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Dynamic multi-dimensional scaling of 30+ year evolution of Chinese urban systems: patterns and performance

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Abstract

Understanding the co-evolution and organizational dynamics of urban properties (i.e., urban scaling) is the science base for pursuing synergies toward sustainable cities and society. The generalization of urban scaling theory yet requires more studies

from various developmental regimes and across time. Here, we extend the universality proposition by exploring the evolution of longitudinal and transversal scaling of Chinese urban attributes between 1987 and 2018 using a global artificial impervious area (GAIA) remotely sensed dataset, harmonized night light data (NTL), and socioeconomic data, and revealed agreements and disagreements with theories. The superlinear relationship of urban area and population often considered as an indicator of wasting land resources (challenging the universality theory β_c=2/3), is in fact the powerful impetus (capital raising) behind the concurrent superlinear expansion of socio-economic metabolisms (e.g., GDP, total wage) in a rapidly urbanizing country that has not yet reached equilibrium. Similarly, infrastructural variables associated with public services, such as hospitals and educational institutions, exhibited some deviations as well and were scaled linearly. However, the temporal narrowing of spatial deviations, such as the decline in urban land diseconomies of scale and the stabilization of economic output, clearly indicates the Chinese government’s effort in charting urban systems toward balanced and sustainable development across the country. More importantly, the transversal sublinear scaling of areal-based socio-economic variables was inconsistent with the theoretical concept of increasing returns to scale, thus validating the view that a single measurement cannot unravel the intricate web of diverse urban attributes and urbanization. Our dynamic urban scaling analysis across space and through time in China provides new insights into the evolving nexus of urbanization, socioeconomic development, and national policies.

Keywords: urban growth, the evolution of cities, power law, temporal scaling, cross-sectional scaling, urban sustainability

1. Introduction

The Earth has entered a new epoch —the Anthropocene, in which humankind dominates planetary change, and roughly two-thirds of the world's population will be living in cities (United Nations, 2018a). The exponential growth of human activities gives rise to both economic opportunities for improved human well-being, as well as concerns about excessive pressure on natural ecosystems (Bettencourt et al., 2007). The study of complex evolving urban systems requires us to be wary of naively taking a systems approach and dividing the system into independent acting parts (Batty, 2012). Instead, if we consider an urban system as an "organism" that need to understand how subsystems like social networks, natural environment, and economies are interrelated and how their evolving interrelationships head toward a sustainable path (Batty, 2008; Bettencourt et al., 2007). Thus, developing a systematic quantitative framework is necessary to decode the coevolution of diverse attributes and process patterns that differ within cities or across cities (Li et al., 2017; McPhearson et al., 2016).

Considerable progress has been made in exploring whether strong order and a pattern exist under the myriad of complications and entanglements in cities (Batty, 2008; Bettencourt and West, 2010; Bettencourt et al., 2007; Zheng et al., 2019). So far, multiple theoretical attempts at city fractality have been done to understand the hierarchical organizations of cities (Zipf’s law) (Soo, 2005; Zipf, 1949), and proportionate growth of city size (Gibrat’s law) (Gibrat, 1931; González-Val and Sanso-Navarro, 2010). However, the diversity of anthropogenic activities in conjunction with an enormous variety of geographic circumstances and social organizations presents significant obstacles to the universality of some of these laws (Meirelles et al., 2018; Zhao et al., 2018; Zhao et al., 2015). Nevertheless, the power scaling law seems to be a better manifestation of social process, both dynamically and organizationally (Bettencourt, 2015; Bettencourt et al., 2007).

The power scaling law, first proposed by Kleiber to quantify the allometric scaling of metabolic rate with body mass (Kleiber, 1947), can simultaneously scale urban properties and characterize their temporal dynamic paradigm, which has often been adopted in the exploration of urban development (Bettencourt, 2013; Bettencourt et al., 2007). Typically, the population (N) is an accurate determinant of the evolution of other urban attributes (Y) in urban metabolism, following the form $Y=Y_0N^\beta$ (Brelsford et al., 2017; Keuschnigg, 2019; Lobo et al., 2019; Meirelles et al., 2018). The magnitude of the scaling exponent β that reflects the dynamic rules of the urban system can be considered as a determinant of three categories of scaling behavior, with $\beta > 1$ (superlinear), for productivity, creativity, and wealth, $\beta = 1$ (linear), for number of houses, number of jobs, and $\beta < 1$ (sublinear), for infrastructure and services (Bettencourt, 2013; Bettencourt et al., 2007). These scientific propositions have been evaluated and verified by empirical data from the United States of America (USA), Brazil, Europe, and China (Bettencourt, 2015; Bettencourt et al., 2007; Meirelles et al., 2018). Knowledge of the scaling relationship between certain types of social and physical interactions is of great significance in recognizing the characteristics, persistence, and sustainability of cities.

A better understanding of the past and contemporary urbanization opens up new possibilities for power-law scaling research. The apparent simplicity of the previous analysis hinges on the limited socio-economic attributes or in a short time period, which are not always made fully explicit, especially in a developing country like China (Jiao et al., 2020). Theoretically and empirically, scaling exponents are projected to be constant and change slowly over several decades in developed countries (Bettencourt, 2013; Bettencourt, 2020; Bettencourt et al., 2007). Differences and deviations in the universal hypothesis may still exist in rapidly urbanizing countries such as those in China, India, and Brazil (Arcaute et al., 2015; Meirelles et al., 2018; Sahasranaman and Bettencourt, 2019; Zhao et al., 2018). Given the diversity of cities around the world, it is essential to test the universality hypothesis of urban scaling law and reveal a multifaceted picture of urban scaling among different urban systems, concerning more comprehensive and representative urban indicators across space and time (Lei et al., 2021; Meirelles et al., 2018). It was found that the interpretation of the paradigm of urban scaling was insufficient, as the population is not the only measure indicating the urban size, and the inclusion of other measures, like total impervious surface area and night light, enables us to identify comprehensive features and dynamic urban evolution and provide insights for future policymaking in contributing to sustainable development in China or globally (Zhao et al., 2018).

The most astonishing and massive urbanization worldwide is undoubtedly China, where the government has been putting the country on a fast track of modernization and industrialization. However, the unprecedented and complicated development has led to rising pollution levels and widening regional disparities (Xu et al., 2020a). Yet, coordinating and controlling urban development based on carrying capacity and the natural environment while alleviating economic inequality has become an important issue of social concern. Here, we integrated the urban expansion dataset and corresponding socio-economic, environmental, and demographic factors to depict the evolutionary processes of the Chinese urban system from 1987 to 2018. The objectives of our research were to investigate the chronological coevolution of city indicators for each city; examine the longitudinal dynamics of scaling exponent of paired urban attributes from the year 1987 to 2018; evaluate the spatial-temporal patterns of economic output efficiency and land-use efficiency; test the validity of scaling by comparing the coevolutionary scaling parameters with theoretical expectations. Our working hypothesis is that the universality proposition plays out in a developing world like China, and the fitted scaling exponents are projected to be constant over several decades.

2. Materials and methods

2.1 Study area

China is an East Asian country along the coastline of the Pacific Ocean with a complex and diverse geographical distribution across the country. The urban system of China consists of cities and towns, which are classified according to their population size, economic and defense significance. The development and backwardness of cities in different periods fully reflect the prevailing urbanization policies and socio-economic development. So, our research takes the top nearly 300 prefectural-level cities in China as the study objects, covering a wide range of physical, social, economic, and geographical scales. As the most complicated and prominent component in mainland China, the prefectural-level cities are an administrative division of the People’s Republic of China. Prefectural level cities may not meet the usual gold standard for scientific analysis of urban systems (like Metropolitan Statistical Areas (MSAs) in the USA and Larger Urban Units (LUZ) in Europe), but instead, administrative units that were defined according to commuting flows and economic activity, which is in line with the demographic, socio-economic data issued by National Bureau of Statistics (Bettencourt, 2015). Moreover, the consistent scaling relations for urban indicators in the USA, Europe, and China indicate that the definitions of city boundaries in China were appropriate (Bettencourt et al., 2007). All the prefecture-level cities were divided into one of four regions based on recognized socio-economic zones (Eastern China, Western China, Central China, and Northeast China) in order to explore the geographical variations in the coevolution of urban attributes (Figure 1).

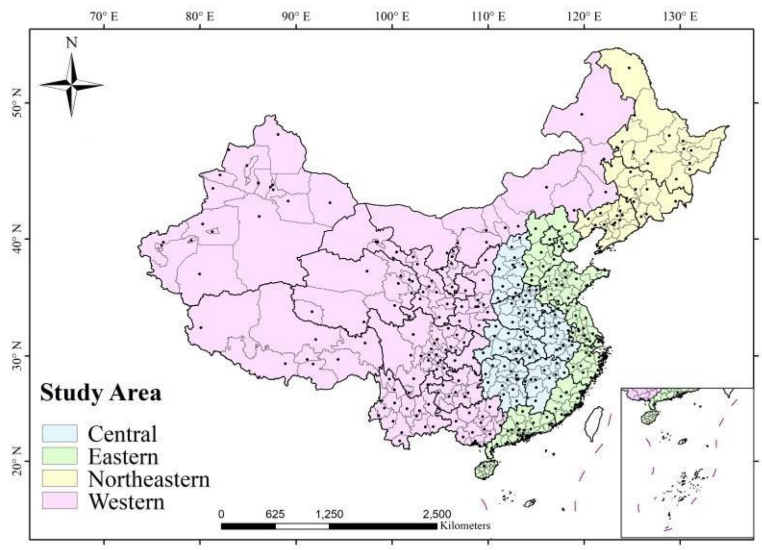

Figure 1: The spatial distribution of the prefecture-level cities in China.

2.2 Data source

Artificial impervious area refers to the artificial structures covered by water-resistant materials such as concrete, brick, and asphalt, chosen as the key indicator of urban area within the administrative unit (Bounoua et al., 2018; Lu and Weng, 2006). The long-term annual global artificial impervious area (GAIA) remotely sensed dataset provides a means for monitoring changes in urban growth for those prefectural-level cities from 1987 to 2018 (http://data.ess.tsinghua.edu.cn/). The dataset showed good performance, with overall accuracy rates exceeding 90% (Gong et al., 2020). The harmonized NTL data for 1992 -2018 was derived from a database by Li et al. (2020, which was generated by integrating the DMSP and VIIRS data and was verified using physical indicators of the sum of NTL (https://doi.org/10.6084/m9.figshare.12312125). Each prefecture-level city's spatial variables (GAIA, NTL) were then summed based on its administrative boundary. It is noteworthy that in our research, we decompose urbanization into population urbanization (population), spatial urbanization (urban area), and social urbanization (NTL) and use area-based and NTL-based scaling in addition to demographic scaling in our study. These alternative measures that exist today can allow for more opportunities to interpret the coevolution of urban areas, NTL with other urban attributes, and thus significantly help urban planning and implementation process toward sustainable development and human well-being.

