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Dynamic spatio-temporal patterns and driving factors of green waste generation based on provincial panel data in China

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Introduction: Green waste is the second largest organic solid waste beyond of household waste in Chinese cities. Clarifying green waste generation is significant for efficient management and utilization.

Methods: Unlike previous studies that mainly concentrated on quantifying green waste at a single time point and within a particular region, this research is grounded in the urban greening data of 30 provinces in China spanning from 2003 to 2022. It systematically computes and analyzes the overall green waste generation scenario and its spatio-temporal distribution traits in China. Moreover, it innovatively employs the adjusted IPAT-LMDI (Environmental Impact = Population × Affluence × Technology - Logarithmic Mean Divisia Index) model to probe into the key driving factors influencing green waste production.

Results and Discussions: Research has found that: 1) From 2003 to 2022, the total amount of landscaping waste resources in China showed an overall upward trend, with a total of 10.7134 million tons in 2003 and an increase of nearly 5 times to 60.9705 million tons in 2022; 2) The overall density of resource generation shows a fluctuating upward trend, with a characteristic of high in the east and low in the west, gradually evolving into high in the southeast and low in the northwest; 3) The factors of population size, economic development, and environmental pressure all have a positive driving effect on the total increase of green waste resources, but urban development shows a negative effect of decreasing the number of green waste resources; 4) Anticipated against the backdrop of global warming, urban sprawl, and improving urban green space management standards, China's green waste production is projected to persistently rise, with forecasting an increase to between 83.35 million and 91.48 million tons in total by 2030. Although this study has achieved some progress in quantifying and analyzing the spatial-temporal characteristics and driving forces of China's green waste, there is still room for further improvement in terms of research accuracy and scope in future studies.

KEYWORDS

green waste, resource quantity, spatiotemporal characteristics, IPAT-LMDI, driving factors

1 Introduction

In recent decades, the progression of urbanization and the enlargement of green areas have significantly escalated the generation of green waste worldwide (UN-habitat, 2022). In 2023, approximately 2.3 billion tons of solid waste were generated globally, with green waste accounting for 11% (Kaza et al., 2018; UNEP, 2024). China, as one of the world's most populous nation, has undergone a period of intensive urban landscaping and green space expansion over the past 2 decades concurrent with economic progress and escalating resident demands. This dynamic has resulted in a sustained augmentation of green cover, which, in turn, has led to a marked rise in green waste output (Xin et al., 2023). Presently, green waste ranks as the second-largest contributor to organic solid waste within Chinese cities, generating between 40 and 70 million tons annually, thereby accentuating the pressing concerns surrounding its treatment and disposal (Song et al., 2023). The persistent escalation in the volume of green waste is imposing a discernible strain on urban ecosystems, rendering it an integral component of urban development that cannot be neglected. Therefore, there exists an exigent necessity for the implementation of scientifically rigorous disposal and utilization strategies for this burgeoning challenge (Shi et al., 2013a).

Distinct from other categories of urban solid waste, green waste exhibits a diverse array of origins and is generally considered cleaner (Raja and Purushothaman, 2023; Reyes Torres et al., 2018). Its composition encompasses a broad spectrum of plant residuals generated through natural senescence, human intervention such as pruning, or harsh weather conditions impacting landscaping vegetation, including discarded twigs, fallen foliage, grass clippings, decomposing flowers, and tree/shrub pruning remnants (NAWDO, 1998; Inghels et al., 2019; Liu et al., 2020a). Relative to other types of solid waste like municipal and industrial refuse, green waste boasts ample organic content, high energy density, and unique characteristics of being high in carbon but low in nitrogen, qualifying it as a relatively clean energy source endowed with considerable ecological, economic, and energy utilization potential (Ahmed et al., 2018). Presently, the avenues for utilizing green waste resources are continually broadening, leading to the emergence of various utilization methods, such as composting for fertilizer, physical mulching, material recycling, and energy conversion (Suryawan et al., 2022; Wang Y. M. et al., 2022; Mahari et al., 2020; Pan et al., 2024). However, there is still a certain gap between the efficiency of green waste disposal and the level of resource utilization in developed countries. In fact, the generation of green waste is influenced by multiple factors, including natural and socio-economic factors (Shu et al., 2021). However, natural factors are exogenous and difficult to change through changes in management strategies and behaviors. Therefore, clarifying green waste generation and exploring their socio-economic driving factors holds immense significance for optimizing the green waste management system. (Xin et al., 2023).

In previous studies, the quantitative methods for assessing green waste primarily encompass direct measurement (Lelicińska-Serafin et al., 2024; Ma et al., 2017) and indirect estimation (Shu et al., 2021; Yu et al., 2009). Direct measurement techniques, such as Springer's (2012) calculation of green waste generated from 445 square meters of green space annually, and Eades et al. s (2020) house-to-house

interview survey conducted in Hampshire, UK—which compared variations in green waste generation between urban and rural areas—yield accurate and real-time data for specific locales. However, due to high costs, extended research cycles, and geographical constraints, these methods are challenging to implement on a large scale. Conversely, the indirect estimation method relies on secondary data sources. For instance, Liu et al. (2020b) estimated national garden waste generation in 2018 based on national greening statistics. Schmidt and Pahl-Wostl (2007) comprehensively utilized literature reviews and statistical data while considering factors such as population density and types of green spaces to calculate *per capita* green waste production in Germany. Nonetheless, this approach is contingent upon the accuracy and completeness of the underlying data; discrepancies in statistical standards across different regions can lead to significant errors. Moreover, with advancements in machine learning technologies, recent studies have employed mathematical models (Adeogba et al., 2019) and remote sensing techniques (Fu et al., 2020) to quantify green waste yield. While these methodologies facilitate rapid acquisition of large-scale information, challenges remain regarding the classification accuracy of green spaces within complex urban environments; accurately distinguishing between various sources of green waste continues to be problematic.

In terms of research methodologies concerning influencing factors, several scholars have employed techniques such as PEST analysis, Analytic Hierarchy Process (AHP), and grey correlation analysis to investigate the degree of correlation between green waste production and its influencing factors (Mi et al., 2011; Li et al., 2015). While these methods can effectively analyze the relationships among various factors and identify key influencers in scenarios with limited data and incomplete information, they fall short in quantitatively decomposing the influence exerted by each factor. Additionally, other researchers have utilized regression analysis to establish a correlational model linking vegetation coverage with green waste generation (Timilsina et al., 2014). However, this approach has specific requirements regarding data distribution and linearity. It struggles to account for interactions among multiple factors and faces limitations when addressing complex variables that affect green waste production. Furthermore, some studies have applied artificial neural network models with time delays to examine the relationship between green waste production and temperature (Vu et al., 2019). This method is capable of identifying nonlinear relationships between variables; however, it demands a substantial amount of data. Moreover, it poses challenges in elucidating internal change mechanisms, thereby limiting its decision-support value in policy-making contexts.

