Cross-City Convergence in Urban Green Space Coverage in China

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Abstract: Cross-city convergence in green space coverage could contribute to our understanding of the law of motion of distribution dynamics of environmental sustainability across cities and provide crucial information for designing policies regarding complex processes relating to human–environment interactions in an urban system. The relationship between socioeconomic factors and green space coverage has been widely discussed, but research on the distribution dynamics of green space coverage across cities is limited. This paper explored the pattern of convergence in green space coverage of a group of 285 Chinese cities over the period of 2002–2012 by using hybrid approaches, including the nonparametric estimation technique, unconditional β-convergence model, and conditional β-convergence model. The results indicated that the green space coverage level in most cities has been substantially improved; the spatial disparity across Chinese cities has shrunk, and the level of green space coverage has converged to 104% of the average level. The β-convergence estimation results demonstrate the existence of unconditional and conditional convergence in green space coverage among Chinese cities, which indicates that cities with a low initial level of green space coverage grow faster than those with an initial high level. Faster sprawling, more compact and wealthier cities are likely to converge to a higher level of green space coverage. Expansion of the population and spatial scale of cities contributes to increasing green space coverage, sprawling of built-up area leads to a decrease of the green space coverage, and economic growth has little impact on green space coverage.

Keywords: green space coverage; cross-city convergence; spatial disparity; socioeconomic factors

1. Introduction

Currently, more than 50% of the global population lives in cities, and by 2050 this number will increase to 80% [1]. With sustained population concentration in cities, many cities tend towards sprawling, especially in built-up areas. Therefore, the remaining nature within cities becomes extremely important to the ecological health and habitability of cities. As the main part of the nature system in cities, green spaces, which can be defined as urban spaces primarily covered by vegetation which are available for urban residents [2], have been called the "lungs of the city" [3]. The interconnected network of green spaces, known as the green infrastructure, contributes to carbon sequestration [4], air purification [5,6], heat island effect mitigation [7,8], stormwater runoff reduction [9], biodiversity conservation [10], and thus improvement of the habitability of cities and public health (both physical and psychological) [11,12]. Therefore, green space coverage can be considered a measurement of environmental sustainability and ecological health for cities [13].

Insights into the distribution of urban green space coverage are important from the perspective of urban habitability, environmental sustainability, and equity [14]. Numerous studies have investigated the spatial distribution of green spaces, both within cities and across cities. Most of the current studies have focused on the green space distribution of a certain city and have often applied remote sensing and landscape ecology methods to investigate the spatial variation of green spaces among various landscape components or land use categories at a fine scale [15–17]. They have found that the green space distribution is highly related to the population density [18], commercial facilities [19], land use pattern [20], and other socioeconomic variations [21]. Furthermore, other scholars have conducted in-depth research by integrating spatiotemporal analysis and socioeconomic activities or processes, such as the accessibility to green spaces [22,23], green justice (or equity) [12,21,24], and environmental effects [25–27] and health impacts [28] of green space distribution.

Regarding green space distribution across cities, a number of relevant studies have investigated the temporal changes in cross-city spatial disparity and its driving factors at the national and above scale, and have found that there is a high level of heterogeneity in the distribution of urban spaces due to urban space expansion, intensive land usage, and increasing population density [14,29–33]. Studies of European cities have shown that the green space provision within a city is primarily related to city area rather than the population size it serves, and a decrease in population does not lead to a decline in residential areas and a subsequent increase in urban green space on a large scale [14,32]. In the case of Southeast Asia, the provision of green space decreased with population density but increased with GDP [34]. In China, the green space coverage of Chinese cities substantially increased with urbanization, which contributed to the increase in green space coverage at an average level, which is different to the phenomenon observed in European cities [33]. However, the existing studies have failed to identify some important features in the evolution of cross-city green space distribution, specifically the distribution dynamics and the process of cross-city convergence.

Cross-city convergence is a method for researching the evolution over time of an entire cross-city distribution of green space. Numerous studies have been conducted to probe the convergence of income or productivities across countries and regions. Recently, the environment-related literature has included studies on the convergence in energy consumption [35,36], water consumption [37], carbon-dioxide emissions [38–40], and eco-efficiency [41]. However, to our knowledge, the cross-city convergence of green space has so far received little attention in the literature. Moreover, little is known about the distribution dynamics of urban green spaces across a large number of cities in China, which possesses the largest number of cities located in geographically and economically diverse regions [42]. This study aims to contribute to the literature on cross-city convergence in green space coverage. By using a large cross-city data set covering the period of 2002–2012 and applying kernel density estimation and β-convergence test techniques, the cross-city convergence patterns of green space coverage, which were indicated by the green space coverage ratio, were investigated. As pointed out by other scholars, a comprehensive understanding of the social–ecology interaction can allow us to better assess how human-induced urbanization impacts green spaces and their ecological services [43]. Thus, this study also explored the impacts of socioeconomic factors on changes in green space coverage.