The demographic and socio-economic variables are mainly collected from the Chinese City Statistical Yearbook or Provincial Statistical Yearbook between 1987 and 2018 (National Bureau of Statistics of China, 1987-2018). These variables included the following for scaling analysis: Population, GDP, Wage, number of High schools, and number of Hospitals. In addition, the emission data were collected from the Emission Database for Global Atmospheric Research (EDGAR), including emissions of nitrogen oxides (NOx) (Salmoral et al.) and particulate matter ($PM_{2.5}$, PM_{10}). The annual emissions have a spatial resolution of 0.1° × 0.1°, covering 1970 to 2012. To explore the nature of horizontal scaling relationships and their temporal evolution for various urban attributes, all of which were divided into three sets of urban characteristics: public infrastructure, economic output, and air pollution. These attributes were chosen with the goal of quantitatively depicting a wide range of urban environments while also taking into account three scaling regimes based on the assumption (Superlinear relates to socio-economic production; Linear associated with individual service variables; Sublinear relates to infrastructural demand). All the demographic, socio-economic, and environmental variables used in our research are summarized in Table S1.

2.3 Urban scaling model

Both the longitudinal scaling within each city and the transversal scaling across cities are analyzed and quantified in our study. The former refers to the coevolutionary trends of paired urban indicators in a given city from 1987-2018, while the latter explores the scaling relationship between various urban properties across cities at different points in time and their temporal evolution from an urban organization perspective. The longitudinal or temporal scaling can better capture the patterns, regimes, and trajectories that involve changes in multiple interwoven dimensions (e.g., area, population, GDP) in a given city. In comparison, transversal or horizontal scaling reflects the relative development of individual urban sectors in a country that could not be obtained using temporal scaling. The combination of these two scaling models can better depict urbanization in China, individually and as a whole, from 1987 to 2018.

2.3.1 Longitudinal scaling within each city

In this study, the coevolution of paired attributes in the single urban system can be well described by the following power-law equation model (Bettencourt, 2013; Bettencourt et al., 2007):

$$Y_t = \alpha_t X_t{}^{\beta_t} e^{x(t)} \tag{1}$$

Where Y_t and X_t represent the two-urban metrics of a given city, respectively, the former indicates some urban attributes (for example, GDP, Wage), and the latter represents the city size (for instance, population, urban area, and NTL). The parameters α_t and β_t are the intercepts and scaling exponent in Equation (1), determined by the power law's fit using orthogonal regression. x(t) is the error term. Instead of only considering the errors in the y direction, orthogonal regression (ORTH) as an alternative approach takes the error of the independent variable and dependent variable into account simultaneously in the model. Furthermore, the dependent and the independent variables in the coevolutionary relationship need to be interconverted (e.g., urban area, population, and NTL) due to the inability to determine if the attribute is x or y (Zhao et al., 2018). We, therefore, choose the ORTH procedure to estimate the nature of scaling effects or agglomeration effects.

Empirical studies showed three types of exponent values (β_t) of urban indicators for a given city and distinct scaling characteristics (Sahasranaman and Bettencourt, 2018; Zhao et al., 2018). The upper and lower tail (2.5 - 97.5) of the 95% confidence interval (CI) for the β_t are computed so as to decide which types it belongs to. (1) Sublinear: the upper limit of 95% CI is below or lower than 1; (2) Superlinear: the lower limit of 95% CI is above or higher than 1; (3) Linear: the threshold 1 falls within the CI.

2.3.2 Transversal scaling across cities

The cross-sectional scaling of a set of cities obeys the power scaling laws in every time period (Bettencourt, 2013; Bettencourt et al., 2007), and it can be repeated to investigate the time dependence of the coefficients. Here, we examined it in

Chinese prefectural-level cities:

$$Y_c = \alpha_c X_c^{\beta_c} e^{\xi(t)} \quad (2)$$

Where X_c and Y_c are urban attributes from all the cities in the system corresponding to a specific year, the parameters α_c and β_c are used to distinguish the intercept and scaling exponent of the temporal scaling and differentiate the scaling type mentioned in the temporal scaling of city indicators in each city. The power scaling relationship between various urban attributes is simple and can be compared conveniently with previous results, which is also why we choose the power scaling law instead of direct comparison. To test the correlation between the paired exponents β (relationship between urban variables with city size), Pearson's correlation coefficient was performed using R 3.6.1(R Core Team, 2019) and the RStudio Integrated Development Environment (Tam, 2019), with p-values <0.001 being statistically significant. We did not measure the degree of responsiveness of GDP or any other economic indicators to changes in the general price levels (inflation rate), mainly because the trend in urban attributes was probably our significant focus rather than the numerical values. Moreover, all types of fitting exponent did not take inflation into account, such bias was expected and therefore did not affect the outcome of the comparison theoretically.

$\xi(t)$ is the deviation from the average for an individual city, also referred to as Scale-Adjusted Metropolitan Indicators (SAMIs) (Bettencourt et al., 2010), and can be used to evaluate the economic performance and land-use efficiency of similar-sized cities. We used the analogous procedures in the temporal scaling case by calculating the confidence intervals. The residuals of the scaling relations are as follows:

$$\xi_i(t) = logY_i - \log(\alpha_c X_i^{\beta_c}) \tag{3}$$

Note that Y_i is the value of the urban indicator for city i; $\alpha_c X_i^{\beta_c}$ is the estimated value of the urban indicator for the city i; X_i represents the size of each city based on an urban area, population, and NTL; α_c and β_c are the fitting parameter of Equation (2). SAMI is an indicator to observe the performance of a city relative to others in the whole urban system. This index is dimensionless and eliminates the agglomeration effects so that different cities within the system can be compared directly.

2.4 Spatial heterogeneity

The Getis-OrdGi* spatial statistical method, also known as hotspot analysis, allows for visualization of spatial distributions (clustering) and the manifestation of the degree of spatial dependency based on location and values simultaneously (Getis, 1992). Thus, we used the Getis-OrdGi* statistic based on SAMIs to detect the spatial distribution of economic output and land-use efficiency across the nation, and identify hotspot/cold spot of spatial aggregation, respectively, based on ArcGIS10.5, whereby:

$$Gi^* = \frac{\sum_{j=1}^{n} W_{i,j}x_j - \bar{X}\sum_{j=1}^{n} W_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} W_{i,j}^2 - \left(\sum_{j=1}^{n} W_{i,j}\right)^2}{n-1}}} \tag{4}$$

$$\bar{X} = \frac{\sum_{j=1}^{n} x_i}{n} \tag{5}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} + \bar{X}^2} \quad (6)$$

Where n is the total number of pixels, x_j illustrates the attribute value related to feature j, $w_{i,j}$ means the spatial weight matrix, d is the distance between i and j location.

The degree of agglomeration, as well as its significance, are assessed using confidence levels and Z-scores. A larger Z-score indicates the high concentration of high values (hot spot), which suggested that the economic output or land-use efficiency of the city and its nonboring is relatively high; conversely, a smaller Z-score indicates a denser concentration of low values (cold spot).

3. Results

3.1 Temporal evolution of urban indicators

Nationally, the scaling exponent γ of almost all urban attributes forms a unimodal distribution with slight differences, except for hospitals (Figure 2A). The economic outputs of cities, like gross domestic product (GDP), wage and its derivatives (GDP density, and GDP per capita), has been expanding throughout this period, with median exponent γ of 0.141, 0.135, 0.088, and 0.130, respectively, marking the accumulation of wealth, and the same goes for the urban area (positive exponents γ). Air pollution ($PM_{2.5}$, PM_{10}, NO_x), was getting worse in most cities in China, as evidenced by the relatively abundant positive exponents γ (median values for exponent γ were 0.017, 0.016, 0.05 for $PM_{2.5}$, PM_{10}, NO_x, respectively). The three socio-economic indicators, nighttime light (NTL), GDP density, and GDP were probably the most volatile variables with respect to time because of their widest range of exponents at 0.176, 0.113, and 0.107, respectively (Table S2).

Across different geographic regions in China, substantial divergences were also observed. It should be noted that the density distribution of wage and GDP in the northeast was distinctly different from the other three regions (Figure 2B), with the lowest average exponent at 0.097 and 0.125, respectively. By contrast, the comparable figures were the highest in east China, 0.145 and 0.141, respectively (Table S3). The results also demonstrated that the urban indicators in the western regions were more dispersed or volatile than those in the eastern, northeastern, and central regions in China, except for wages (Table S3). The mean value of the estimated γ of urban area ranked first in western China (0.061), followed by the eastern (0.056), the central (0.051), and northeast regions (0.044). However, the analysis showed that urban areas exhibited the lowest variability in northeast China.

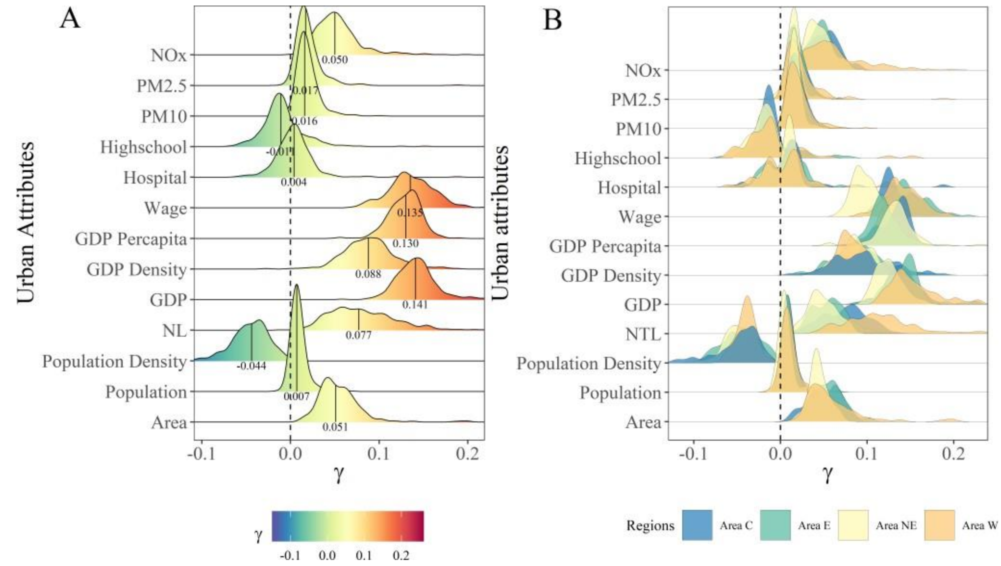

Figure 2. The distribution of the estimated exponent coefficient γ of the power-law relations between urban characteristics and time in China (A), and in four regions of China (B) ("C" for central, "E" for Eastern, "NE" for the northeast, and "W" for western)(i.e.,$y = at^{\gamma} + b$). Urban characteristics include area (km^2), population (person), gross domestic product (GDP), wage (RMB), number of high schools, number of hospitals, particulate matter 10 micrometers or less in diameter (PM_{10}), particulate matter 2.5 micrometers or less in diameter ($PM_{2.5}$), nitrogen oxides (NOx), nightlight (NTL), population density (population per square kilometer of urban area), GDP density (RMB per square kilometer of urban area), and GDP per capita (RMB per population). The solid black line indicates the median value of the exponent coefficient γ for various urban attributes. The black dashed line represents the boundary line between positive and negative changes of urban characteristics in time.

