineffectiveness of the centralized planned economy in stimulating economic growth. The superlinear scaling of GDP with urban population since 2000 is a characteristic of growing economy, as suggested by Strano and Sood (2016).

The magnitude of the scaling exponent β_s of GDP versus population effectively represents the change rate of GDP with population, which can simply be referred to as the population~GDP scaling efficiency. The higher the scaling exponent, the higher the population~GDP scaling efficiency (i.e., higher GDP generated by the same amount of population). Based on the similarity of the β_s values derived from these cities in this study and those from Germany and the USA (Figure 5K and 5L), we can see that the population~GDP scaling efficiency across these cities had caught up with those in the developed countries in recent years. This suggests that for a given change in population across cities, the GDP difference is similar across these cities in China, Germany, and the USA. However, the absolute GDP differences among countries suggested that the GDP efficiency in these Chinese cities, measured per capita, remains 5 to 10 years behind those of Germany and the USA, as seen from the differences of the intercepts among these countries and the change rate of the intercept over time for Chinese cities.

4.6 Cross-city scaling of wage and population

The cross-city scaling between total wage and population showed a clear transition from linear to superlinear over time and the change from 1978 to 2010 was significant ($p<0.05$) (Figure 4H). The scaling was linear before 1990 when wages were mostly fixed and about the same across cities under the planned economy and total wages were roughly proportional to population. The migration of population from rural to urban, controlled by the *Hukou* (household registration) system, was extremely difficult in China before the implementation of the "Reform and Opening-up" policy in the late 1970s (Chan and Zhang, 1999). The transition from linear to superlinear scaling reflects the gradual loosening of the governmental control on rural to urban and inter-provincial migration (Fan, 1999; Zhang and Song, 2003; Poncet, 2006; Li and Sui, 2013). The 95% confidence bounds of the scaling exponent between wage and population were much narrower than those of GDP versus population, probably suggesting that wages rather than GDP drove the migration of population from rural to urban and across regions. This temporal trajectory of β_s signifies that the "Reform and Opening-up" policy successfully transitioned Chinese cities from a rather tightly controlled uniform wage system to a more market-oriented dynamic one that exhibits increasing returns to scale.

4.7 Cross-city scaling of automobile and population

The scaling relationship between automobiles and population across cities was linear for all time periods (Figure 4I). However, the 95% predictive intervals of the scaling exponent β_s between automobiles and population showed temporal shifts: the interval in 1990 contained the theoretical value of the sublinearity (β_s =5/6) as summarized in Bettencourt (2013) for transportation network volume, but not the theoretical value of superlinearity (β_s =7/6) , and this pattern switched to the opposite since 1995. Therefore, the automobiles versus population scaling across these cities was between linear (automobiles were proportional to city population) and superlinear (the higher the population, the increasingly higher the number of automobiles per capita) since 1995 as the scaling exponents were not significantly different from either 1 (linearity) or 7/6 (superlinearity). Nevertheless, they were significantly different from the theoretical sublinear scaling law (β_s =5/6). This deviation might be caused by several factors including increased income for individuals and unique social psychology on automobile ownership. In China, owning automobiles remains an important symbol of social and economic status that may outweigh the inconvenience and stress resulting from transportation congestion.

4.8 Methodology Considerations

Our study showed fundamental differences in temporal (β_t) and spatial (β_s) scaling for the same urban attributes (Figures 2, 3 and 4). For example, unlike the rather consistent exponent (~7/6) for the scaling between GDP and population across cities at any of the times, the temporal scaling exponent β_t, averaged at 3.92 with large cross-city variability from 1.72 (Shenzhen) to 8.91 (Shenyang), was much higher than its spatial scaling counterpart β_s. The drastic difference between spatial and temporal scaling reflects the fundamental differences in driving forces across time and space. Spatial scaling reflects the consequences of contemporary cross-city scaling (e.g., the magnitude of knowledge spillover or economies of scale) at a given point in time, and does not have the temporal dimension reflecting the continuous innovation of information and technology over time as seen from the temporal scaling. This finding clearly shows that the concept of substituting "space for time" frequently used in ecological research (Pickett, 1989) ought not be applied to study urban dynamics.

Some aspects of our study might have introduced uncertainties. First, our study only included 32 major cities, which is relatively small comparing with the number of cities in China. Our attempt to include more cities in this research was hampered by the challenge of consistently getting city-specific socio-economic data. Future studies should include more cities, especially small to medium ones, as well as trying to understand the ways in which "special purpose" cities conform to or deviate from theory (e.g., Shenzhen). Second, additional sampling points in time would also help reduce the uncertainty in determining the temporal course and spatial details of urban expansion. With the free Landsat data and new computing power, it is possible to map land surface changes annually (Zhu and Woodcock, 2014). Third, in dealing with economic data, we were unable to separate the contributions from rural and urban areas. For future studies, one needs to consider metropolitan areas only as they are the economic functional areas related to the places from where people commute to work (Arcaute et al., 2015).

4.9 Science and Policy Implications

Our results reveal an interconnected, multifaceted picture of the temporal coevolution of urban attributes and the spatial organization of the urbanization processes of 32 major cities from 1978 to 2010. The findings from this study have significant implications for both China's policy and the understanding of urbanization in general. On the one hand, demographic growth was well synchronized with other urban attributes. In fact, the scaling of GDP versus population, an effective indicator of the GDP efficiency with population change, showed that the urban GDP efficiency of these cities might be comparable to those from Germany and the United States, certainly a highlight of Chinese urbanization. This result confirms that the national policy of promoting urbanization to enhance economic growth did hit a high mark from the demographic perspective, at least in these 32 cities.