2. Methodology

2.1. Spatial Distribution Analysis

A nonparametric estimation technique—kernel density estimation (KDE)—was applied to explore the spatial distribution of green space coverage ratio (GCR) measured by the ratio of green space coverage area in total in relation to built-up areas between 2002 and 2012. KDE is an effective technique for estimating the probability density function of GCR and investigating the external shape of the spatial distribution [44]. For the KDE, the computed result is sensitive to the selection of the bandwidth or smoothing parameter. In this case, we used Gaussian kernel functions as the kernel weighting function, and the value of the bandwidth was selected following the method outlined by Silverman ([45], p. 47)

2.2. Cross-City Convergence Analysis

Convergence was first introduced to describe the process of equalization of growth rates across regions (or countries), and much of the related discussions have been conducted to investigate convergence in economic growth [46–48]. Numerous scholars have investigated convergence in environmental indicators, such as resource consumption [37,49–51], atmosphere pollutant emissions [52], CO_2 emissions [53–56], environmental quality [57,58], and ecological efficiency [41,59–61]. The investigation of convergence in environmental variables is important from the perspective of compatibility between economic growth and environmental preservation in the long run and could provide useful information for the design of policies regarding the complex processes featured in the interactions between economic and ecological processes [48,62]. In this paper, the definition of cross-city convergence is the process of equalization of development rates across city districts. On the contrary, divergence is the process of expanding disparities among city districts in green space coverage [63,64].

There are two main types of convergence: α-convergence and β-convergence, which can be further distinguished between absolute (or unconditional) and conditional β-convergence, and each notion of convergence is linked to different methodological models [46,48,49,63–65]. β-convergence is the negative relationship between the growth rate of the variable and the initial level of the variable and refers to the fact that regions with a low initial level grow faster than regions with an initially high level in a given variable. In most recent studies, β-convergence has been estimated by employing the following function:

$$Ln(\frac{E_{i,t+1}}{E_{i,t}}) = \alpha + \beta LnE_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ refers to the value of the variable in region i at time t, $R_{i,t+1}$ refers to the value of the variable in region i at time t+1, α and β are estimated coefficients, and ε is the random error term. A negative value of β implies β-convergence. Equation (1) models absolute (unconditional) β-convergence, in which all regions tend to move toward a common value. If the regression equation includes other variables (Equation (2)), it depicts a model of conditional β-convergence.

$$Ln(\frac{E_{i,t+1}}{E_{i,t}}) = \alpha + \beta LnE_{i,t} + \lambda_j x_{i,t,j} + \varepsilon_{i,t} \tag{2}$$

where $x_{i,t,j}$ refers to the conditional variables j in region i at time t, and λ is estimated coefficient. The other variables are same as in Equation (1). Both Equations (1) and (2) are estimated by panel data.

This paper used Equations (1) and (2) to test β-convergence. The indicator of urban green space coverage was the green space coverage ratio (GCR), which was measured by the ratio of green space coverage area in total in relation to built-up areas.

To study β-convergence, the letter E in Equation (1) represents GCR. Thus, Equation (1) represents unconditional β-convergence, which refers to the fact that cities are converging toward a common level of GCR. However, due to differences in city-specific characteristics, such as population scale, population density, spatial scale, built-up areas, and economic growth, all cities may not converge to a common level, but may converge to different levels depending on city-specific characteristics; this is conditional β-convergence. The model for conditional β-convergence estimation can be specified by adding the appropriate conditioning variables that may affect the change in GCR over time to Equation (1). In this paper we chose the population (indicating the city scale), population density (indicating the compactness of the city), area of the city district (indicating the spatial scale of the city), the built-up area (indicating the spatial sprawl of the city), and the GDP per capita (indicating the economic growth) as the conditioning factors.