3.2 Scaling of paired urban attributes

Population growth in all but three cities increasingly lagged behind its area expansion (Figure 3A), and the remaining three grew proportionally to the urban land with the exponent $\beta \approx 1$ (Table 1). Specifically, Shenzhen appeared to be an exceptional city for urban area expansion as it matched population growth, with the 95% confidence bounds for the β_t being [0.9,1.39]. The same scaling pattern has emerged in Urumqi and Xining, where their scaling exponent ranged from 0.65 to 1.57 and 0.88 to 1.64, respectively. Urban GDP expanded superlinearly with the urban population growth in every city from 1987 to 2018 since scaling exponents were larger than 1 for all cities (Figure 3B). Similar to GDP, NTL in most parts of China increasingly outpaced the growth in population, with only Shenzhen and Dongguan showing a sublinear scaling and linear scaling relationship, respectively (confidence limits being [0.17,0.3], [0.85,2.34]) (Figure 3C). The total wage as a function of the population size was superlinear in each city, signifying that the total wage increased faster than population growth (Figure 3D). In the case of air pollution indicators (PM_{10}, NO_x), all cities showed superlinear scaling (Figure 3E, 3F) except Xining, which demonstrated linear scaling.

The increase in GDP and total wage progressively exceeded its urban area expansion in almost all cities (273 of 274 cities and 282 of 283 cities, respectively) (Table 1), leading to a superlinear scaling appearing in socio-economic metrics relative to the urban area horizontally (Figure 3G, 3H). The relations between infrastructure attributes (number of high schools and hospitals) and the urban area showed a sublinear regime in most cities (Figure S1D, S1E). Of the 343 cities with PM_{10} records, 7 and 36 cities presented sublinear and linear scaling between PM_{10} and urban areas, respectively. Likewise, 262 cities, or 76.6% of all cities, followed superlinear scaling relations between $PM_{2.5}$ and urban areas (Table 1).

When comparing the average fitting coefficients of different regions, it is revealed that the superlinear scaling for population verses area and population verses GDP in the northeast (β_{NE} is 11.19 and 28.53, respectively) was relatively prominent, indicating a larger gap in the growth rates of area and GDP relative to population in northeast China. The highest average scaling exponent between population and NOx also showed a comparatively rapid rate of air deterioration in this region. Western China and central China ranked first when using the urban area as the independent variable to scale GDP and Wage (β_w=3.41, β_c=3.19). For cities in eastern China, the average scaling exponent of PM_{10} and NO_x with respect to the urban area was the lowest, followed by the northeast regions and central regions.

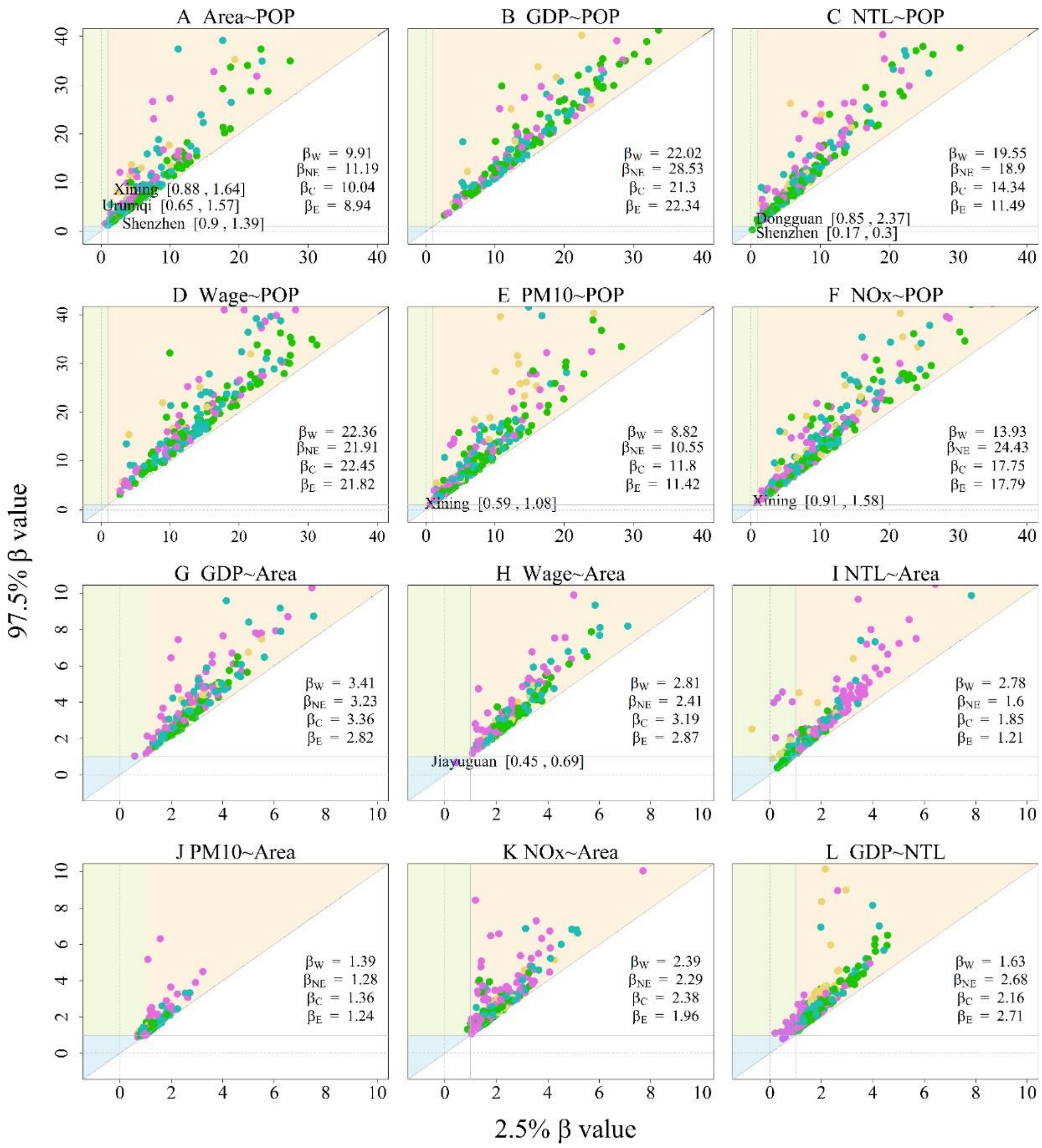

Figure 3. The temporal scaling exponent (β_t) and 95% CI (2.5% and 97.5% percentiles) for paired city indicators with an urban area, population, and nighttime light as independent variables in Chinese cities. The three distinct background colors represented three scaling regimes: pale orange for the superlinear regime, light green for the linear regime, and light blue for the sublinear regime. The gray vertical and horizontal lines separate the sublinear (the upper CI of β_t <1) from superlinear regime (the bottom CI of β_t>1). The colors of dots

represented four regions in China: green for the Eastern, blue for the Central, purple for the Western, and yellow for the Northeast regions. The β values shown in the text are the average value of all cities in each region. The values of β_t and its 95% confidence range emanated from the coevolution of two indicators in a specific city from 1987 to 2018 using orthogonal regressions.

Table 1. The temporal scaling of the coevolution of two urban indicators within each city from 1987 to 2018.

y	x	Total number of cities	Sublinear	Linear	Superlinear
GDP	Area	274	0	1	273
NTL	Area	344	31	69	244
Total wage	Area	283	1	0	282
High school	Area	280	248	30	2
Hospital	Area	287	244	38	5
PM_{10}	Area	343	7	36	300
$PM_{2.5}$	Area	342	10	70	262
NO_x	Area	343	0	1	342
Area	POP	234	0	3	231
GDP	POP	235	0	0	235
NL	POP	247	1	1	245
Total wage	POP	243	0	0	243
High school	POP	254	204	25	25
Hospital	POP	243	95	89	59
PM_{10}	POP	254	0	1	253
$PM_{2.5}$	POP	254	0	2	252
NO_x	POP	254	0	1	253
GDP	NL	288	2	28	258

3.3 Temporal change of the transversal scaling across cities

Transversal scaling relationships of urban attributes and their temporal dynamics are pivotal to capture the multifaceted nature of urbanization. From 1987 to 2018, the area displayed superlinear scaling with a population in the Chinese urban system (Figure 4H), demonstrating that the pace of urban area growth outpaced the speed of population growth. The strong positive correlation between the scaling exponent of GDP and wage ($r=0.87$, $p<0.001$) suggested a tight coevolutionary relationship between these two urban attributes (Figure 5). The coevolution of GDP and total wage with urban area did exhibit similar trends in the urban system, i.e., a sublinear relationship, but with a decreasing degree of sublinearity, as evidenced by the increasing β for GDP since 2011 (from 0.77 to 0.89) and increasing β for total wage since 2004 (from 0.68 to 0.88) (Figure 4A, 4C). Conversely, the scaling exponent of economic output elements with population shifted from linear to superlinear, in which the 95% CIs of the GDP and wages ranges from [0.94, 1.27] and [0.81,1.2] in 1987 to [1.24,1.66] and [1.29,1.85] in 2018 (Figure 4I, 4K). As for the hospital and high school variables, the scaling relation with the area was sublinear from 2000 to 2018 and from 1997 to 2018, respectively (Figure 4F, 4G), suggesting that the rate of these social infrastructures increased much slower than the expansion rate of urban areas. Using population as the independent variable, the infrastructure attributes showed sublinear or linear patterns during the study period. For example, the number of high schools grew more slowly than the population growth from 1997 to 2018, with the 95% CI for the exponent being [0.92, 0.98] and [0.93,1], respectively (Figure 4N).

Similarly, the scaling relationship between hospital and population remained linear since 2000 until it skewed to sublinear in 2003 (Figure 4O).