Based on this, this study adopts the IPAT-LMDI (Impact = Population * Affluence * Technology - Logarithmic Mean Divisia Index) model, which can decompose the environmental impact (green waste generation) into the influence of multiple factors such as population, wealth level, and technology, thus clearly quantifying the contribution of each factor to green waste generation, and better handling the interaction of multiple factors. Meanwhile, the model is relatively concise in mathematical principles, easy to understand and apply, and has been widely validated and applied in the field of environmental science, with high reliability and comparability. For example, Zaman and Moemen (2017) used this model to confirm the relationship

between economic growth, energy consumption, and carbon dioxide emissions in countries at different stages of development. Ren et al. (2023) used its extended version to evaluate the impact of various technological interventions on China's wastewater emissions. Although some emerging machine learning models, such as random forests and neural networks, have advantages in handling complex nonlinear relationships, they often require a large amount of data for training. In the current situation of insufficient green waste production data, it is difficult to intuitively reveal the intrinsic relationship between various factors and the amount of green waste generated. Therefore, considering the research objectives, data availability, and interpretability of the model, this study selects the IPAT-LMDI model to quantitatively analyze the driving factors of changes in green waste generation.

Currently, one of the crucial tasks in advancing the treatment and resource utilization of green waste in China is to gain a comprehensive understanding of the current state of urban green waste, ascertain its total volume, distribution, and developmental trends. Nevertheless, there is currently no official data available on the total quantity of garden waste resources. Despite several studies exploring the quantification and analysis of green waste, challenges persist, including limited research scope, inconsistent methodologies, and inadequate attention to dynamic shifts. Regarding research scope, there is a notable absence of comprehensive and comparative regional studies at the national level. Most research efforts are centered on individual cities or regions (Liu et al., 2020c; Peng et al., 2018; Li, 2018). In terms of methodology, current studies typically employ surveys, estimations, or a combination of both (Cai, 2019; Chun et al., 2009). The lack of consensus on statistical methods and standards impedes comparability across different regions. From a research standpoint, existing studies primarily concentrate on single-point analysis (Liu X. et al., 2020), with limited focus on the dynamic changes in the quantity of green waste resources. Moreover, most existing research remains at the stage of estimating green waste production and qualitatively analyzing its influencing factors, with few studies quantitatively assessing the impact of different factors. Therefore, there is an urgent need to systematically and objectively elucidate the dynamic changes and spatiotemporal characteristics of green waste resources, conduct an in-depth analysis of the driving factors behind these changes, and establish a foundation for scientific disposal and resource utilization.

Based on this, this paper quantified the green waste generation in China (excluding Tibet, Hong Kong, Macau, and Taiwan) from 2003 to 2022 and established an analytical framework encompassing national, regional, and provincial levels. This framework explores the dynamic spatiotemporal patterns of green waste output across China at different spatial scales. Building on this foundation, we improved the IPAT model and applied the enhanced IPAT-LMDI model to quantitatively decompose the socioeconomic drivers of changes in green waste resources. The methodology aims to identify the key factors influencing the generation of green waste and provides references for enhancing the scientific disposal and utilization of green waste, thereby fostering cleaner and more sustainable urban environments.

The remaining parts of this study are as follows. The second part elaborates on the research methods and data sources in detail. The third part presents the calculation results of green waste production,

analyzes the spatiotemporal characteristics and driving factors, and discusses them. The fourth part summarizes the research results and proposes targeted suggestions.

2 Methods and data

2.1 Calculation of green waste

Due to the serious lack of statistics on the amount of green waste generation in China, existing statistics mostly focus on individual cities or regions, with significant differences in statistical methods and caliber. Based on literature review and field interviews, this article defines green waste as the dead branches, fallen leaves, grass debris, and trimmings generated during the growth and management of trees, shrubs, and lawns used for urban greening and beautification within the built-up area. Using the yield factor method, the calculation formula for the annual generation of green waste (in 10,000 tons) is set as Equation 1:

$$GW = GA \times \alpha \quad (1)$$

Among them, GA (km^2) is the green space area of urban built-up areas; α is the green waste production factor (kg/m^2), which is the average annual green waste generated per square meter of urban green space. Drawing on the findings from field research interviews and prior research on green waste generation calculations (He et al., 2012; Wu et al., 2010; Li, 2016; Gong, 2014; Zhu et al., 2023; Li, 2024; Liu, 2014; Wu et al., 2014; Yan et al., 2016; Cai, 2019), this article establishes a green waste generation factor of $1.7 \text{ kg}/\text{m}^2$ to standardize calculation and statistical methods. Taking into account variations in climate and vegetation across different regions, a sensitivity analysis is performed on this yield coefficient. The coefficient is adjusted within a range of $\pm 30\%$, varying from $1.19 \text{ kg}/\text{m}^2$ to $2.21 \text{ kg}/\text{m}^2$, aligning with the range of yield factors reported in current literature (Table 1). Utilizing a single-factor sensitivity analysis approach, we alter only the yield coefficient while maintaining all other factors constant (Equation 2).

$$\text{Sensitivity coefficient} = \frac{(GW_2 - GW_1)/GW_1}{(\alpha_2 - \alpha_1)/\alpha_1} \quad (2)$$

In the formula, α_1 represents the yield coefficient before the change, while α_2 denotes the yield coefficient after the change. Therefore, the rate of change in the yield coefficient is calculated as $(\alpha_2 - \alpha_1)/\alpha_1$. Additionally, the green waste generation amounts before and after the corresponding yield coefficient changes are calculated as GW_1 and GW_2 , respectively. The rate of change in green waste generation is denoted as $(GW_2 - GW_1)/GW_1$. The ratio of these two rates of change represents the sensitivity coefficient, which gauges the extent of the yield coefficient's impact on green waste production, thereby ensuring the scientific rigor of our calculation results.

2.2 IPAT model construction and inference

Green waste, as an organic solid waste generated during urban landscaping construction, if not scientifically disposed of, will bring

TABLE 1 Green waste production factors in public literature.