Urban land expansion is an indispensable process to accommodate demographic expansion and to improve the average living space for urban dwellers. However, the horizontal organization of urban area across these 32 cities in China, judged by its scaling relationship with other urban attributes, is in a state that is significantly different from theoretical predictions (Bettencourt, 2013). For example, cross-city scaling between urban area and population contradicts economies of scale (i.e., cost advantages or increasing savings in infrastructural quantities with increasing population size) and that between wealth creation (e.g., GDP and Wage) and urban area does not conform to increasing returns to scale. Urbanization has been regarded as an effective vehicle ("land finance") to propel economic growth at local to national level in China (Ye and Xie, 2012; Lin et al., 2015). This ideology has resulted in massive urban space expansion and reorganization across cities that apparently has progressively outpaced population growth through time and across cities. China's policy instruments related to land ownership and land-use rights created a positive feedback between urban sprawl and economic growth (i.e., urban land expansion is not only the consequence but also an important driver of economic growth) in recent decades that at least partly explained the complex mechanism of nonlinear, accelerated growth in city size and wealth (Bai et al., 2012; Huang et al., 2015). However, the over-utilization of urban land expansion as an economic growth instrument has led to excessive urban land expansion that has resulted in low socioeconomic efficiency of urban land. Although improving urban land use efficiency has been a national policy (Liu et al., 2014) and studies have discussed the issue of urban land use efficiency (e.g., Cao et al., 2008; Jiang et al., 2013; Liu et al., 2014; Deng et al., 2015), our study was the first at the national level to systematically demonstrate the efficiency or inefficiency of urbanization process and organization across 32 major cities in China in several major dimensions. Another consequence of excessive urban land expansion is the conversion of the arable land resources, threatening food security (Chen, 2007). For example, 74% of the urban expansion in the Beijing-Tianjin-Hebei metropolitan area in the 1990s was at the cost of arable land (Tan et al., 2005). Urbanization can have indirect impacts on agricultural land use as well. Jiang and colleagues (2013) found urban expansion is associated with a decline in agricultural land use intensity in China, and that industrial GDP negatively affects agricultural land use intensity. Their results imply that continued urban expansion is highly likely to push agricultural land expansion, pressuring on the country's natural land resources.

China's urbanization is going to continue to unfold. This presents opportunities to develop new and test old theories of urban scaling and organization. Chinese government announced its new plans in the "National New Type Urbanization Plan" for 2014-2020 to expand its cities to support economic growth by allowing millions more rural residents to migrate to cities. The government still sees domestic demand is the fundamental impetus for China's development, and the greatest potential for expanding domestic demand lies in urbanization (Chan, 2014). Chinese urbanization is entering uncharted waters, and some consequences might not be foreseeable in the short term and, thus, hard to evaluate at present. However, given the importance of limited arable land resources in China to feed its large and growing population and its relatively low per-unit-area socioeconomic efficiency compared to the rest of the world, future efforts should focus on increasing urban socioeconomic efficiencies than continued area expansion, especially in larger cities.

5 Summary

The density distributions of the scaling exponent γ values, depicting the temporal evolution of city attributes, revealed three phenomena: (1) all cities have been expanding in area, population, GDP, total wage, the number of automobiles, and GDP density, signifying wealth accumulation over time; (2) air pollutants have been decreasing in most of the 32 cities; and (3) population density (persons per unit urban area) has been decreasing, implying the living space per capita has been improving, in most cities.

We have found for the first time that the population and urban area co-evolved in these cities with all three types of scaling (i.e., superlinear, linear, and sublinear), resulted from interactions of a myriad of forces including geographic factors, economic growth and development, policy shifts, and institutional changes. Urban areal expansion progressively exceeded population growth in most cities.

The relationship between urban area and total population across cities should be sublinear according to the existing urban scaling theory (Bettencourt, 2013), signifying a population densification process and economies of scale. The cross-city scaling of area and population in our study did not conform to the theory, suggesting that the theory might not be universal and/or the scaling of these Chinese cities might be unique. This study also shows that all area-based cross-city scaling for socioeconomic factors did not conform to the theoretical prediction of economies of scale, suggesting a tremendous waste of land resources in the expansion of these cities. Our area-based scaling revealed important new characteristics of the urbanization processes that could not be obtained using the traditional demographic scaling.

Another significant finding of this study is that the cross-city scaling of GDP versus population changed from linear scaling in the late 1970s to the theoretical superlinear scaling since 2000, signifying the realization of increasing returns to scale over time. This major temporal shift in the scaling pattern tracked the trajectory of China’s social and economic vitality and efficiency resulted from various local to national economic reform policies.

Acknowledgments

We gratefully acknowledge Professor M. Batty and Dr. E. Arcaute for their comments and suggestions on an earlier version of the manuscript. This study was supported by the National key R&D plan of China Grant (2018YFA0606104), the National Natural Science Foundation of China Grants 41590843, 41771093 and 41571079, and, in part, the Geospatial Sciences Center of Excellence at South Dakota State University.