The fact that emissions of particulate pollutants ($PM_{2.5}$, PM_{10}) scaled superlinearly with population and area over the period (Figure 4D, 4E, 4L, 4M). It was noteworthy that changes in GDP may strongly predict changes in NOx, $PM_{2.5,}$ and PM_{10}, as evidenced by the high correlation coefficients of $\beta_{POP\text{-}GDP}$ and $\beta_{POP\text{-}NOx}$ ($r=0.890$, $p<0.001$), $\beta_{POP\text{-}GDP}$ and $\beta_{POP\text{-}PM2.5}$ ($r=0.819$, $p<0.001$), $\beta_{POP\text{-}GDP}$ and $\beta_{POP\text{-}PM10}$ ($r=0.823$, $p<0.001$) (Figure 5). Thus, it seems that the degree of environmental degradation has progressively outpaced the speed of city development, that is, the larger the area or, the denser the population, the more serious the environmental pollution and the greater the harm caused by the city. The scaling of GDP with NTL transitioned from linear (1992-1993) to superlinear (since 1993), with a temporal trend that remained primarily stable until 2013, followed by a fairly steep rise in the last five years (from 1.27 in 2013 to 1.73 in 2014) (Figure 4P).

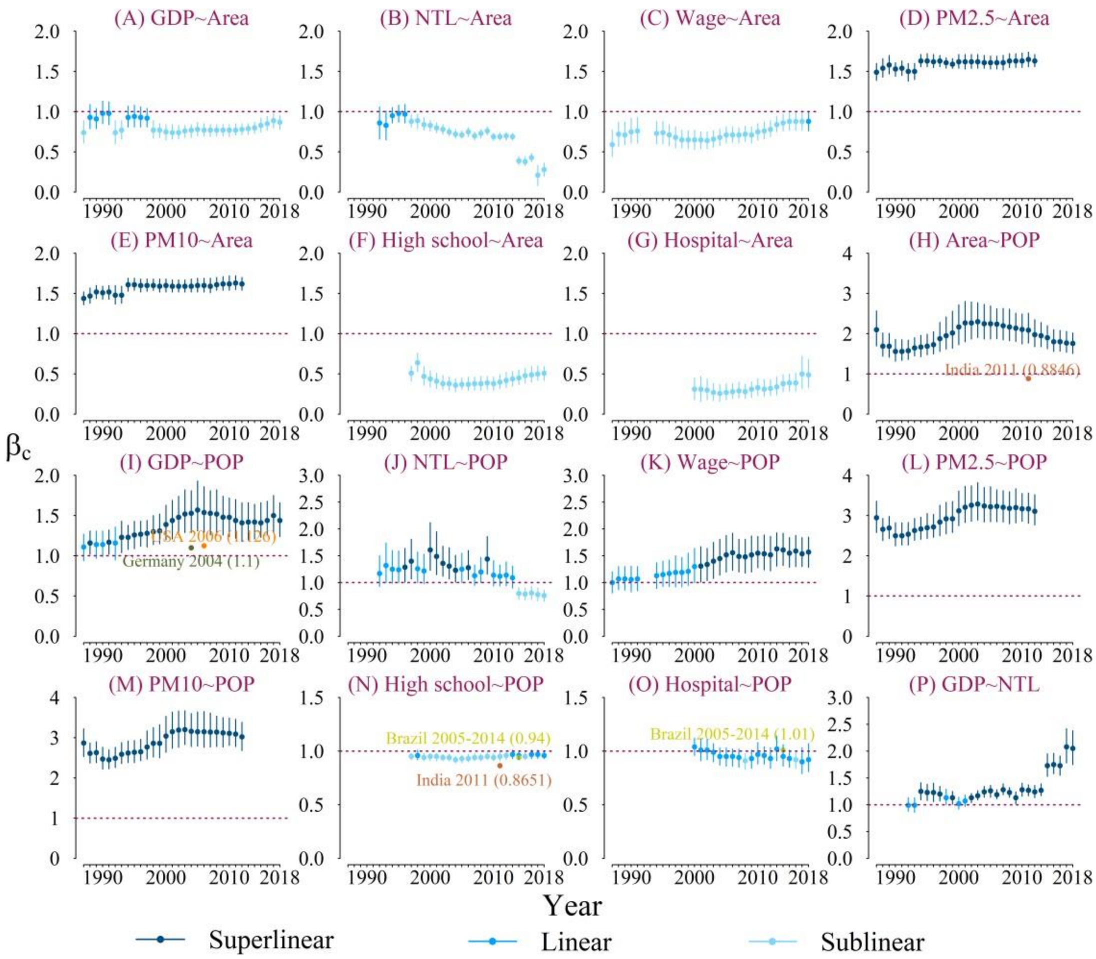

Figure 4. Temporal variations of transversal scaling exponent(β_c) with 95% confidence intervals for various urban attributes against the urban area, population, and nighttime light from 1987 to 2018. The β_c coefficients were derived from observations of all cities using orthogonal regression. The purple horizontal line (β_c=1) was plotted as a guide to distinguish between sublinear (β_c<1) and superlinear (β_c>1). The colors represent the diverse scaling regime: dark blue—superlinear scaling regime; blue—linear scaling regime; light blue—sublinear scaling regime.

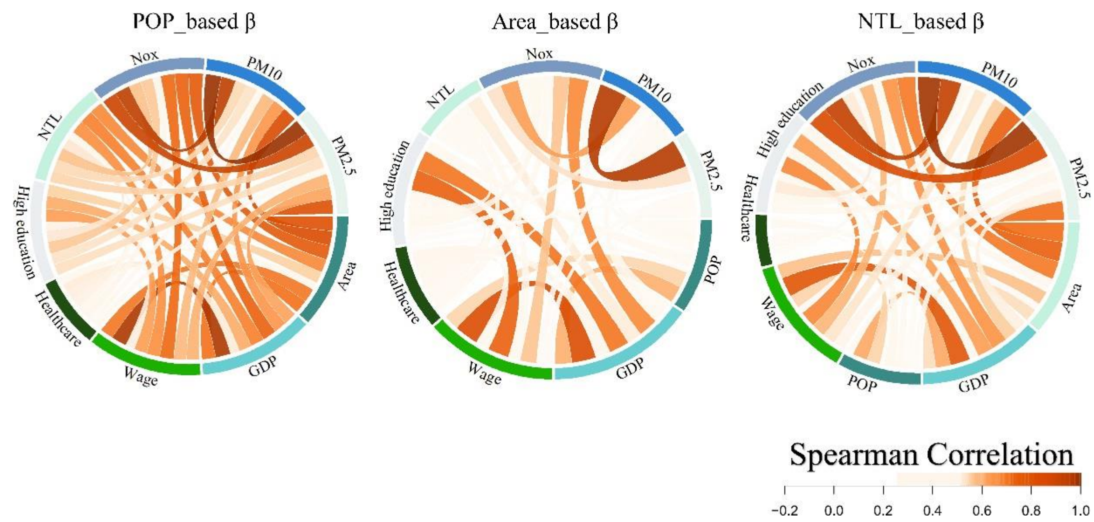

Figure 5. The correlation matrix for Area_based exponents, PoP_based exponents, and NTL_based exponents, respectively (P<0.01). The yellow and white colors correspond to positive and negative correlations, respectively.

3.4 Assessment of economic output and land-use efficiency

To assess the spatial-temporal dynamics of economic output efficiency and land-use efficiency specific to a given city, scale-adjusted metropolitan indicators (SAMI) were used to directly compare cities using city-level indicators instead of per capita indicators. Results from our study present substantial spatial variations in SAMI of Area or NTL and GDP, but with slight variations over time. Notably, southern coastal cities appeared reasonably good for their economic output given their greater GDP than cities of the same magnitude (Area, NTL), even though that advantage did not appear until 2010 and after (Figure 6). Concerning SAMI Area-GDP, the degree of deviation decreased from southwest to northeast, cities located in southwest China exhibited a substantial positive deviation from scaling for GDP in 2010 and 2018, which means that southern regions are more conducive to economic growth even within the same urban area. similarly, the same pattern occurred in SAMI NTL-GDP in 2010 (Figure 6). In addition, the hot spot area of Area-GDP, and NTL-GDP expanded from 2000 to 2018 but with different temporal variation characteristics. For instance, Area-GDP SAMIs, the cities with high SAMI of the area were mainly located in southwest regions consistently, while the hot spot areas in NTL-GDP SAMIs were shifted from the south to the southeast coastal region. In terms of POP-Area, there was a significant positive deviation from expectation in sparsely populated areas such as northeast and Xinjiang province (Figure 6G); that is to say, these cities occupied more area than cities with the same population in the above regions. On the contrary, cities in areas with limited land resources, such as Yunnan-Guizhou Plateau occupied less area than other regions with the same population size.

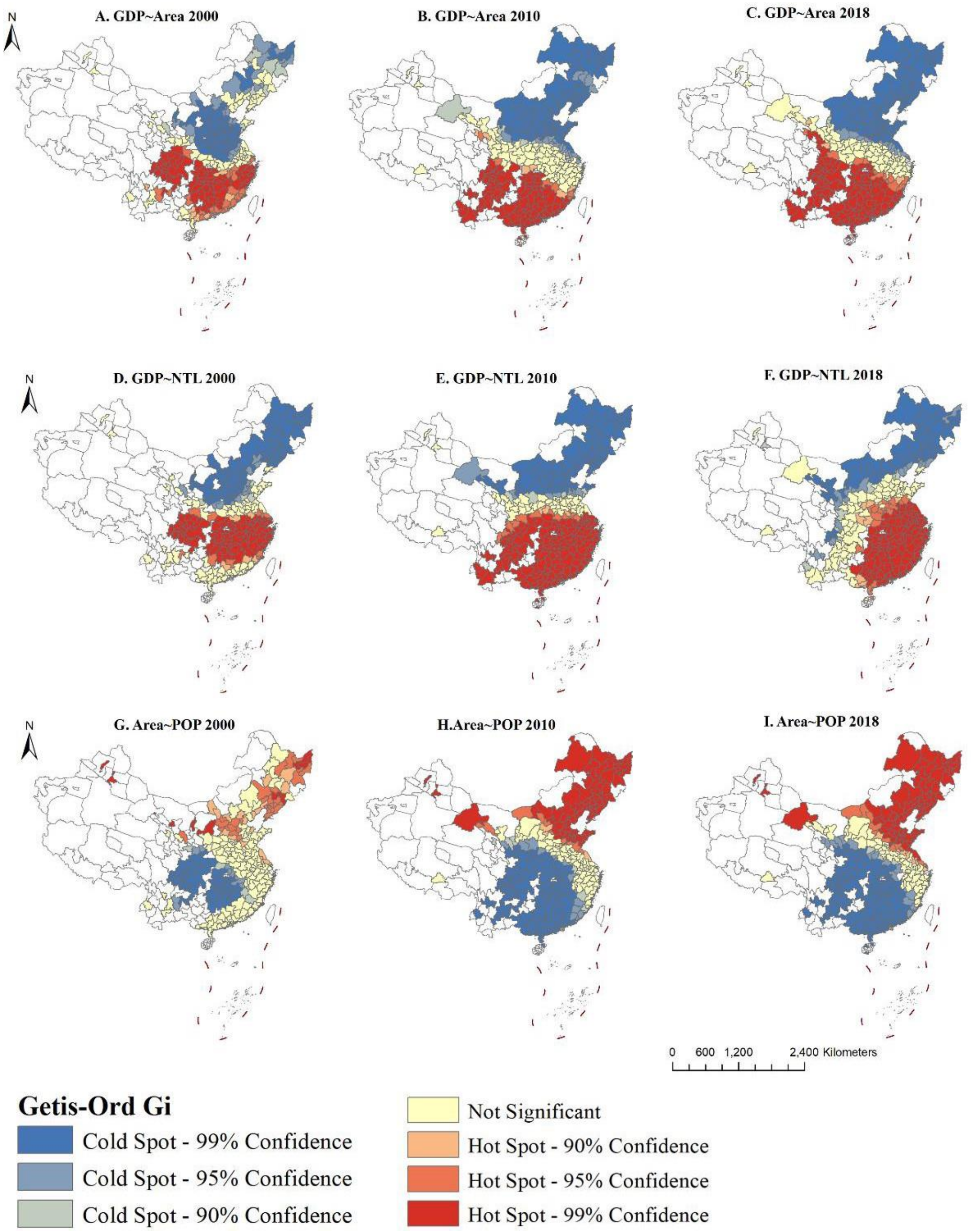

Figure 6. Hotspot analysis of SAMI GDP~Area, SAMI GDP~NTL and SAMI Area~POP in 2000, 2010, and 2018, respectively. Hot spot and cold spot represent the areas of high occurrence and areas of low occurrence, respectively; 90%, 95%, and 99% mean the significant level at 90%, 95%, and 99%, respectively.