Research area	Statistic-al year	Statistical methods	Green waste production factor (kg/m ²)	Literature sources
Wuxi, Jiangsu	2009	Classification calculation	1.42	He et al. (2012)
Beijing	2010	Estimate	1.83	Wu et al. (2010)
Tianshui, Gansu	2012	Statistics	1.43	Liu (2014)
Suzhou, Jiangsu	2012	Statistics	0.70	Wu et al. (2014)
Xi'an, Shanxi	2013	Classification calculation	0.53	Li (2016)
Foshan, Guangdong	2014	Statistics	1.55	Yan et al. (2016)
Jing'an, Shanghai	2014	Classification calculation	1.31	Gong (2014)
Huai'an, Jiangsu	2018	Statistics	0.79	Cai (2019)
Shanghai	2020	Classification calculation	0.64	Zhu et al. (2023)
Dezhou, Shandong	2022	Estimate	2.1	Li (2024)

certain pressure to the ecological environment. To illustrate the impact of socio-economic factors on the ecological environment, (Ehrlich and Holdrens, 1971), indicating that environmental pressure (I) is determined by population size (P), affluence (A), and technological level (T). As shown in Equation 3:

$$I = PAT \tag{3}$$

To further explore the driving factors of green waste generation, we considered the amount of green waste resources as environmental pressure I in the IPAT model, with richness A expressed in *per capita* gross domestic product (G/P) and technological level expressed in green waste generation intensity (GW/G), which is the amount of green waste resources per unit of economic output. As shown in Equation 4:

$$I = GW = PAT = P \times \frac{G}{P} \times \frac{GW}{G} \tag{4}$$

Among them, the intensity of green waste generation can be further decomposed into the product of green waste production factor, urban green space rate, and unit output built-up area, As shown in Equation 5:

$$T = \frac{GW}{G} = \frac{GW}{GA} \times \frac{GA}{BA} \times \frac{BA}{G} \tag{5}$$

Therefore, the IPAT model can evolve into:

$$I = PAT = P \times \frac{G}{P} \times \frac{GW}{G} = P \times \frac{G}{P} \times \frac{GW}{GA} \times \frac{BA}{G} = GW \tag{6}$$

In the formula, P represents population, G represents regional gross domestic product, GW represents annual green waste resources, GA represents urban green space area, and BA represents urban built-up area.

2.3 Decomposition of driving factors

Based on field research and previous research, and based on the construction and evolution of the IPAT model mentioned earlier, Utilizing the Logarithmic Mean Divisia Index (LMDI) method to decompose the driving factors of green waste generation enables

efficient elimination of residual terms and a thorough breakdown of the overall impact. Accordingly, the driving factors for the variation in green waste generation can be decomposed into four factors

$$GW = P \times \frac{G}{P} \times \frac{GW}{GA} \times \frac{GA}{BA} \times \frac{BA}{G} = P \times \frac{G}{P} \times \frac{GW}{BA} \times \frac{BA}{G} = P \times A \times S \times U \tag{7}$$

In Equation 7, the driving factors affecting the generation of green waste resources are decomposed into population size factor P, denoted by the regional population count; economic development factor A, enoted by the *per capita* economic output value (G/P); environmental pressure factor S, expressed as the product of the green waste generation factor and the urban green space ratio, which is the amount of green waste generated per unit area (GW/BA); and urban development factor U, reflected by the reciprocal of the output per unit area of built-up areas (BA/G). The specific meanings of indicators are shown in Table 2.

Based on Equation 6 above, the change in green waste production in year t relative to the base period is:

$$\Delta Z = Z^t - Z^0 = P^t A^t S^t U^t - P^0 A^0 S^0 U^0 = \Delta Z_P + \Delta Z_A + \Delta Z_S + \Delta Z_U \tag{8}$$

In Equation 8, ΔZ_P, ΔZ_A, ΔZ_S and ΔZ_U respectively represent the changes in population size effect, output size effect, environmental pressure effect, and urban development effect relative to the base period in the tth year, that is, the contribution values of each factor to the changes in green waste production.

Using LMDI to decompose the changes in *per capita* green waste production, the decomposition results of each factor are shown in Equation 9:

$$\begin{aligned} \Delta Z_P &= W \ln \frac{P^t}{P^0} = W \ln D_P \\ \Delta Z_A &= W \ln \frac{A^t}{A^0} = W \ln D_A \\ \Delta Z_S &= W \ln \frac{S^t}{S^0} = W \ln D_S \\ \Delta Z_U &= W \ln \frac{U^t}{U^0} = W \ln D_U \end{aligned} \tag{9}$$

TABLE 2 Variable description table.

Dimension	Symbol	Formula	Variable	Symbol	Variable description
Environmental effect	<i>I</i>	<i>PAT</i>	Green waste annual resource quantity	<i>GW</i>	/10,000 tons
Population	<i>P</i>	<i>P</i>	Regional population	<i>P</i>	/10,000 people
Affluence	<i>A</i>	$\frac{G}{P}$	Per capita gross domestic product	<i>G</i>	Regional gdp/100 million yuan
Technical factors	<i>T</i>	$\frac{GW}{G}$	Green waste discharge intensity	—	$\frac{GW}{G} = \frac{GW}{GA} \times \frac{GA}{BA} \times \frac{BA}{G}$
Environmental pressure level	<i>S</i>	$\frac{GW}{BA}$	Green waste output per unit area	<i>GA</i>	Green space area in built-up areas/hectare
Urban development level	<i>U</i>	$\frac{BA}{G}$	Output per unit area of built-up areas (reciprocal)	<i>BA</i>	Built-up area/hectare

Among them The value of *W* is shown in Equation 10:

$$W = \frac{Z^t - Z^0}{\ln Z^t - \ln Z^0} \tag{10}$$

2.4 Data sources and visualization

This study focuses on 30 provinces, autonomous regions, and municipalities in mainland China from 2003 to 2022. Due to the complex geographical environment, Tibet was excluded from the study due to difficulties and gaps in data statistics in some years, which made it challenging to ensure the integrity and accuracy of the data. Additionally, Hong Kong, Macao Special Administrative Region, and Taiwan were also excluded due to differences in statistical systems and data collection standards compared to mainland China. To ensure the consistency and comparability of the research data, they were not included in this study. This research meticulously investigates the spatial-temporal patterns and underlying driving factors associated with the green waste resources within these regions. Data pertaining to population size, GDP, and green space area utilized in the study were obtained from authoritative sources such as the China Statistical Yearbook (covering the years 2003–2022) and the Urban Construction Statistical Yearbook (also covering the same period). Among them, some missing data were filled in using linear interpolation method.

ArcGIS, a geographic information system (GIS) software crafted by the American firm Environmental Systems Research Institute (ESRI), holds a prominent position as one of the most extensively used tools in the global GIS sector. Our research employed this powerful software to map and visualize the generation and spatial distribution of green waste, capitalizing on a series of official urban boundary datasets disseminated by China’s Ministry of Natural Resources for the years 2003, 2008, 2012, 2017, and 2022. This analytical endeavor illuminated temporal shifts and regional disparities in green waste production across China.