2.3. Data Source

The dataset of the municipal districts consists of 285 cities located in mainland China, including all prefecture-level and above cities (except Lhasa city and Chaohu city, due to the unavailability of data). All data relating to the indicators, including GCR, GDP, population, built-up area, and city area, were extracted from The China Urban Statistical Yearbook. Since we could only obtain all the required data on green space coverage for the 285 cities from the year 2002, this paper focuses on the time period of 2002–2012.

3. Results

Figure 1 presents the temporal changes in average green space coverage of Chinese cities. For ease of comparison, the value of the GCR was standardized such that the value of the GCR for 2002 was set to equal to 100; that is, 2002=100 (Figure 1). Along with the fast economic growth and urbanization that occurred in China, the green space coverage ratio (GCR) has increased by 1.35 times since 2002.
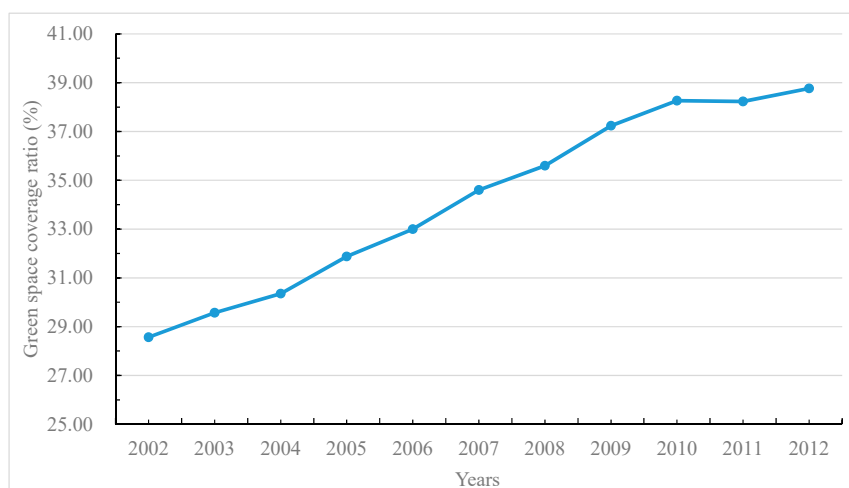

Figure 1. The changes in average green space coverage (GCR) of Chinese cities, 2002–2012 (year 2002=100).

3.1. Spatial Distribution

The 285 Chinese prefecture-level cities accounted for 1.26 billion (93% of the Chinese population) people, and the municipal districts of the 285 cities accounted for 0.401 billion inhabitants (30% of the Chinese population) in 2012. Green space coverage varied remarkably (averaging 28.6% and ranging from 1.06 to 57.9 in 2002; averaging 34.6% and ranging from 3.71 to 49.2 in 2007; averaging 38.6% and ranging from 2.98 to 57.1 in 2012) and showed a clear eastern tendency (Figure 2). Although the green space coverage in most of the cities has been substantially improved, the regional variation among Chinese cities formed a clear spatial pattern, with the highest level in eastern China, followed by central China, and decreasing into western China.

Figure 3 presents the density function for the GCR, which was estimated according to the kernel density estimation approach for three years (2002, 2007, and 2012), of the period 2002–2012. To remove the influence of changes in green coverage at the city level [39], we normalized each city's level of GCR according to the average of the distribution for the years, and the average was assigned a value of 100. The probability mass of the GCR was concentrated around a low level, and the probability mass decreased from 120% to 104%. Meanwhile, the distance between both ends of the distribution shrank. The shift in the distribution of the GCR indicates the existence of a process of cross-city convergence (α-convergence) in the GCR. Specifically, the probability of finding values both at the lower end of the distribution (less than 80% of the average) and higher end of the distribution (higher than 150% of the average) has significantly decreased, while the probability of finding values around 104% of