4. Discussion

4.1 Hits and misses of the universality proposition

According to the urban scaling law on economies of scale (Bettencourt, 2013), the transversal scaling of urban area and population should fall into the sublinear regime with $\beta_c = 2/3$ (Bettencourt, 2013; Bettencourt et al., 2007; Sahasranaman and Bettencourt, 2018). However, the analyzed scaling exponent β_c for urban area verses population in our study varies from 1.56 to 2.25 throughout the period (Figure 4), generally suggesting diseconomies of scale in China. The prevailing view holds that land plays a marginal role in socioeconomic development (i.e., western economic growth theories). Our unexpected result may indicate the opposite in China, possibly because China's dramatic urban expansion is government-led and driven by a variety of complex and intercorrelated factors (i.e., the influx of rural population, industrial restructuring, advancement of transport) rather than market forces alone, as in the USA (Tian et al., 2017). Admittedly, China's pioneering use of land expansion as one of the major driving forces for socio-economic development has created "growth miracles" in human history (Zhao et al., 2015). The state power reshuffling, urban land development, and municipal financing have all become intertwined and mutually reinforced to promote growth and transformation (Lin et al., 2014). But counterintuitively, this land-centered mechanism implies a massive waste of land resources in China and poses enormous challenges for humanity in the coming decades, including greenhouse emissions (Hankey and Marshall, 2010), fragmentation of landscape (Irwin and Bockstael, 2007), and exacerbating the risk of food security (Chen et al., 2020), failing to make cities inclusive, safe, resilient and sustainable (United Nations' Sustainable Development Goal 11). One encouraging signal from the temporal evolution of the β_c for urban area verses population is the decline in the degree of superlinearity since 2005 (Figure 4), indicating Chinese government's effort in charting sustainable urban development across the country.

Similarly, infrastructure variables associated with public services, such as hospitals and educational institutions, exhibit some deviations as well. Variables related to education (i.e., number of high schools) scaled sublinearly, as expected, but this pattern has shifted in a way that contradicts theory since 2013. By contrast, variables related to health facilities (i.e., number of hospitals) differ from the theoretical sublinear regimes proposed by Bettencourt (Bettencourt et al., 2007) and are scaled linearly almost all the time. The same pattern was also found in Brazilian urban system, with a scaling exponent of 1.01 from 2005 to 2014 (Meirelles et al., 2018). Probably, these deviations related to infrastructural variables that can reach everyone in a city or be decided by the local government are determined by social network features and spatial limits (Bettencourt, 2013). As for developing countries like China and Brazil, top-down national investments or policies may cause infrastructure indicators to depart from the sublinear regime since the central government cannot get involved in all municipal infrastructure projects. In this instance, a centralized decision might reflect itself in linear scaling relations or in a sublinear relationship resulting from interactions at the local level.

Urban expansion scaled superlinearly with population growth in individual cities over the past three decades (Figure 3) with scaling exponents (9.94) on average much higher than its cross-sectional counterpart (1.56-2.3). The large difference between the spatial and temporal scaling exponents demonstrates unequivocally that individual temporal dynamics do not collapse in the universal curve of urban systems (Keuschnigg, 2019). This finding casts doubt on the "space for time" concept in the study of urban evolution and organization and calls for more longitudinal studies. In addition, the much higher superlinearity found in individual cities suggests the diseconomies of scale were more pronounced longitudinally than laterally. In other words, the waste of land resources, examined from cross-city analysis at a given point in time, was not as severe as that during the urban expansion of individual cities. From another perspective, most Chinese cities currently rely heavily on revenue from land sales or leasing for urban development.

4.2 Paradigm shift to dynamic scaling of urban properties

Intrinsic social and economic dimensions of Chinese cities, scaled superlinearly (β>1) and agreed well in principle with the existing proposition (Bettencourt, 2013), signifying increasing returns with city size. In light of knowledge spillover, the superlinear scaling exponent for GDP and wage can be elucidated as a consequence of social interactions among individuals in relatively congested metropolitan areas (Keuschnigg et al., 2019). Alternatively, it can be interpreted as a result of increased productivity and advance of innovation due to the coexistence of increased overall diversity and a broad spectrum of expertise that accompany the expansion of city (Bettencourt et al., 2014). However, the magnitude and temporal dynamics of β_c are fascinating and beyond theoretical expectations, which were intimately related to social and economic vitality stimulated by Chinese and local development strategies and policies. For example, the scaling exponent of population-GDP was significantly larger than 7/6 since 1995 after being in line with theoretical value (7/6) from 1987 to 1990 (Figure 7). The approximately linear correlation in the early period reflected the stagnation and stability of the economy and the ineffectiveness of the centrally planned economy in propelling the economy (Kuang et al., 2016). The market-oriented mechanism, accompanied by fiscal centralization policy and tax reform, has proved to be a powerful means that allow economic growth to exceed the pace of demographic development (Lu et al., 2019). Globalization has given rise to these forces, contributing to rapid urbanization since the start of the 21st century, especially in coastal areas.

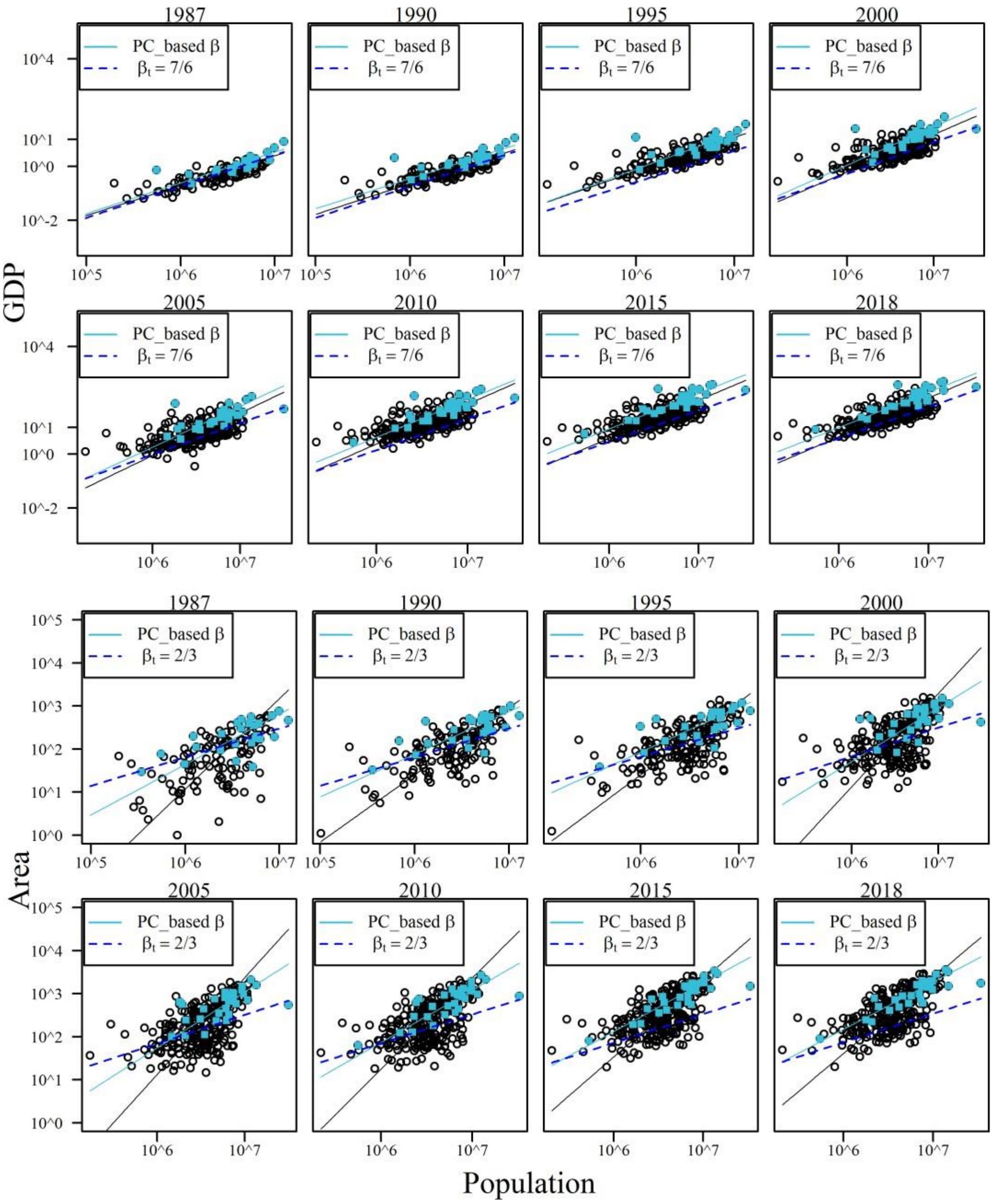

Figure 7. Transversal power scaling relationships between urban area, GDP, and population for prefecture-level cities（black dot）and provincial capitals(sky blue dot), with the expected theoretical value (β_c=2/3) in dark blue.