Advancing our investigation, we also adopted prospective urban expansion boundary data for the period of 2022–2030, as proposed by Huang et al. (2022a), which encompass diverse socioeconomic scenarios and alternative models of urban sprawl. This adoption allowed for a nuanced discussion on the prospective trends in green waste generation in China, considering the compounding effects of urban growth patterns under various development frameworks.

3 Results

Considering the vastness of China’s territory, which encompasses a multitude of terrains, climates, cultures, economies, and political structures, this study delves deeper into the temporal and spatial distribution patterns of green waste resources across the nation (excluding Tibet, Hong Kong, Macao, and Taiwan). Leveraging a scientific and multidimensional approach that incorporates factors such as geography, history, and ethnicity, the country is divided into six distinct regions: North China (Beijing, Tianjin, Hebei Province, Shanxi Province, Inner Mongolia), Northeast (Liaoning, Jilin, Heilongjiang), East China (Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong), Central South (Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan), Southwest (Chongqing, Sichuan, Guizhou, Yunnan), and Northwest (Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang). To investigate the changes in green waste generation over time, the years 2003–2022 are segmented into four phases, each consisting of 5-year intervals.

3.1 Total amount and distribution of green waste

3.1.1 Total amount of green waste

Employing the production factor approach, an estimated 60.97 million tons of green waste were generated across the nation in the year 2022. At the same time, considering the differences in climate and vegetation conditions in different regions, the yield factors in the northwest, northeast, and north China regions were reduced by 30%, 20%, and 10% respectively, while the yield factors in the southwest, central southern, and east China regions were increased by 30%, 20%, and 10% respectively. Sensitivity coefficients were calculated, and the range and sensitivity coefficients of green waste production obtained are shown in Table 3.

The calculated sensitivity coefficient of the yield factor is approximately 0.18. This indicates that for every 1% change in the yield factor based on 1.7 kg/m², the generation amount of green waste will change by approximately 0.18%. The green waste generation is not very sensitive to minor changes in the yield factor, which means that the shift in the yield coefficient within a certain range will not have a significant impact on the generation amount of green waste.

TABLE 3 Comparison of green waste generation in public literature with our study.

Year	Estimated value	Adjustment value (-)	Adjustment value (+)	Sensitivity coefficient	Prior studies
2003	10.71	10.13	12.01	0.1780	
2004	22.47	21.45	25.28	0.1852	21.54 (Shi et al., 2013a)
2005	24.96	23.89	28.15	0.1866	23.92 (Shi et al., 2013b)
2006	22.44	21.47	25.19	0.1875	21.52 (Shi et al., 2013a)
2007	29.29	27.53	32.60	0.1779	27.86 (Shi et al., 2013b)
2008	29.96	28.68	33.80	0.1871	28.88 (Shi et al., 2013a)
2009	33.85	32.46	38.12	0.1889	
2010	36.25	34.72	40.80	0.1883	
2011	38.08	36.47	42.85	0.1882	22.45 (Shu et al., 2021)
2012	40.19	38.42	45.16	0.1873	
2013	41.20	39.34	46.23	0.1872	
2014	42.90	40.95	48.11	0.1871	
2015	45.29	43.17	50.77	0.1864	
2016	47.26	45.10	53.06	0.1866	
2017	49.58	47.25	55.59	0.1862	>30 (Wang et al., 2022c)
2018	51.70	49.30	58.05	0.1861	34.12 (Liu et al., 2020c)
2019	53.50	51.02	60.06	0.1859	33.13 (Shu et al., 2021)
2020	56.20	53.55	63.08	0.1854	
2021	59.05	56.29	66.43	0.1847	52.1 (Wan et al., 2023)
2022	60.85	58.01	68.49	0.1846	70 (Liu, 2024)

To further validate the effectiveness of the research results, in Table 3, this study systematically compared the estimation results based on the yield factor method with the actual values of green waste production reported in previous studies. Given that most of the previous related research focused on single-time points and lacked long-term and coherent data monitoring, resulting in the absence of data for some years, this study conducted a precise comparative analysis only for the years with complete data.

The comparison results show that the prior studies values of green waste production are basically consistent with the estimated values and the adjusted value ranges of this study (Shi et al., 2013a; Wan et al., 2023; Liu, 2014). This result strongly validates the rationality of the selection of the yield factor and the accuracy of the calculation results in this study, providing reference data support and method verification for the quantitative research on green waste generation.

3.1.2 Distribution of green waste

Figure 1 illustrates the provincial heterogeneity of green waste generation across China in 2022. The chromatic scale reflects total annual green waste yield, with darker hues corresponding to higher production intensities. The geographical dispersion of green waste generation within China demonstrates a prevailing trend of higher volumes in the southeastern regions and relatively lower quantities in the northwestern territories. Notably, East China and Central South China collectively account for the most substantial amount of