Literature Cited

Alberti M (2015) Eco-evolutionary dynamics in an urbanizing planet. Trends Ecol Evol 30:114-126.
Angel S, Parent J, Civco DL, Blei A, Potere D (2011) The dimensions of global urban expansion: Estimates and projections for all countries, 2000-2050. Prog Plann 75:53-107.
Arcaute E, et al. (2015) Constructing cities, deconstructing scaling laws. J R Soc Interface 12:20140745.
Bagan H, Yamagata Y (2012) Landsat analysis of urban growth: How Tokyo became the world's largest megacity during the last 40 years. Remote Sens Environ 127:210-222.
Bai X, Chen J, Shi P (2012) Landscape Urbanization and Economic Growth in China: Positive Feedbacks and Sustainability Dilemmas. Environ Sci Technol 46:132-139.
Bai X, Shi P, Liu Y (2014) Realizing China's urban dream. Nature 509:158-160.
Batty M (2008) The size, scale, and shape of cities. Science 319:769-771.
Batty M (2013) A theory of city size. Science 340:1418-1419.
Batty M, Longley P (1994) Fractal cities: a geometry of form and function. Academic Press, San Diego, CA, USA.
Bettencourt L (2013) The origins of scaling in cities. Science 340:1438-1441.
Bettencourt L, Lobo J, Helbing D, Kuhnert C, West G (2007) Growth, innovation, scaling, and the pace of life in cities. P Natl Acad Sci USA 104:7301-7306.
Bettencourt L, West G (2010) A unified theory of urban living. Nature 467:912-913.
Bloom DE, Canning D, Fink G (2008) Urbanization and the Wealth of Nations. Science 319: 772-775
Cao G, Feng C, Tao R (2008) Local "land finance" in China's urban expansion: challenges and solutions. China & World Economy 16: 19-30.
Chan KW (2014) China's urbanization 2020: a new blueprint and direction. Eurasian Geogr Econ 55:1–9.
Chan KW, Zhang L (1999) The Hukou system and rural-urban migration in China: Processes and changes. China Quart: 818-855.
Chen J (2007) Rapid urbanization in China: A real challenge to soil protection and food security. Catena 69:1-15.
Cristelli M, Batty M, Pietronero L (2012) There is more than a power law in Zipf. Sci Rep 2: 812.
Deng X, Huang J, Rozelle S, Zhang J, Li Z (2015) Impact of urbanization on cultivated land changes in China. Land Use Policy 45: 1-7.
Eaton J, Eckstein Z (1997) Cities and growth: Theory and evidence from France and Japan. Regional

science and urban Economics 27: 443-474.
Eeckhout J (2004) Gibrat's law for (all) cities. Am Econ Rev 94:1429-1451.
Fan C (1999) Migration in a socialist transitional economy: Heterogeneity, socioeconomic and spatial characteristics of migrants in China and Guangdong province. Int Mig Rev 33:954-987.
Florida R (2005) Cities and the creative class. Routledge.
Huang Q et al. (2015) Detecting the 20 year city-size dynamics in China with a rank clock approach and DMSP/OLS nighttime data. Landscape and Urban Planning 137: 138-148.
Gibrat R (1931) Les inégalités économiques. Recueil Sirey, Paris, France.
Grimm N, et al. (2008) Global change and the ecology of cities. Science 319:756-760.
Jiang B, Jia T (2011) Zipf's law for all the natural cities in the United States: a geospatial perspective. Int J Geogr Inf Sci 25:1269-1281.
Jiang L, Deng X, Seto K (2013) The impact of urban expansion on agricultural land use intensity in China. Land Use Policy 35: 33-39.
Kaye J, Groffman P, Grimm N, Baker L, Pouyat R (2006) A distinct urban biogeochemistry? Trends Ecol Evol 21:192-199.
Kleiber M (1947) Body size and metabolic rate. Physiol Rev 27:511-541.
Leitao J, Miotto J, Gerlach M, Altmann E (2016) Is this scaling nonlinear?. Open Science 3(7): doi.org/10.1098/rsos.150649.
Li S, Sui D (2013) Pareto's law and sample size: a case study of China's urban system 1984-2008. GeoJournal 78: 615-626.
Lin G (2007) Reproducing spaces of Chinese urbanisation: New city-based and land-centred urban transformation. Urban Stud 44:1827-1855.
Lin G, Li X, Yang F, Hu F (2015) Strategizing urbanism in the era of neoliberalization: State power reshuffling, land development and municipal finance in urbanizing China. Urban Stud 52:1962-1982.
Lin G, Yi F (2011) Urbanization of capital or capitalization on urban land? Land development and local public finance in urbanizing China. Urban Geogr 32:50-79.
Liu J, Diamond J (2005) China's environment in a globalizing world. Nature 435:1179-1186.
Liu Y, Fang F, Li Y (2014) Key issues of land use in China and implications for policy making. Land Use Policy 40:6-12.
Lobo J, Bettencourt L, Strumsky D, West G (2013) Urban scaling and the production function for cities. PloS ONE 8: e58407.
Lucas RE (1988) On the mechanics of economic-development. J Monet Econ 22:3-42.
McPhearson T, et al. (2016) Advancing urban ecology toward a science of cities. BioScience 66:198-212.
Pickett S (1989) Space-for-time substitution as an alternative to long-term studies. In: Likens GE, editor. Long-Term Studies in Ecology: Approaches and Alternatives. New York: Springer; pp. 110–135.
Pickett S, Cadenasso M, Grove J (2005) Biocomplexity in coupled natural-human systems: A multidimensional framework. Ecosystems 8:225-232.
Poncet S (2006) Provincial migration dynamics in China: Borders, costs and economic motivations. Reg Sci Urban Econ 36:385-398.
R Development Core Team (2013) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
Ramalho CE, Hobbs RJ (2012) Time for a change: dynamic urban ecology. Trends Ecol Evol 27:179-