Likewise, the transversal scaling of wage verses population was superlinear most of the time, except for the linear relationships in the previous few years. The linear scaling agreed with the fixed-wage plan under the stringent planned economy, meaning that the wage was roughly proportional to population, which may be a consequence of the restrictions of the household registration system that prevented the free flow of labor from rural to urban environments (Jia et al., 2020). The changeover from linear scaling to superlinear scaling reflected the steady liberalization of hukou restrictions since the beginning of the 21st century, with large cities thus expanding through their attraction and retention of talent, and reaping the privileged benefits of rapidly rising wages from economic development (Keuschnigg et al., 2019). The high correlation and the similar trend between population-GDP and population-wage (Figure 5) are due to the fact that rapid growth of GDP will boost domestic demand, which may trigger a rise in salaries.

Despite the importance and pervasiveness of scaling theory in understanding the multifaceted nature of urban systems, the universality framework has its limitations in assuming scaling exponent is invariant over time. The dynamic scaling of social, spatial, and infrastructure properties reflecting the past or current trajectories of urban system evolution, can be viewed as complementary to the existing theoretical paradigm to clarify the impacts of changes in social development, economic reforms, and national policies. Scaling relationships change over time, and the lack of temporal flavor in the existing scaling laws limits their applications in depicting the evolution and sustainable development of urban systems.

4.3 Area-based and NTL-based transversal scaling

“Urban” is a commonly used and intuitively understood term—as it refers to a densely packed populace (Seto et al., 2010). In this way, urban was drawn up based on population size from major to small urban areas by 20% of countries (United Nations, 2018b), scaling and scalability analysis has emphasized the significance of using population size as a basis to analyze the intriguing link with various urban metrics (Bettencourt et al., 2007; Lobo et al., 2013). However, any single measurement can hardly fully comprehend the process and evolution of urbanization, which needs to be enriched by considering the combination of other factors. Urbanization is a process of re-location of people within or across areas and a complex and dynamic socio-economic process, accompanied by the transformation of the social network, economic structure, and mode of living style (Kuang et al., 2020). That is the reason why we decompose urbanization into population urbanization (population), spatial urbanization (urban area), and social urbanization (NTL) and use area-based and NTL-based scaling in addition to demographic scaling in our study.

Additionally, using area-based and NTL-based scaling analysis can help us reshape interactions between drivers and outcomes of urban evolution, which cannot obtain by using original demographical scaling. The theoretical scaling exponent for population-based can be obtained from Bettencourt’s analysis (Bettencourt, 2013), from which we can also derive the hypothetical areal scaling association for socio-economic elements ($Y \propto A7/4$) (based on previous relations $Y \propto N7/6$ and $A \propto N2/3$, Y for socio-economic variables, N for population, A for an urban area). It was noteworthy that all exponents of areal transversal scaling for socio-economic variables (e.g., GDP, wage) were far from the theoretical values ($\beta c=7/4$)—scale sublinearly, thereby falling in the rejection of theoretical prediction (Figure 4). Thus, the inconsistency can be summarized as follows: the phenomenon that the larger the cities in the area, the higher the socioeconomic efficiency in other countries may not exist in China (Bettencourt et al., 2007; Sahasranaman and Bettencourt, 2018). Furthermore, the sublinear relations for the population are mainly attributed to multiple internal and external factors (Schneider and Mertes, 2014), including political decentralization and marketization, the abuse of eminent domain by local government, rapid development of transportation and information technology, and the uncontrolled and imperfect land market reform (Zhao, 2011). The sublinear scaling relations between population and urban area meant that addressing China's massive waste of land resources may seem like an increasingly daunting task. From another point of view, the results of area-based scaling were in accordance with the view that a single measurement cannot unravel the intricate web of diverse urban attributes and urbanization. In addition, many types of research have shown that nighttime light can provide an alternative proxy to measure urbanization (Li et al., 2020). The NTL-based temporal transitioned from linear to superlinear for socio-economic quantities, manifesting systematic increasing returns to scale over time (Figure 4), which explicitly considered the dynamics, growth, and evolution of the entire urban system regarding a broad range of metrics.

4.4 Future sustainability governance

Our work developed an integrated conceptual framework for diverse urban development over an enormous range of scales while providing a basis for policy recommendations toward sustainable development. On the one hand, the demographic scaling for GDP exhibited a relatively high transversal scaling exponent at the same point in time compared to United States of America (USA) and Germany (Figure 4), implying that China’s population-GDP efficiency is gradually surpassing those advanced countries in recent years as the same amount of population produces relatively higher economic output, which has become a bright spot in the Chinese development process. On the other hand, expanding the urban areas to accommodate rapid population growth can provide better benefits in terms of more living space and high-quality housing options. However, the development of China’s land-dependent economies synonymous with uncontrolled and haphazard urban sprawl have both added new sources of unsustainability in local and tele-connected regions (Lu et al., 2019). Therefore, a timely and effective regulatory policy to promote a more intensive and economic land use pattern, mainly based on technological advances and efficiency gains, remains a key and urgent task for sustainable urban planning and management. Most critically, policymakers need to impose more rigorous and effective policies, including urban growth boundaries, green belts, and urban renewal, to create synergies that curb land increment and promote land stock optimization, thereby safeguarding farmland and natural land and reversing unsustainable trends (Hassan and Lee, 2015).

Regarding the disparity and diversity of development in China, we found that the gaps in socio-economic development (GDP, urban area) among prefecture-level cities are more pronounced than among provincial capitals, indicating that these cities should be the focus of urban administrations in terms of coordinated development. China is characterized by significant interregional inequalities in economic development and urban expansion (Figure 6), which can be partly attributed to regional resource and natural endowments but are mainly a result of urban development policies (Wei et al., 2017). In the face of regional disparities, the central government has promulgated a series of macro strategies in support of the coordinated development broadly (Jia et al., 2020) ("Western Development Program"(1999), "Rise of Mid-China Strategy"(2016), "Reviving the Northeastern Region"(2004)) in the past three decades. To achieve China's goals of Vision 2035, region-based development policies and highly tailored economic development plans should be implemented to halt unequal economic growth while maintaining stable mobility of talent towards a long-term path of inclusive and sustainable growth (Xu et al., 2020b).

Paralleling the experiences of advanced western countries in the early period of urbanization, China's rapid urban development has yielded a broad portfolio of air pollution emissions and environmental damages (Guan et al., 2012). The superlinear scaling of ecological indicators with the urban area and population, and the strong positive correlation with GDP (Figure 4, Figure 5), means that increasing urban size would enhance the magnitude of human activities and productivity of economic growth, which will directly or indirectly exacerbate environmental issues in larger and more congested cities (Han et al., 2016). The pattern is also consistent with the first stage of the "Environmental Kuznets Curve" (EKC) (Grossman and Krueger, 1991), in which the economic development initially leads to a deterioration in environment. The degree of superlinearity declined slowly since 2003, probably reflecting a "turning point" in this growth pattern, at which it would switch to a decoupling of economic growth and environmental degradation as economy undergoes technological and structural changes. This is confirmed by the decreasing trend of particulate pollutant concentrations ($PM_{2.5}$, PM_{10}) in China from 2015 to 2018 (Kuerban et al., 2020). Nonetheless, the objective of the "Blue Sky" plan and carbon neutrality necessitated a thorough implementation of compulsory emission reduction and upgrade of transportation and electricity systems towards environmentally sustainable systems (i.e., wind and solar energy) (Soares et al., 2018). Reform and opening-up should continue to promote socio-economic efficiencies scientifically based on carrying capacity and resource-environmental context while taking into account the practical needs of urban expansion.

5. Conclusion

We analyzed socioeconomic and environmental data of Chinese urban systems in light of urban scaling laws and known empirical patterns from other nations, aiming to quantitatively depict the temporal coevolution and spatial organization of urban attributes in the urbanization process in terms of scaling and agglomeration effects, and economies of scale.

The results of the evolution of city indicators throughout time revealed the economic agglomeration of most cities in China, accompanied by the accumulation of pollution. The density distribution of the scaling coefficient β for population density also implied that the average living space per person is on the rise. The superlinear relationship of urban area and population often considered as an indicator of wasting land resources (challenging the universality theory β_c=2/3), is in fact the powerful impetus (capital raising) behind the concurrent superlinear expansion of socio-economic metabolisms (e.g., GDP, total wage) in a rapidly urbanizing country that has not yet reached equilibrium. Infrastructural variables associated with public services, such as hospitals and educational institutions, exhibited some deviations as well and were scaled linearly. The observed deviations were a product of China’s political systems and national conditions as a developing country, whereas the tremendous waste of land resources poses enormous challenges to natural environment and social system at the regional and national scales. One encouraging signal from the decline in urban land diseconomies and the stabilization of economic output indicates the government’s engagement and commitment to common sustainability goals. In a word, our results reject the hypothesis and challenge the universality proposition of urban scaling.

Despite the importance and pervasiveness of scaling theory in understanding the multifaceted nature of urban systems, the universality framework has its limitations in assuming the scaling exponent is invariant over time. These conclusions should be validated and extended to other developing countries, and more comprehensive variables, which is crucial not only for well-being of Chinese residents, but for the sustainability of the entire planet.

Acknowledgments

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Tables

Table 1. The temporal scaling of the coevolution of two urban indicators within each city from 1987 to 2018.

y	x	Total number of cities	Sublinear	Linear	Superlinear
GDP	Area	274	0	1	273
NTL	Area	344	31	69	244
Total wage	Area	283	1	0	282
High school	Area	280	248	30	2
Hospital	Area	287	244	38	5
PM_{10}	Area	343	7	36	300
$PM_{2.5}$	Area	342	10	70	262
NO_X	Area	343	0	1	342
Area	POP	234	0	3	231
GDP	POP	235	0	0	235
NL	POP	247	1	1	245
Total wage	POP	243	0	0	243
High school	POP	254	204	25	25
Hospital	POP	243	95	89	59
PM_{10}	POP	254	0	1	253
$PM_{2.5}$	POP	254	0	2	252
NO_X	POP	254	0	1	253
GDP	NL	288	2	28	258

Figures

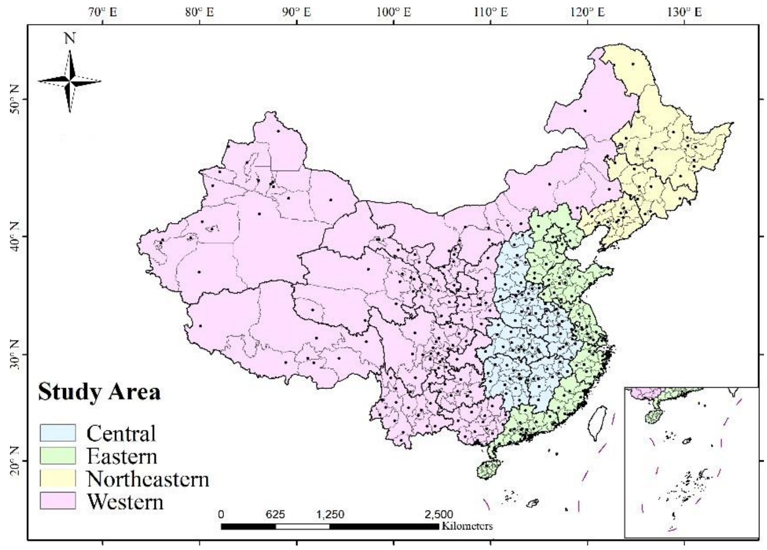

Figure 1: The spatial distribution of the prefecture-level cities in China.