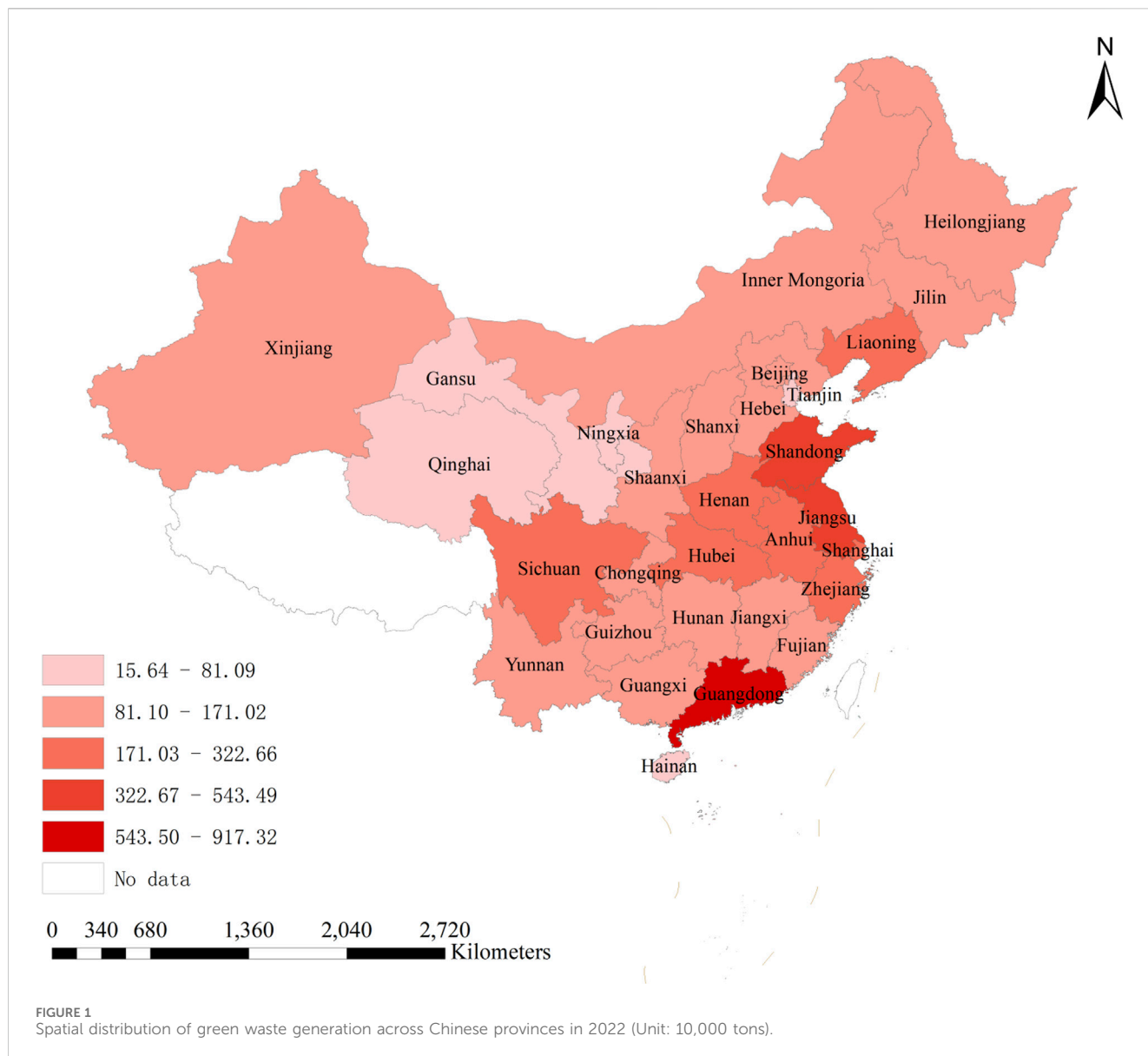
total resources, topping the national distribution chart. Following closely behind are the northeastern, northern, and southwestern regions of the country. In contrast, the northwest region registers the least overall volume of green waste production.

3.2 Dynamic evolution of spatiotemporal pattern of green waste generation

3.2.1 National green waste generation

Over the past 20 years, China has witnessed a steady overall increase in the cumulative volume of green waste resources. In the year 2003, the nationwide production of green waste stood at 10.71 million tons, which escalated to a staggering 60.97 million tons by 2022, representing an almost quintuple increase. The changes in the amount of green waste generated and growth rate are shown in Figure 2.

The growth rate of total green waste resources initially exhibited a pattern of fluctuation followed by stabilization. Post-2010, the growth rate steadied. The pronounced fluctuations during this initial phase might be attributed to the revisions made by the Ministry of Construction to the “Urban Construction Statistical Reporting System” in 2006. These revisions included adjustments to the urban boundaries and statistical standards, which likely impacted the comparability and interpretability of the data during those



years. Currently, the annual growth rate of total green waste resources in China maintains a stable trajectory, hovering between 3% and 5%.

3.2.2 Regional green waste generation

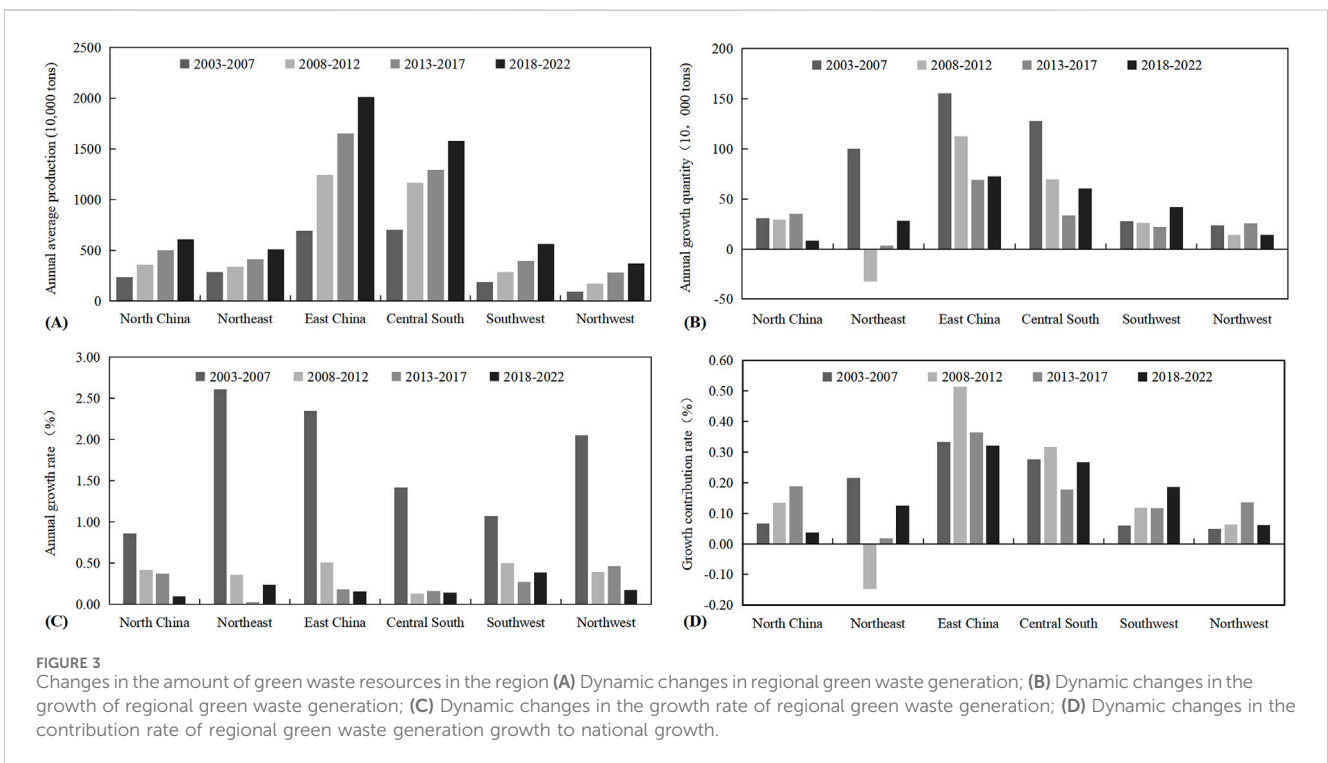
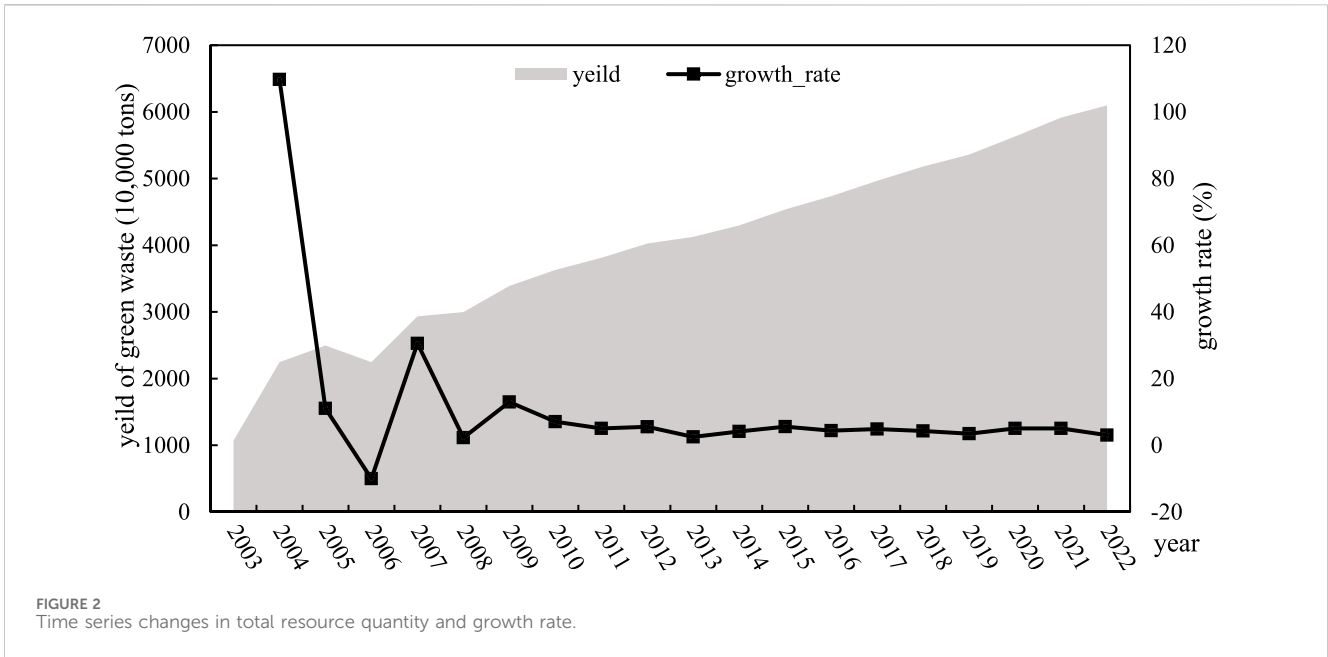
(1) Dynamic changes in regional green waste generation