the average level has greatly increased. In short, the value of the GCR has converged to 104% of the average level.
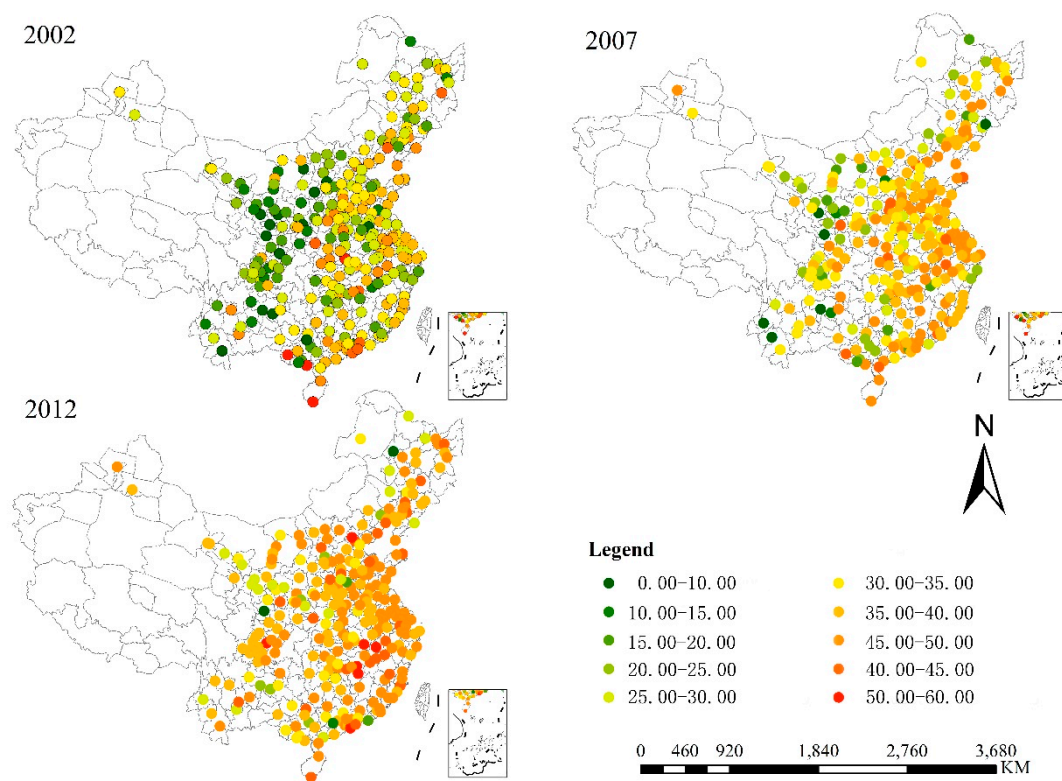

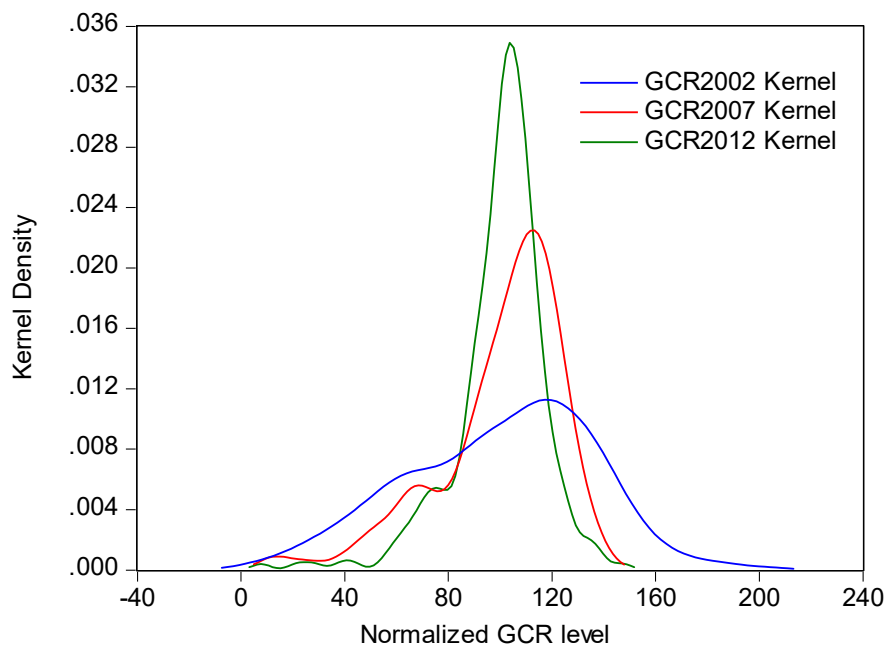**Figure 2.** The spatial distribution of the green space coverage ratio (GCR) in China (2002, 2007, and 2012).

Figure 3. Shifts in the distribution of the GCR for Chinese cities.