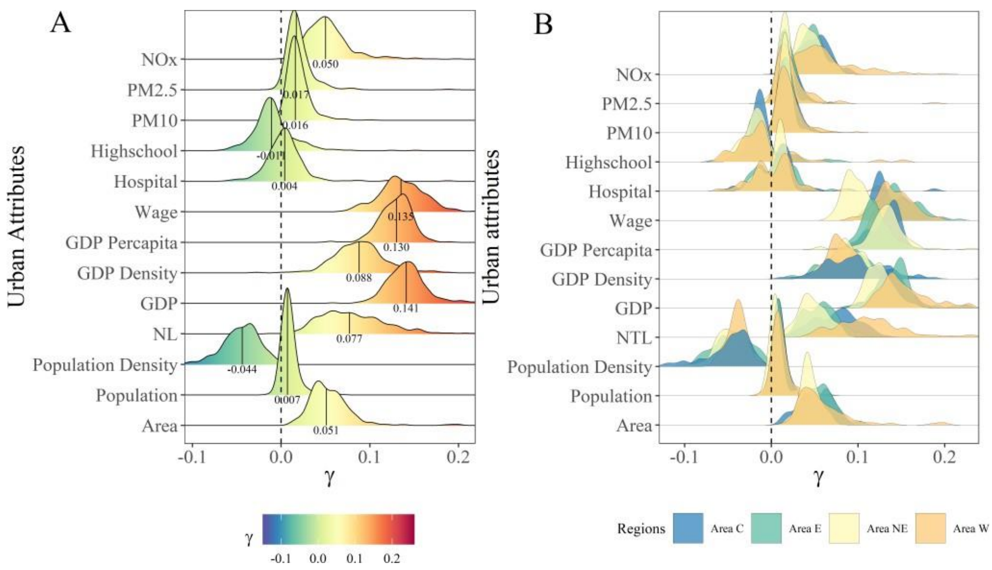

Figure 2. The distribution of the estimated exponent coefficient γ of the power-law relations between urban characteristics and time in China (A), and in four regions of China (B) ("C" for central, "E" for Eastern, "NE" for the northeast, and "W" for western)(i.e., $y = at^{\gamma} + b$). Urban characteristics include area (km^2), population (person), gross domestic product (GDP), wage (RMB), number of high schools, number of hospitals, particulate matter 10 micrometers or less in diameter (PM_{10}), particulate matter 2.5 micrometers or less in diameter ($PM_{2.5}$), nitrogen oxides (NOx), nightlight (NTL), population density (population per square kilometer of urban area), GDP density (RMB per square kilometer of urban area), and GDP per capita (RMB per population). The solid black line indicates the median value of the exponent coefficient γ for various urban attributes. The black dashed line represents the boundary line between positive and negative changes of urban characteristics in time.

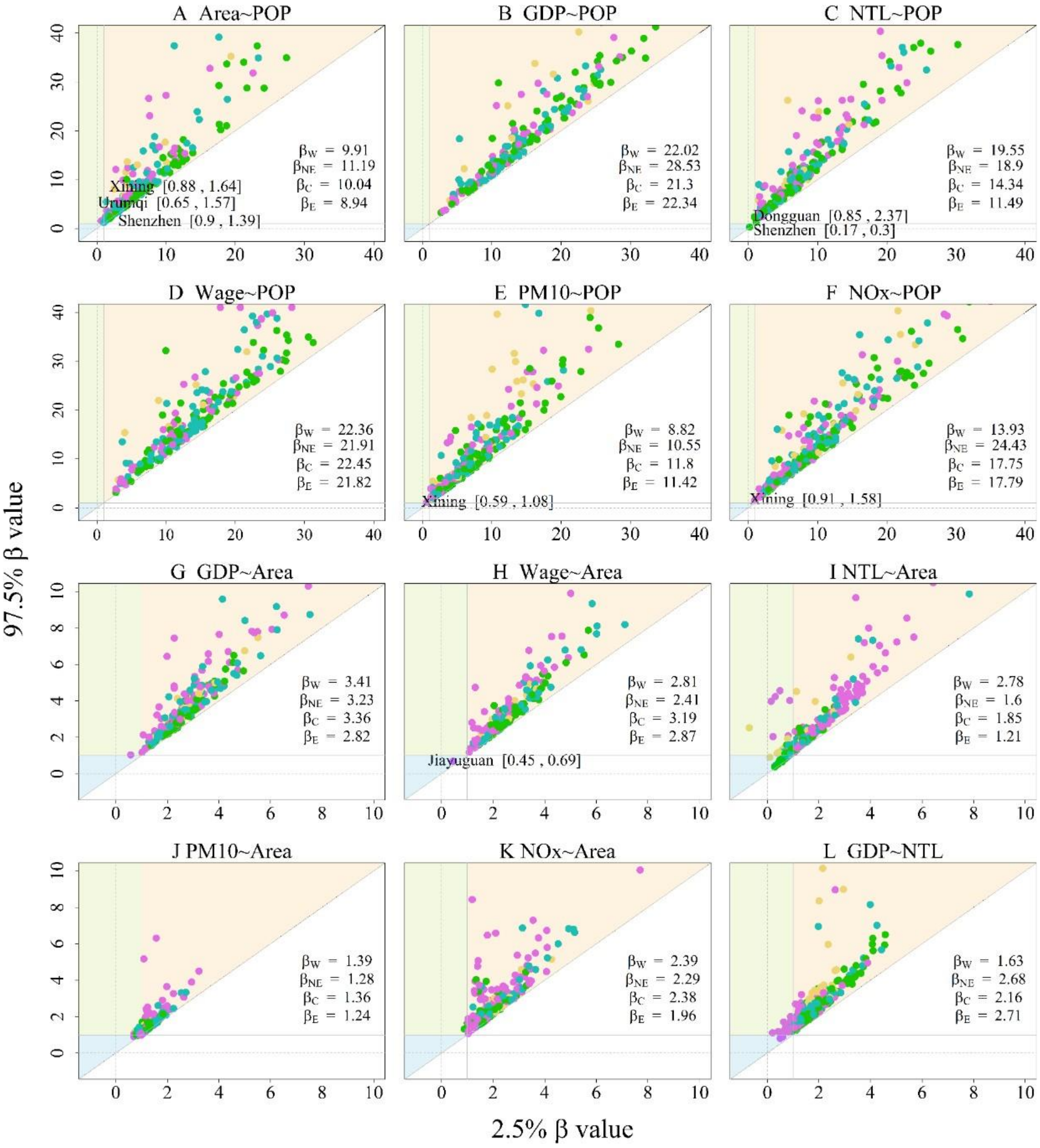

Figure 3. The temporal scaling exponent (β_t) and 95% CI (2.5% and 97.5% percentiles) for paired city indicators with an urban area, population, and nighttime light as independent variables in Chinese cities. The three distinct background colors represented three scaling regimes: pale orange for the superlinear regime, light green for the linear regime, and light blue for the sublinear regime. The gray vertical and horizontal lines separate the sublinear (the upper CI of β_t <1) from superlinear regime (the bottom CI of β_t>1). The colors of dots represented four regions in China: green for

the Eastern, blue for the Central, purple for the Western, and yellow for the Northeast regions. The β values shown in the text are the average value of all cities in each region. The values of β_t and its 95% confidence range emanated from the coevolution of two indicators in a specific city from 1987 to 2018 using orthogonal regressions.

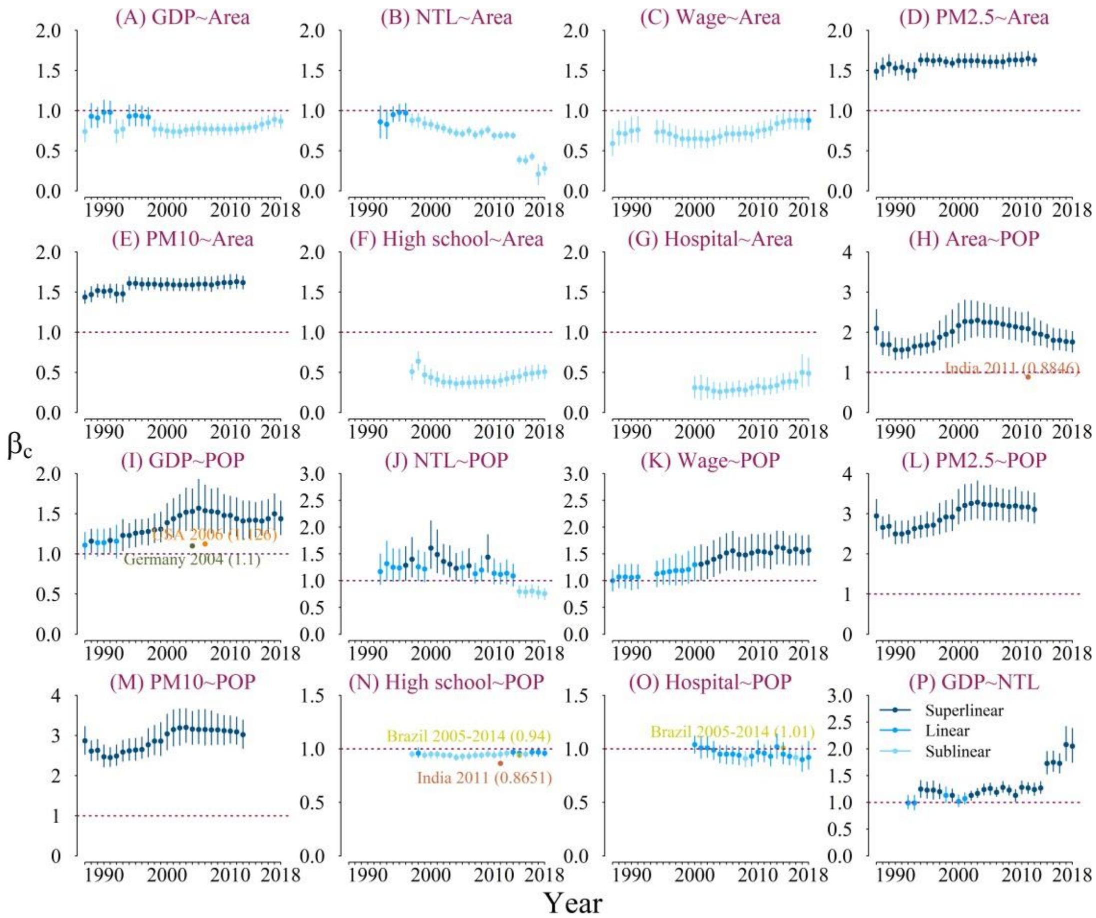

Figure 4. Temporal variations of transversal scaling exponent(β_c) with 95% confidence intervals for various urban attributes against the urban area, population, and nighttime light from 1987 to 2018. The β_c coefficients were derived from observations of all cities using orthogonal regression. The purple horizontal line (β_c=1) was plotted as a guide to distinguish between sublinear (β_c<1) and superlinear (β_c>1). The colors represent the diverse scaling regime: dark blue—superlinear scaling regime; blue—linear scaling regime; light blue—sublinear scaling regime.