188.
Romer PM (1986) Increasing returns and long-run growth. J Polit Econ 94:1002-1037.
Rosenthal SS, Strange WC (2004) Evidence on the nature and sources of agglomeration economies. Handbook of regional and urban economics 4:2119-2171.
Rozenfeld H et al. (2008) Laws of population growth. Proc Natl Acad Sci USA 105:18702-18707.
Schneider A, Friedl M, Potere D (2009) A new map of global urban extent from MODIS satellite data. Environ Res Lett 4: 044003.
Schneider A, Mertes C (2014) Expansion and growth in Chinese cities, 1978-2010. Environ Res Lett 9: 024008.
Segal D (1976) Are there returns to scale in city size? Rev Econ Stat: 339-350.
Seto K, Fragkias M (2005) Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics. Lands Ecol 20: 871-888.
Seto K, Sánchez-Rodríguez R, Fragkias M (2010) The new geography of contemporary urbanization and the environment. Annu Rev Env Resour 35:167-194.
Shepard W (2015) Ghost Cities of China. Zed Books, London.
State Statistical Bureau (SSB) 2015. China Statistical Yearbook. China Statistics Press, Beijing, China.
Strano E, Sood V (2016) Rich and poor cities in Europe. An urban scaling approach to mapping the European economic transition. PLoS ONE 11(8): e0159465. doi:10.1371/journal.pone.015946.
Sveikauskas L (1975) The productivity of cities. Quart J Econ 89:393-413.
Tan M, Li X, Xie H, Lu C (2005) Urban land expansion and arable land loss in China—a case study of Beijing–Tianjin–Hebei region. Land use policy 22:187-196.
United Nations, Department of Economic and Social Affairs, Population Division (2015) World Urbanization Prospects: The 2014 revision. New York, United Nations.
Xu J (2008) Governing city-regions in China: Theoretical issues and perspectives for regional strategic planning. Town Plann Rev 79:157-185.
Ye X, Xie Y (2012) Re-examination of Zipf's law and urban dynamic in China: a regional approach. The Annals of Regional Science 49: 135-156.
Zhang K, Song S (2003) Rural-urban migration and urbanization in China: Evidence from time-series and cross-section analyses. China Econ Rev 14:386-400.
Zhao S, et al. (2006) Ecological consequences of rapid urban expansion: Shanghai, China. Front Ecol Environ 4:341-346.
Zhao S, et al. (2015a) Spatial and temporal dimensions of urban expansion in China. Environ Sci Technol 49: 9600-9609.
Zhao S, et al. (2015b) Rates and patterns of urban expansion in China's 32 major cities over the past three decades. Lands Ecol 30:1541-1559.
Zhao S, Liu S, Zhou D (2016) Prevalent vegetation growth enhancement in urban environment. P Natl Acad Sci USA 113:6313-6318.
Zhou D, Zhao S, Liu S, Zhang L, Zhu C (2014) Surface urban heat island in China's 32 major cities: Spatial patterns and drivers. Remote Sens Environ 152:51-61.
Zhu Z, Woodcock C (2014) Continuous change detection and classification of land cover using all available Landsat data. Remote sens Environ 144:152-171.
Zipf GK (1949) Human behavior and the principle of least effort. Addison Wesley, Cambridge, MA.

Supporting Information

Additional supporting information may be found in the online version of this article at http://onlinelibrary.wiley.com/doi/10.1002/eap.xxxx/suppinfo

Table 1 Temporal scaling or coevolution of paired urban attributes from 1978 to 2010 in individual cities. See text and equation 1 for the explanation of the scaling exponent β_t. The β_t value for each pair of urban attributes in each city was tested to see if it was sublinear (β_t<1), linear (β_t≈1) or superlinear (β_t>1) at α=0.05, and this table presents the summary results of the significance test.

y	x	Total number of cities[1]	β_t		Number of cities		
			Mean	C.V.[2]	Sublinear	Linear	Superlinear
Population	Area	32	0.73	0.39	19	12	1
GDP	Area	31	2.78	0.34	0	0	31
GDP efficiency	Area	31	1.80	0.53	1	14	16
Total wage	Area	31	3.10	0.33	0	0	31
Automobiles	Area	16	2.46	0.38	0	3	13
PM_{10}	Area	26	0.15	0.38	16	9	1
NOx	Area	29	0.89	0.39	3	25	1
SO_2	Area	29	0.74	1.83	8	20	1
GDP	Population	31	3.92	0.33	0	0	31
Total wage	Population	31	4.28	0.25	0	0	31
Automobiles	Population	16	3.38	0.36	0	2	14
PM_{10}	Population	26	0.43	2.03	5	19	2
NO_x	Population	29	1.49	0.49	1	21	7
SO_2	Population	29	1.19	1.18	2	25	2
Total wage	GDP	31	1.13	0.09	1	14	16
Automobiles	GDP	16	0.84	0.15	5	11	0
PM_{10}	GDP	26	0.12	1.58	26	0	0
NO_x	GDP	29	0.36	0.54	28	1	0
SO_2	GDP	29	0.23	0.97	27	2	0

[1]The number of cities was not always 32 was because some cities did not have enough data points for regression analysis; [2]Coefficient of Variation.