From the absolute value of annual green waste production, the green waste production in different regions has shown an increasing trend over time (Figure 3A). In the early phase (2003–2007), East China topped the list with the highest average annual green waste resources, followed by Central South, Northeast, North China, Southwest, and Northwest respectively. However, during the middle period (2008–2012), there was a notable surge in the green waste production in East and North China, overtaking Central South and Northeast regions. The new hierarchy, based on average annual resource levels, shifted to Central South > East China > North China >

Northeast > Southwest > Northwest. Moving into the next phase (2013–2017), the growth rate of green waste resources in Northeast China slowed down, with its average annual resource quantity marginally exceeding that of the Southwest region. Finally, in the latest segment (2018–2022), the Southwest region saw a significant increase in green waste production, eventually surpassing the Northeast region, securing the position as the third-highest producer of green waste resources in the country.

(2) Dynamic changes in the growth of regional green waste generation

In terms of the annual growth of green waste resources across China, the general pattern reflects a fluctuating yet declining tendency (Figure 3B). While most regions have been witnessing an increase in the number of green waste resources every year, the Northeast region uniquely registered a negative annual growth rate



between 2008 and 2012, signifying a decrease in its green waste production. During the period from 2003 to 2007, the East China, Central South, and Northeast regions demonstrated relatively high average annual growth rates, with increases surpassing 1 million tons. Conversely, North China, Southwest, and Northwest China experienced more modest increments, adding roughly 200,000 to 300,000 tons annually. Between 2008 and 2012, the average annual growth rates in all regions declined to differing extents. The

Northeast region saw the sharpest drop, entering negative growth territory. From 2013 to 2017, the average annual growth rate in North China, Northeast China, and Northwest China rose compared to the preceding period, whereas there was a minor dip in the growth rates for East China, Central South China, and Southwest China. Lastly, in the final period from 2018 to 2022, the Northeast, Central South, and Southwest regions experienced an upturn in their average annual growth rates compared to the

previous period. However, North China, East China, and Northwest regions noted a decrease in their respective average annual growth rates.

(3) Dynamic changes in the growth rate of regional green waste generation

Overall, while the annual growth rate of green waste resources across China has generally decreased over time, there are variations in the changing trends among different regions (Figure 3C). Specifically, the annual growth rates in North China and Northeast China have consistently decreased over the years, aligning with the overarching national trend of diminishing annual growth in green waste resources. In contrast, the Northeast and Southwest regions display a pattern of decline followed by an upturn. Their average annual growth rates dropped from 2003 to 2017, but then slightly recovered from 2018 to 2022. Meanwhile, the Central, Southern, and Northwestern regions exhibit a fluctuating downward trend. Their growth rates dipped from 2003 to 2012, and then showed a temporary rise followed by another decline between 2013 and 2017.

(4) Dynamic changes in the contribution rate of regional green waste generation growth to national growth

The analysis reveals that nearly 60% of the overall growth in green waste resources in China can be attributed to the expansion in the East China and Central South regions (Figure 3D). However, in recent years, East China's contribution rate to this growth has been on a declining path, while the Central South region's contribution has stayed relatively constant but with some fluctuations. The Southwest region is emerging as a significant contributor, with its share in the growth of national green waste resources increasing and showing a rising trend. By 2018 to 2022, the Southwest region's contribution rate reached 19%. In contrast, the contribution rates of growth for North China and Northwest China were on the rise prior to 2018, but they experienced a substantial decline afterward. From 2018 to 2022, North China's contribution rate fell to 4%, while Northwest China's contribution dropped to 6%. The Northeast region displays a highly variable contribution rate. Between 2003 and 2007, it accounted for 22% of the total national green waste resource growth. Nevertheless, from 2008 to 2012, the decline in green waste resources in the Northeast negatively impacted the overall national figure. Starting from 2013, however, the Northeast region's contribution rate began to steadily recover, reaching 13% by 2018–2022.