3.2. Convergence Analysis

This paper attempted to discover whether the tendency of cross-city convergence in the GCR would remain statistically significant for China by applying multiple regression aims to test the

unconditional (Column 1, Table 1) and conditional β-convergence phenomenon (Column 2, Table 1). To figure out if the cities in China are converging toward a common value for the GCR, we conducted a β-convergence test for China. The estimated coefficients are statistically significant at conventional levels (Table 1).

Table 1. The estimation results of the cross-city convergence test and the socioeconomic driving factors.

	Model 1		Model 2		Model 3	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
β	−0.424***	−39.323	−0.446***	−33.035		
P			0.008	0.340	0.049***	2.995
PD			0.014**	2.046	0.012*	1.795
AOB			0.068***	7.262	−0.136***	−12.115
AOC			0.009	0.815	0.036***	3.271
Y			0.039***	8.748	0.000***	7.601
C	1.504***	40.354	0.719***	8.208	3.539***	59.057
AR(1)					0.613***	48.694
R^2	0.407		0.357		0.832	
F-test	5.465		4.891		43.770	
D-W stat	2.006		2.466		2.096	

Notes: Model 1 is the unconditional convergence test model, Model 2 is the conditional convergence test model, and Model 3 is the model for socioeconomic drivers analysis; the symbol *, ** and *** denote statistical significance at the 10%, 5% and 1% level.

The negative value of the β-coefficient in Table 1 indicates that changes in the GCR appear to have a negative relationship with the levels in the base year (2002), and thus the value of the GCR converges to the base levels of value. The cross-city convergence in the GCR suggests that Chinese cities tend to be greener than before, and the inter-city inequity of the GCR is decreasing.

Our results show that unconditional cross-city β-convergence does exist for green space convergence in China. However, would the tendency of β-convergence in green space coverage still remain statistically significant when other potential factors are taken into account? That is, is there a conditional β-convergence phenomenon in Chinese cities? To figure out the answer to this question, we conducted a conditional β-convergence test (Column 2, Table 1).

The β-coefficients of the conditional convergence estimation are statistically significant at the 1% confidence level, and the coefficients of PD, AOB, and Y are significantly positive. This suggests that, when controlling the population density, built-up area, and per capital GDP, the convergence mechanism of green space across cities still exists. The negative value of β supports the hypothesis that lagging cities tend to catch up with advanced cities, with convergence tending to be conditional on city-specific characteristics. The higher value of the estimated coefficient compared with the unconditional convergence test model implies that the convergence speed is higher when socioeconomic factors are considered. The results of the conditional model confirmed that the factors of compactness of the city (PD), spatial sprawl (AOB), and economic growth (y) are significant for cross-city convergence. The positive value of the estimation coefficient indicates that more compact cities, cities possessing larger built-up areas, and wealthier cities are likely to converge to a higher level of GCR; that is, the three factors increased the improvement of the green coverage ratio and also had an auxiliary effect on the uneven inter-city GCR. In short, faster sprawling, more compact, and wealthier cities are likely to converge to higher level of green space coverage; the compactness of the city, urban sprawl, and economic growth may mitigate the convergence speed of the GCR.

3.3. Socioeconomic Drivers

Given that both unconditional and conditional convergence exist for green space coverage in China, the effects of conditional factors on cross-city convergence have been investigated. To explore the impact of conditional factors on the changes in green coverage space, we conducted a panel multiple

regression analysis to estimate the impacts of socioeconomic factors, including the population scale, economic growth, spatial sprawl, and spatial scale of the city, and the compactness of the city (Column 3 in Table 1). The results verified that all the estimated coefficients of the factors are statistically significant (the factors of population scale (P), spatial sprawl (built-up areas, AOB), spatial scale (AOC), and economic growth (y) are significant at the 1% confidence level, and compactness of city (PD) is significant at the 10% confidence level). Although the estimated coefficient of the factor of economic growth is statistically significant, the value is zero, which indicates that economic growth has no direct impact on the changes in the GCR. When the other conditions are constant, a 1% increase of the population scale, built-up area, and spatial scale are associated with an 0.049% increase of the GCR, 0.136% drop of the GCR, and 0.036% increase of the GCR, respectively. Further, we also found a significant relationship between population density and the GCR (a 1% increase of the population density is associated with a 0.012% increase of the GCR).

4. Discussion

The green space coverage in Chinese cities was substantially improved between 2002 and 2012 due to the implementation of the National Garden City and National Ecological City Project, which mainly focused on the improvement of the level of green space provision. Alongside an unprecedented urbanization process, the green space coverage of cities in China has been substantially improved. However, after the year of 2010 which is the end of the tenth five-years plan of China and the urbanization rate exceeded 50%, the increasing rate of GCR has declined along with the rapid urbanization in China. This phenomenon indicated that the urbanization (by the way of sprawl or densification) greatly impacted on the provision of green space.