Table 2 The 95% confidence intervals of the spatial cross-city scaling coefficient β_s of paired urban attributes for six time periods. The derivation of the scaling exponent β_s was described in the text (see equation 2). Bold values indicate the 95% confidence interval of β_s does not include its theoretical value, therefore they are significantly different at α=0.05. Theoretical values for the exponents are from Bettencourt (2013).

y	1978	1990	1995	2000	2005	2010	Theory
				x=Pop			
Area	[**1.03,2.62**]	[**1.24,2.29**]	[**1.06,2.16**]	[**0.97,2.06**]	[**0.98,1.96**]	[**0.96,1.94**]	2/3
GDP	[0.98,1.36]	[1.06,1.34]	[1.1,1.51]	[1.18,1.48]	[1.15,1.43]	[1.11,1.42]	7/6
Total wage	[**0.98,1.07**]	[**0.97,1.14**]	[1.04,1.27]	[1.12,1.38]	[1.04,1.36]	[1.11,1.33]	7/6
Automobiles	NA	[0.72,1.15]	[0.82,1.31]	[0.91,1.37]	[0.92,1.26]	[0.86,1.27]	
PM_{10}	[1.81,5.43]	[1.19,5.19]	[1.24,2.62]	[1.01,3.29]	[1.14,2.4]	[1.08,2.28]	
NO_x	[2.05,5.45]	[1.57,2.84]	[1.54,2.45]	[1.26,2.35]	[1.29,2.4]	[1.26,2.45]	
SO_2	[1.65,6.4]	[1.56,3.64]	[1.62,3.4]	[1.58,3.5]	[1.19,2.52]	[1.17,3.18]	
				x=Area			
GDP	[**0.37,0.89**]	[**0.46,0.99**]	[**0.6,1.2**]	[**0.81,1.39**]	[**0.81,1.33**]	[**0.79,1.28**]	7/4
Total wage	[**0.31,0.69**]	[**0.42,0.91**]	[**0.45,1.2**]	[**0.6,1.67**]	[**0.64,1.47**]	[**0.59,1.52**]	7/4
Automobiles	NA	[0.34,0.82]	[0.47,1.11]	[0.57,1.32]	[0.6,1.11]	[0.57,1.09]	
PM_{10}	[0.98,1.26]	[0.93,1.34]	[0.96,1.41]	[0.87,1.35]	[1.02,1.27]	[0.99,1.25]	
NO_x	[1.09,1.3]	[1.04,1.39]	[1.15,1.54]	[1.08,1.37]	[1.15,1.43]	[1.09,1.34]	
SO_2	[0.78,1.32]	[0.85,1.96]	[1.05,2.32]	[1.07,2.32]	[0.96,1.54]	[0.95,1.62]	

Figure Captions

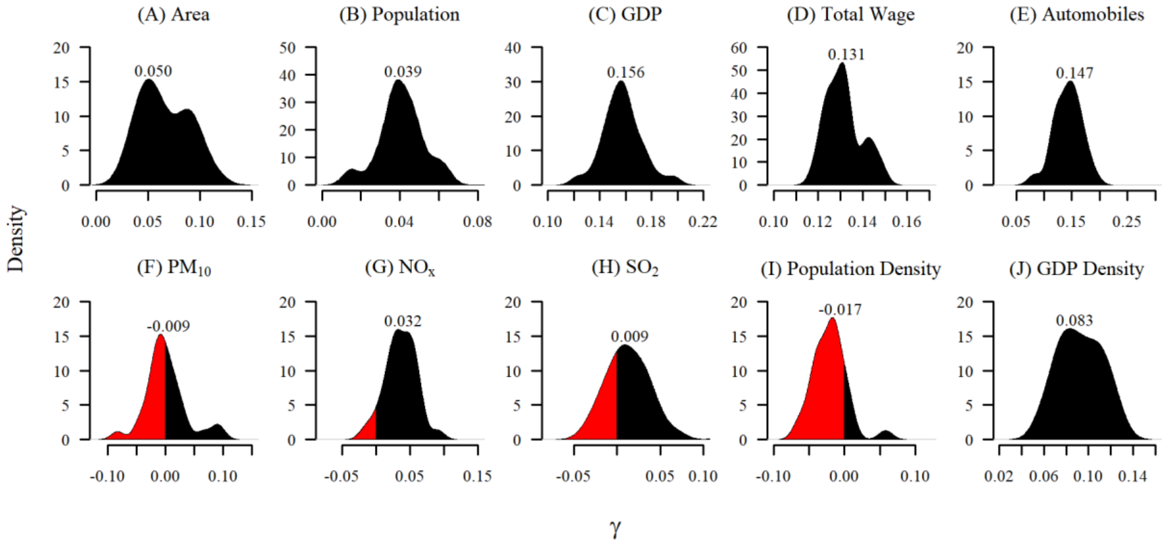
Figure 1 Density function of the exponent γ of the power relationship between an urban attribute y and time t (i.e., $y = at^{\gamma} + b$). The attributes are (A) area, (B) population, (C) GDP, (D) total wage, (E) number of automobiles, (F) PM_{10}, (G) NO_x, (H) SO_2, (I) population density (persons km^{-2} of urban area), and (J) GDP density (RMB km^{-2} of urban area). The value on top of the density curve is the mode. Black and red colors indicate positive and negative exponent, respectively.