3.2.3 Provincial green waste generation

When examining the situation province by province, from 2018 to 2022, the six provinces with the highest average annual green waste resources were Guangdong, Jiangsu, Shandong, Zhejiang, Shanghai, and Liaoning—all situated along the coastlines (Table 4-Rank A). Notably, Guangdong Province recorded an average of 8.1917 million tons of green waste annually between 2018 and 2022, while Jiangsu Province generated an average of 5.2095 million tons per year, placing them firmly at the forefront of the nation. The elevated green

waste production in these coastal provinces could be attributed to their high levels of economic development. As a result, residents have a higher demand for quality living environments, leading to increased investment by local governments in urban landscaping construction and upkeep. This emphasis on landscaping has led to a larger scale of green space development and consequently, a higher volume of green waste being produced. Moreover, inland provinces such as Sichuan, Henan, Anhui, Hubei, and Hebei also reported relatively high amounts of green waste resources over the past 2 decades.

3.3 Spatiotemporal patterns of green waste generation density

3.3.1 National green waste density

The density of green waste resources, defined as the ratio of green waste generated to the total built-up area, has displayed a predominantly fluctuating yet ascending trend over time. Between 2003 and 2010, this growth rate was particularly brisk. Initially, in 2003, the green waste generation density in China's built-up areas stood at 378.46 tons per square kilometer, which soared to 905.89 tons per square kilometer by 2010—a significant leap. From 2010 to 2013, there was a noticeable decline in the volatility of this growth rate, after which it resumed a steady climb. By 2022, the density of green waste generated within China's built-up areas hit 935.91 tons per square kilometer, reflecting an average annual growth rate of approximately 1%–2% over the years. The temporal variation of green waste generation density is shown in Figure 4.

3.3.2 Regional and provincial green waste density

Figures 5A–E illustrate annual green waste generation density (tons/km²/year) across provinces for 2003, 2007, 2012, 2017, and 2022. Color intensity scales with production density (see legend), where dark green indicates high-intensity zones and light green represents low-density regions. The spatial distribution of green waste resource generation density follows a clear pattern where it is significantly higher in the eastern part of China and lower in the western regions. Over time, the resource density in the southern areas has escalated rapidly, creating a geographic distinction where the southeast holds a higher density, while the northwest remains relatively low.

3.3.3 Provincial green waste density

Provinces with the highest green waste resource generation per unit area are primarily concentrated in eastern coastal regions, including Beijing and Tianjin in North China, Heilongjiang and Liaoning in Northeast China, Shanghai, Jiangsu, Shandong, Zhejiang, and Anhui in East China, Hainan in Central South China, and Chongqing in Southwest China (Table 4-Rank B). This uneven distribution can be attributed to the rapid economic development of the eastern coastal provinces. These areas initiated urban landscaping projects earlier and have maintained a high standard of management and conservation. Consequently, they have a larger volume of green waste resources per unit area and a faster growth rate over time.

TABLE 4 Top 10 provinces with annual green waste generation and density.

Rank A	2022–2018		2017–2013		2012–2008		2007–2003		Rank B	2022–2018		2017–2013		2012–2008		2007–2003	
	Province	Yield	Province	Yield	Province	Yield	Province	Yield		Province	Density	Province	Density	Province	Density	Province	Density
1	Guangdong	879	Guangdong	741	Guangdong	684	Guangdong	422	1	Shanghai	432.0	Shanghai	344.5	Shanghai	277.7	Shanghai	69.3
2	Jiangsu	521	Jiangsu	464	Jiangsu	382	Jiangsu	253	2	Beijing	93.9	Beijing	79.5	Beijing	62.2	Beijing	47.7
3	Shandong	446	Shandong	365	Shandong	265	Shandong	160	3	Tianjin	64.6	Jiangsu	45.4	Guangdong	38.1	Jiangsu	24.7
4	Zhejiang	303	Zhejiang	242	Shanghai	176	Heilongjiang	130	4	Jiangsu	51.0	Tianjin	44.1	Jiangsu	37.3	Guangdong	23.5
5	Shanghai	274	Shanghai	218	Liaoning	160	Liaoning	114	5	Guangdong	48.9	Guangdong	41.3	Tianjin	27.8	Tianjin	21.4
6	Liaoning	237	Liaoning	206	Zhejiang	153	Sichuan	93	6	Zhejiang	29.3	Zhejiang	23.4	Hainan	24.5	Shandong	10.0
7	Sichuan	221	Anhui	159	Sichuan	121	Zhejiang	86	7	Shandong	28.1	Shandong	23.0	Shandong	16.7	Zhejiang	8.3
8	Henan	207	Sichuan	158	Anhui	120	Beijing	78	8	Liaoning	16.0	Liaoning	13.9	Zhejiang	14.8	Liaoning	7.7
9	Anhui	204	Henan	154	Heilongjiang	115	Hubei	77	9	Anhui	14.6	Chongqing	11.5	Liaoning	10.8	Hainan	7.0
10	Hubei	179	Hebei	139	Henan	114	Anhui	72	10	Chongqing	14.6	Anhui	11.4	Anhui	8.6	Anhui	5.2

The unit of yield in Rank A is 10,000 tons. The unit of density in Rank B is t/km².

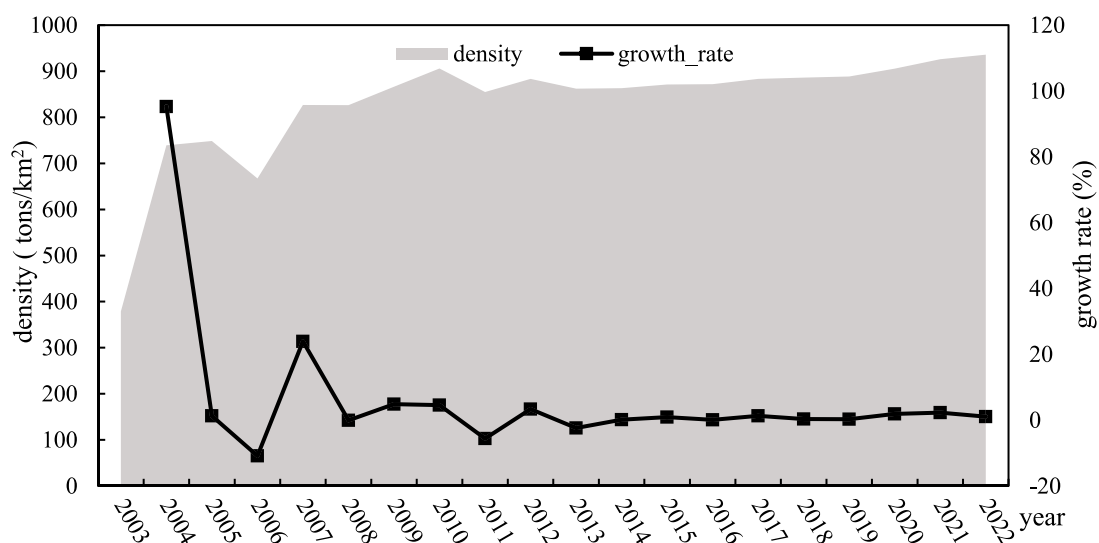


FIGURE 4 Time series variation of green waste generation density and growth rate.