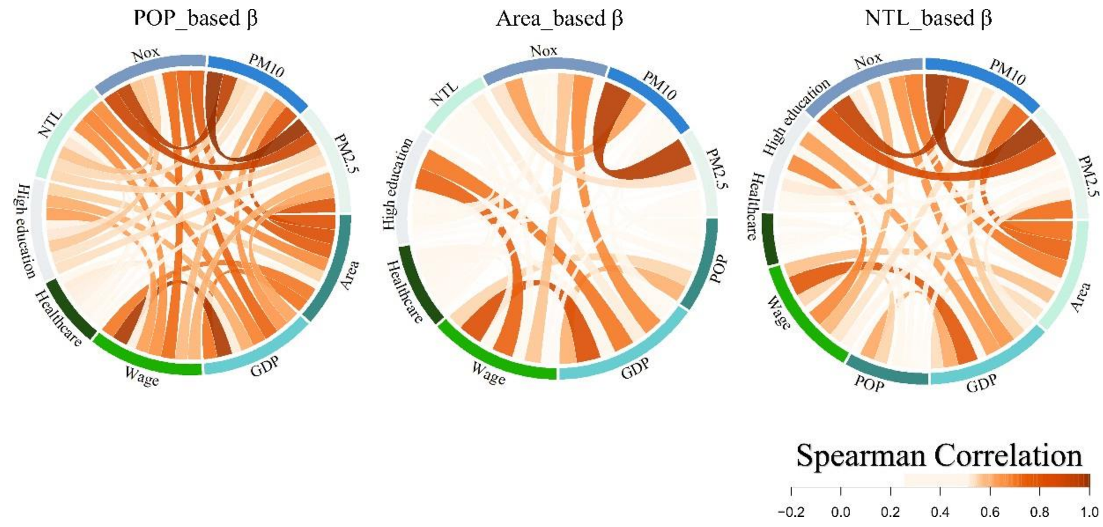

Figure 5. The correlation matrix for Area_based exponents, PoP_based exponents, and NTL_based exponents, respectively (P<0.01). The yellow and white colors correspond to positive and negative correlations, respectively.

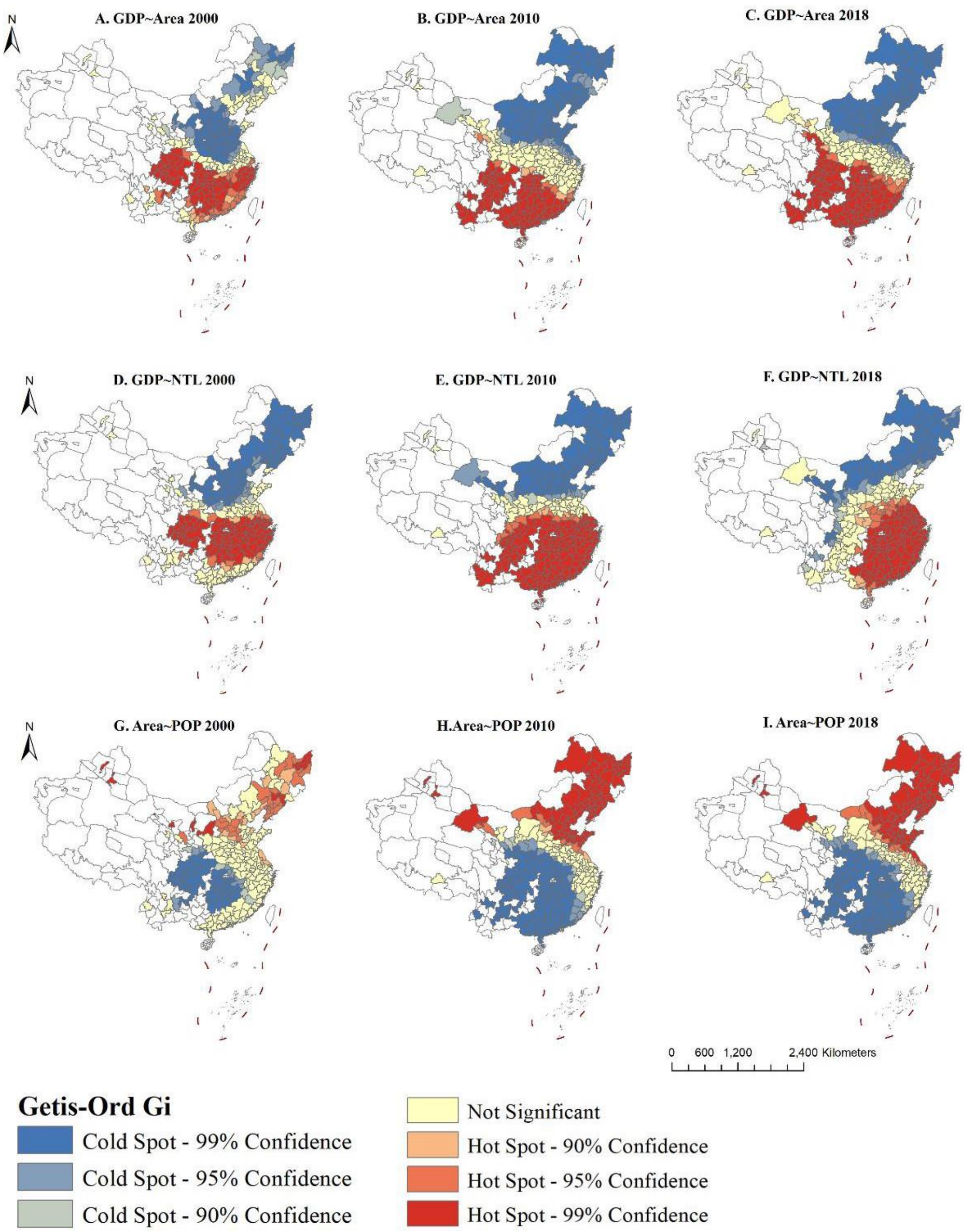

Figure 6. Hotspot analysis of SAMI GDP~Area, SAMI GDP~NTL and SAMI Area~POP in 2000, 2010, and 2018, respectively. Hot spot and cold spot represent the areas of high occurrence and areas of low occurrence, respectively; 90%, 95%, and 99% mean the significant level at 90%, 95%, and 99%, respectively.

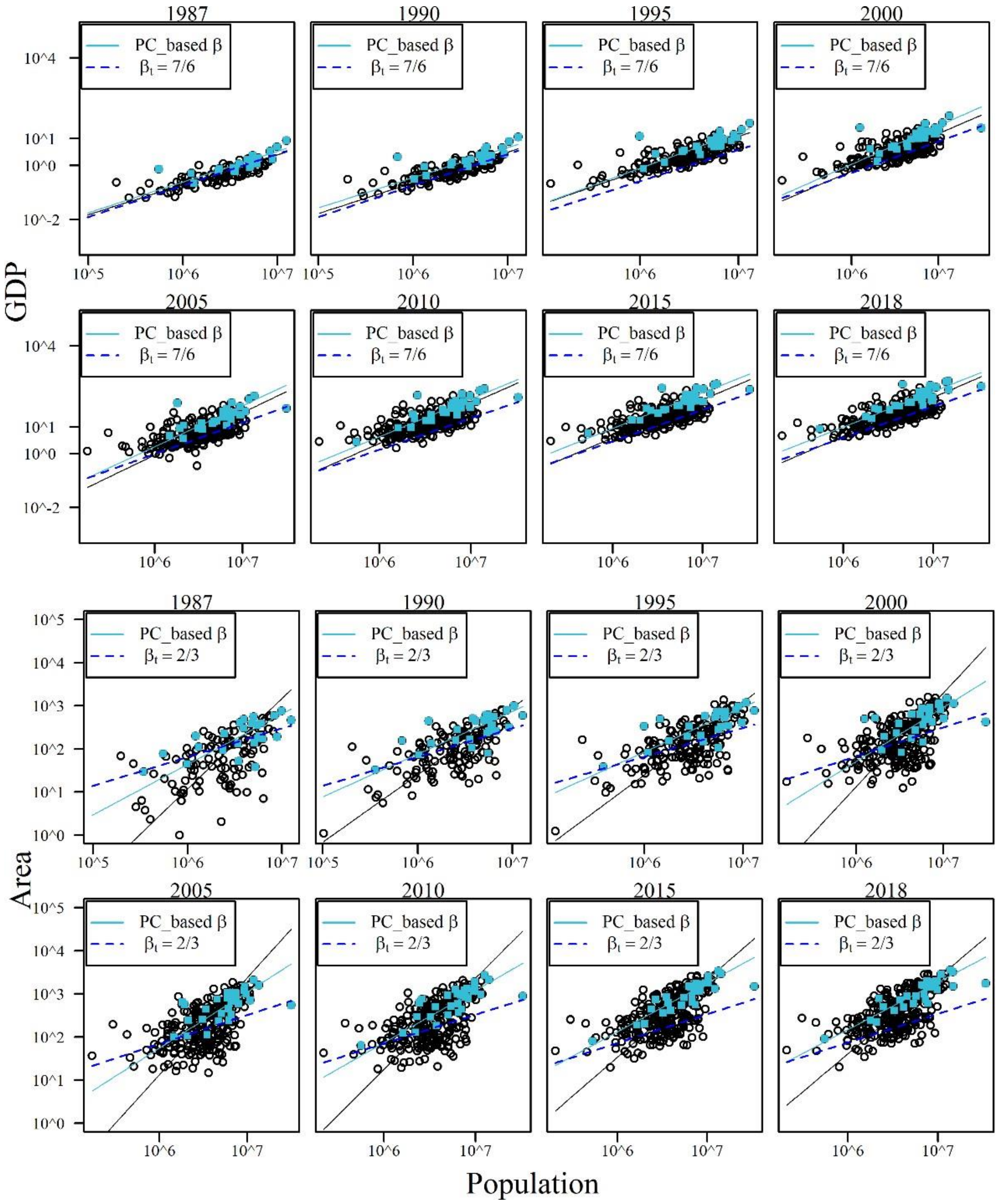

Figure 7. Transversal power scaling relationships between urban area, GDP, and population for prefecture-level cities（black dot）and provincial capitals(sky blue dot), with the expected theoretical value (β_c=2/3) in dark blue.

Shuailong Feng: Writing – review & editing.