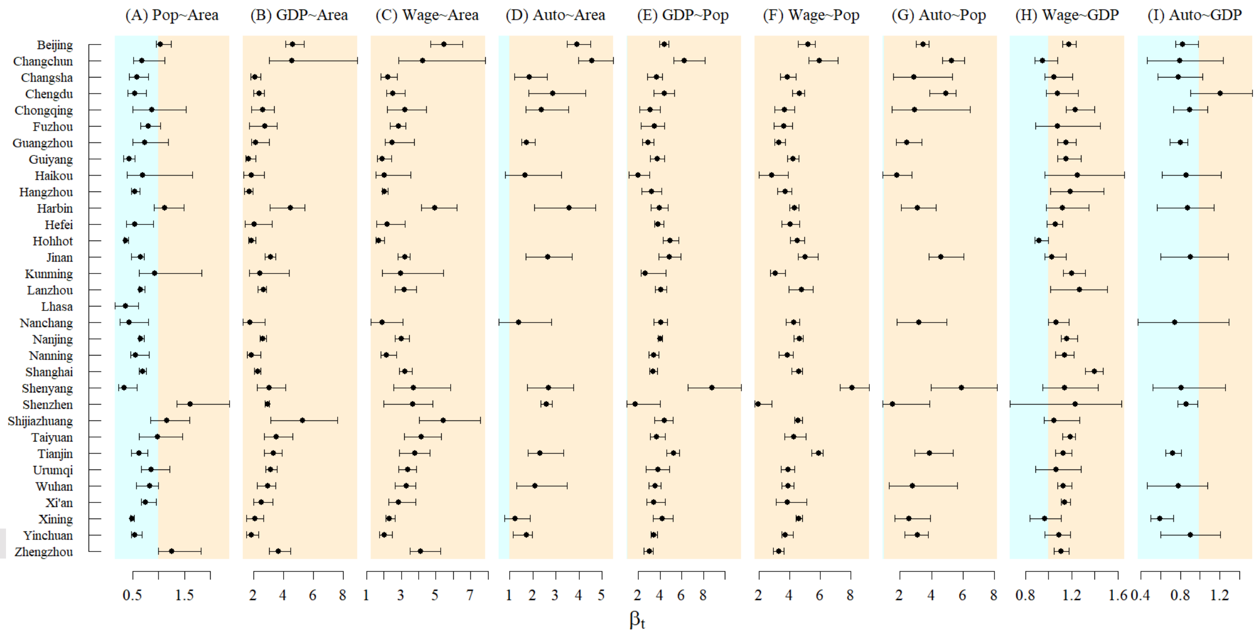
Figure 2 Temporal power scaling exponents (β_t) and their 95% confidence intervals for various urban socio-economic attributes against urban area (A-D), urban population (E-G), and urban GDP (H-I) from 32 major cities in China. The shaded areas in light cyan and tan provide visual references to sublinear (the upper confidence bound of β_t is less than 1) and superlinear (the lower confidence bound of β_t is larger than 1) scaling, respectively. The β_t values were derived from temporal observations of paired attributes in a given city from 1978 to 2010 using bootstrapped orthogonal regression. No values indicate the number of observations was not enough to perform bootstrapped regression.

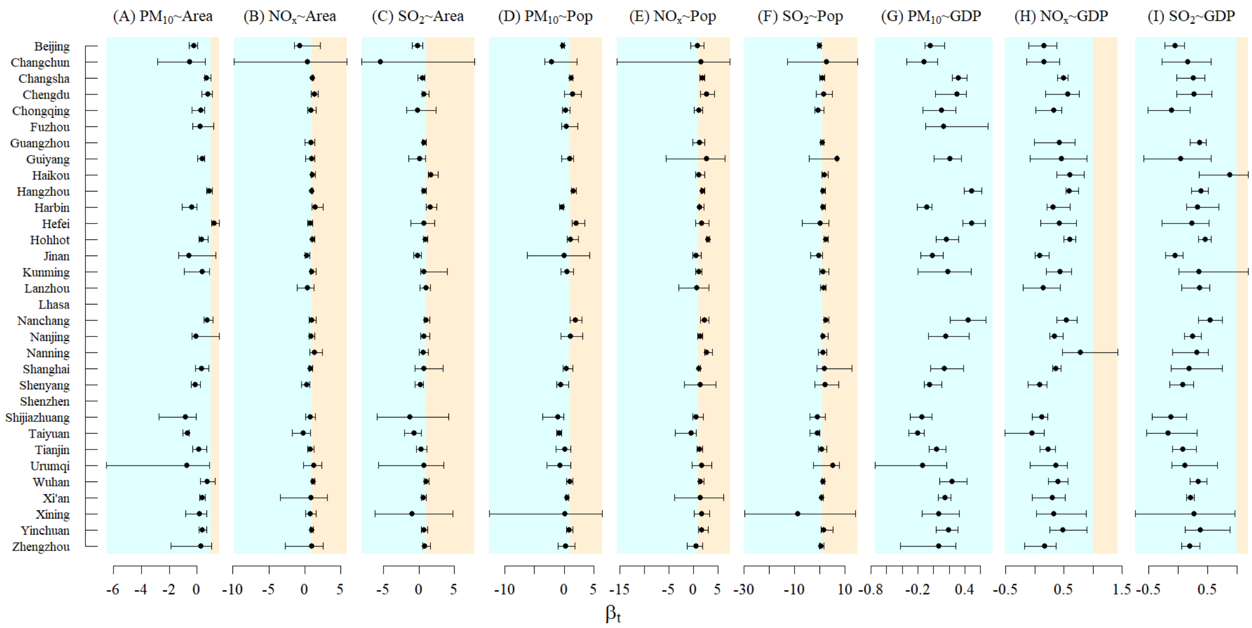
Figure 3 Temporal power scaling exponents (βt) and their 95% confidence intervals for various urban environmental attributes against urban area (A-C), urban population (D-F), and urban GDP (G-I) from 32 major cities in China. The shaded areas in light cyan and tan provide visual references to sublinear (the upper confidence bound of βt is less than 1) and superlinear (the lower confidence bound of βt is larger than 1) scaling, respectively. The βt values were derived from temporal observations of paired indicators in a given city from 1978 to 2010 using bootstrapped orthogonal regression. No values indicate the number of observations was not enough to perform bootstrapped regression.