The spatial disparity of the green space coverage across Chinese cities is conspicuous due to the unbalanced development of different Chinese cities. Overall, the cities in eastern China show the highest level of green space coverage, followed by those in central China and western China. The spatial pattern of green space coverage is similar to the spatial pattern of economic growth and urbanization in China.

The study confirmed the existence of cross-city convergence in green space coverage in China. The absolute convergence in the GCR implies the decline in spatial disparity of green space provision (or green inequity) across Chinese cites. The convergence mechanism or distribution dynamics in green space coverage could be driven by different impact factors. According to the conditional convergence test, as noted in Section 3.2, the population density, built-up areas, and economic growth are the three main factors that have affected the evolution over time of the overall cross-city distribution of green space. Thus, increasing population density, expanding built-up areas, and improving the economic growth level will lead to an expansion of the gap in green space coverage across cities in China. The increasing population density or expanding built-up area indicate the city expand through densification or sprawl, i.e., the two different ways of urbanization. Thus, the expanding of the gaps in urbanization (whether urban sprawling or compacting) and economic level will lead to an increase in inequality of green space provision among cities.

Previous studies have shown that the changes in green space coverage were not driven by a single factor but the combined effects of urbanization and greening policies [66]. In our case, we found that the enlarging of the spatial scale of a city may lead to an increase in the GCR and expansion of the built-up areas, however, the expansion of built-up areas results in a decrease in the GCR. The economic growth has little impact on green space coverage, which suggests that economic development does not always lead to improvement in green space coverage, and China requires the design and implementation of specific policies, which have also been reported to contribute to the increase in the urban green space area [67,68] and to guarantee green space demand.

Combining the results of the conditional convergence test and socioeconomic drivers analysis, we found that an increasing level of urban compactness impedes cross-city convergence in the GCR and meanwhile leads to improvement of the GCR. The continual sprawling of built-up areas impedes

cross-city convergence but leads to a decline in the GCR. Economic growth impedes convergence but has no effect on the GCR. These findings indicate that economic growth and urban sprawl cannot guarantee both urban sustainability and inter-city equity relative to green space coverage. Only compactness can guarantee both, which should be considered in the future direction of urban development.

5. Conclusions

This study is probably the first study of cross-city convergence in green space. The distribution dynamics of green space coverage across 285 cities were investigated, and we also explored the impacts of socioeconomic driving factors on the changes in green space coverage. The α-convergence test certified the existence of the shrinking process of spatial disparity across Chinese cities, and the level of green space coverage converged to 104% of the average level. The β-convergence estimation results also demonstrated the existence of unconditional and conditional convergence in green space coverage among Chinese cities, which indicated that cities with a low initial level of green space coverage tend to grow faster than cities with an initial high level; that is, the lagging cities tend to catch up with more advanced cities. Faster sprawling, more compact, and wealthier cities are more likely to converge to a higher level of green space coverage. Unbalanced economic growth, population density, and sprawling of built-up areas resulted in the expansion of the gap in green space coverage across cities in China. Both population growth and city spatial expansion contribute to green space coverage increases. The sprawling of built-up areas leads to a decrease of the green space coverage level, and economic growth has little impact on green space coverage, which suggests that economic development does not always lead to improvement of green space coverage, and China needs to design and implement series policies.

The cross-city convergence in environmental variables (such as green space coverage) could contribute to discovering the law of motion of distribution dynamics of environmental sustainability across cites, and provide crucial information for the design of policies regarding complex processes featured in the human–environment interactions in urban systems. Cities with a higher level of green space coverage have better environmental quality and a healthy ecological system, and therefore increasing pressure should be placed on policymakers to enact effective green space planning and management. For these cities, urban planning should carry out incremental green land planning on the premise of ensuring the stock of green space. For cities with less green space development, although the catch-up effect has already emerged, most of these cities are located in less developed regions (like central and western China) and have an urgent need to expand their built-up areas, which will lead to a decrease in the level of green space coverage. Therefore, for these cities, future urban planning should pay more attention to ensuring enough public green space and should introduce mandatory quantitative indicators to ensure green land is maintained in and around the built-up areas.

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