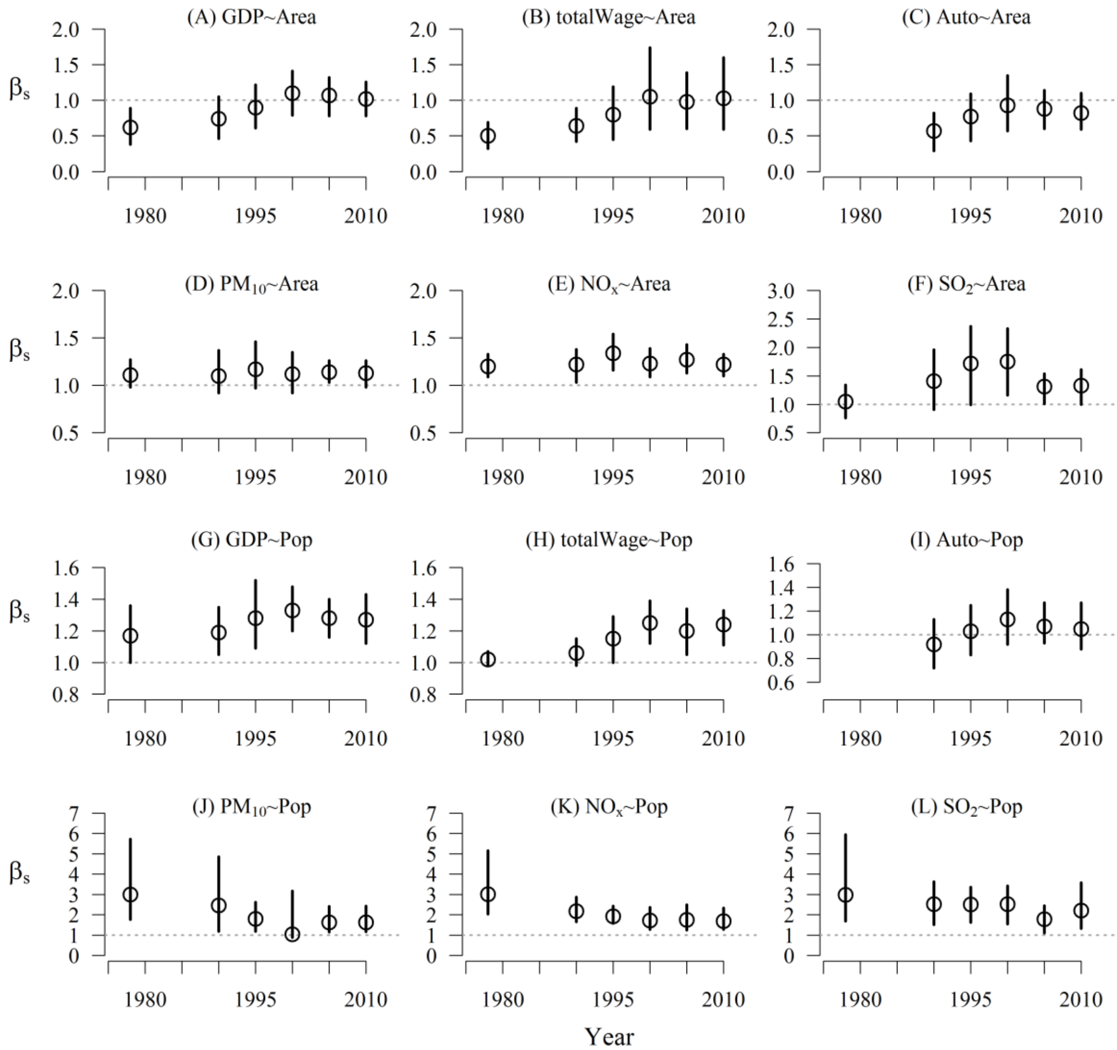
Figure 4 Temporal changes of the cross-city scaling exponent β_s for various attributes versus urban area (panels A-F) and various attributes versus urban population (panels G-L). The β_s values were derived from observations from 32 cities using orthogonal regression. Vertical lines across symbols show the 95% confidence intervals of β_s. The reference line of linear scaling ($\beta_s \approx 1$) is plotted to visualize the difference of superlinear ($\beta_s > 1$) and sublinear scaling ($\beta_s < 1$).

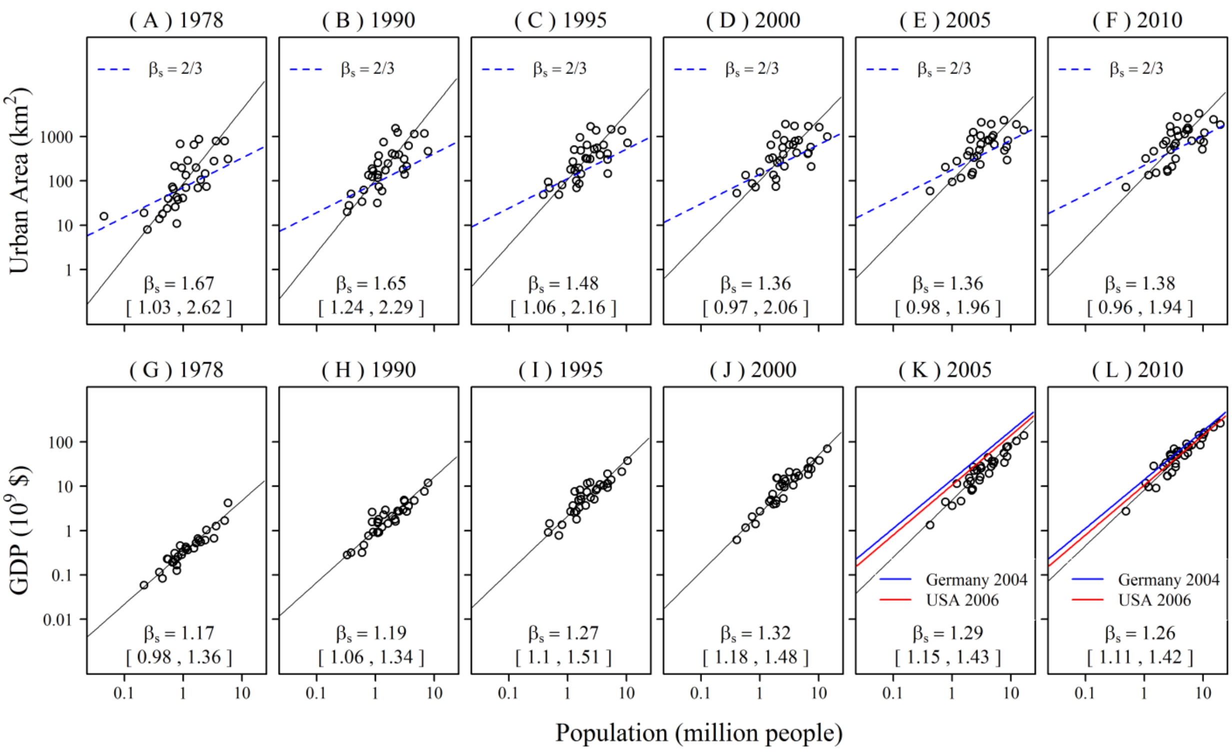
Figure 5 Cross-city power scaling relationships between urban area and population (panels A-F) with the theoretical β_s of 3/2 shown in blue, and urban GDP and population (panels G-L) across 32 major cities in China at different years. Scaling relationships between urban population and GDP for Germany and USA were from Bettencourt (2013). The β_s values were derived from observations from 32 cities using orthogonal regression. Data in the brackets in panels A-L show the predictive intervals of β_s defined by the 2.5th and 97.5th percentiles. The actual number of cities for some years is less than 32 (the total number of cities in this study) as some cities do not have records in these years (e.g., the smallest city Lhasa does not have GDP value in 1978, panel G).


(A) Area
(B) Population
(C) GDP
(D) Total Wage
(E) Automobiles
(F) PM_{10}
(G) NO_x
(H) SO_2
(I) Population Density
(J) GDP Density
Density
γ


(A) Pop~Area
(B) GDP~Area
(C) Wage~Area
(D) Auto~Area
(E) GDP~Pop
(F) Wage~Pop
(G) Auto~Pop
(H) Wage~GDP
(I) Auto~GDP
Beijing
Changchun
Changsha
Chengdu
Chongqing
Fuzhou
Guangzhou
Guiyang
Haikou
Hangzhou
Harbin
Hefei
Hohhot
Jinan
Kunming
Lanzhou
Lhasa
Nanchang
Nanjing
Nanning
Shanghai
Shenyang
Shenzhen
Shijiazhuang
Taiyuan
Tianjin
Urumqi
Wuhan
Xi'an
Xining
Yinchuan
Zhengzhou
β_t


(A) PM10~Area
(B) NOx~Area
(C) SO2~Area
(D) PM10~Pop
(E) NOx~Pop
(F) SO2~Pop
(G) PM10~GDP
(H) NOx~GDP
(I) SO2~GDP
Beijing
Changchun
Changsha
Chengdu
Chongqing
Fuzhou
Guangzhou
Guiyang
Haikou
Hangzhou
Harbin
Hefei
Hohhot
Jinan
Kunming
Lanzhou
Lhasa
Nanchang
Nanjing
Nanning
Shanghai
Shenyang
Shenzhen
Shijiazhuang
Taiyuan
Tianjin
Urumqi
Wuhan
Xi'an
Xining
Yinchuan
Zhengzhou
βt


(A) GDP~Area
(B) totalWage~Area
(C) Auto~Area
(D) PM10~Area
(E) NOx~Area
(F) SO2~Area
(G) GDP~Pop
(H) totalWage~Pop
(I) Auto~Pop
(J) PM10~Pop
(K) NOx~Pop
(L) SO2~Pop
βs
1980
1995
2010
Year



(A) 1978
(B) 1990
(C) 1995
(D) 2000
(E) 2005
(F) 2010
Urban Area (km^2)
β_s = 2/3
β_s = 1.67
[1.03 , 2.62]
β_s = 1.65
[1.24 , 2.29]
β_s = 1.48
[1.06 , 2.16]
β_s = 1.36
[0.97 , 2.06]
β_s = 1.36
[0.98 , 1.96]
β_s = 1.38
[0.96 , 1.94]
(G) 1978
(H) 1990
(I) 1995
(J) 2000
(K) 2005
(L) 2010
GDP (10^9 $)
Germany 2004
USA 2006
β_s = 1.17
[0.98 , 1.36]
β_s = 1.19
[1.06 , 1.34]
β_s = 1.27
[1.1 , 1.51]
β_s = 1.32
[1.18 , 1.48]
β_s = 1.29
[1.15 , 1.43]
β_s = 1.26
[1.11 , 1.42]
Population (million people)