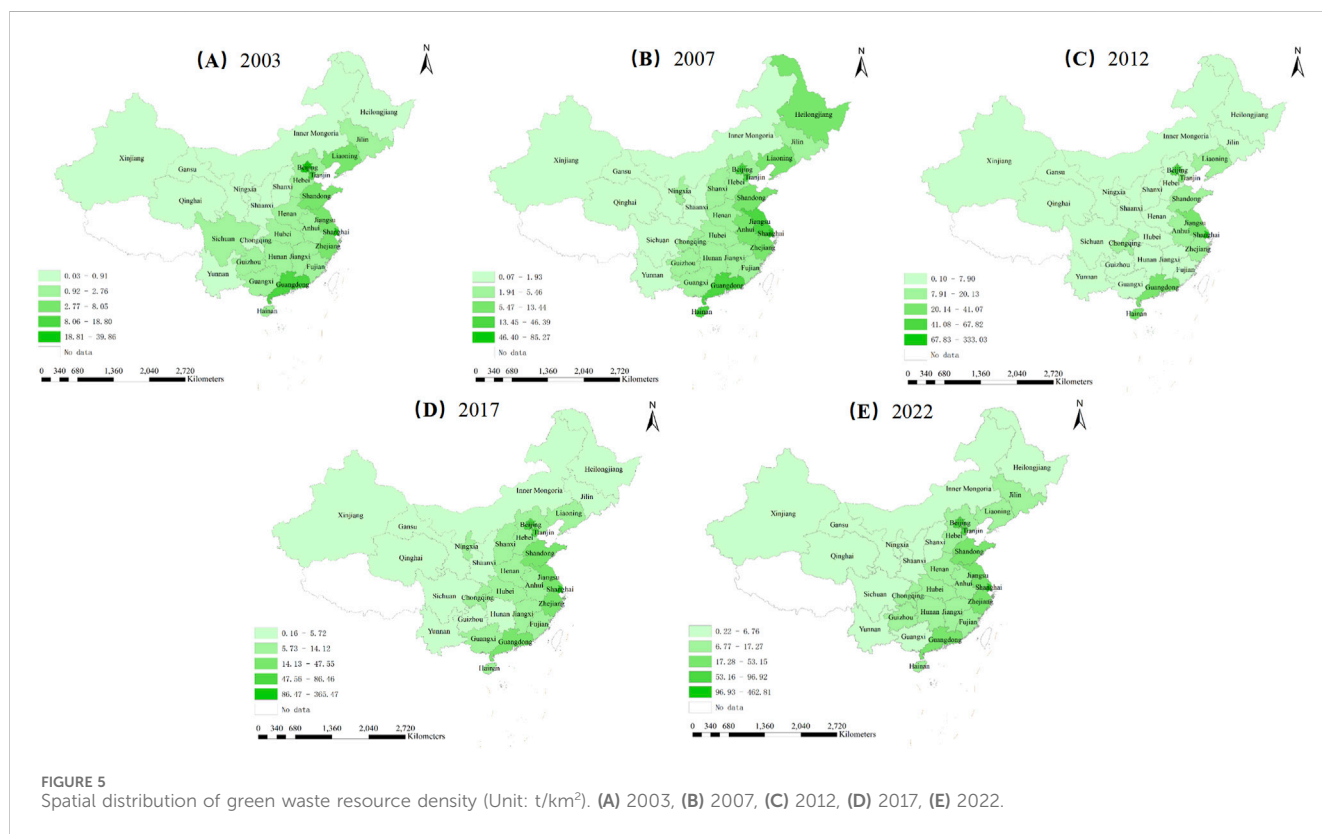


FIGURE 5 Spatial distribution of green waste resource density (Unit: t/km²). (A) 2003, (B) 2007, (C) 2012, (D) 2017, (E) 2022.

3.4 Analysis of driving factors for changes in green waste production

The LMDI model was employed to decompose the driving factors of green waste production, with the results presented in Table A1 (in the Appendix). As illustrated in Figure 6, from 2003 to 2022, population size, economic development, and environmental

pressure exhibited relatively stable positive impacts on green waste generation. Among these factors, economic development emerged as the most significant driver, contributing 143.05% to the increase in green waste generation. The contribution rates of environmental pressure and population size were 39.75% and 10.16%, respectively. Conversely, urban development exerted a consistently negative influence, contributing 92.97% to the reduction of green waste

generation. Specifically, the economic development effect contributed the most to the total effect of the change of green waste resources, which was the most important driving factor, indicating that the increase of *per capita* GDP had a strong explanatory ability for the increase of green waste resources, and showed an accelerating trend over time. The environmental pressure effect positively drove the increase of green waste production, but the contribution rate fluctuated greatly in different years. The driving effect of population size on the increase of green waste production was small and relatively stable, and the driving effect showed an inverted U-shape over time. On the whole, the effect of urban development is negative, that is, the decrease of the measured value of urban development level and the increase of actual urbanization level have a negative driving effect on green waste resources, and the driving effect is first enhanced and then weakened.

4 Discussions and policy recommendations

4.1 Discussions

4.1.1 Spatiotemporal heterogeneity of green waste generation

The analysis reveals a persistent upward trajectory in China's green waste generation from 2003 to 2022, aligning with the temporal patterns identified by Shi et al. (2013b). This trend likely reflects synergistic effects of rapid urbanization and population growth, which have elevated environmental quality standards nationwide. Consequently, municipal authorities have substantially increased investments in urban greening infrastructure, resulting in both spatial expansion of green areas and enhanced maintenance practices that collectively contribute to amplified green waste outputs.

Our quantification methodology yields higher estimates than those reported by Shu et al. (2021) and Liu et al. (2019), primarily due to expanded parameter definitions encompassing herbaceous residues (grass clippings, leaf litter, etc.). This comprehensive approach positions our 49.58 million tonne estimate for 2017 within the broader spectrum of Wang et al. (2022b) 30-million-tonne threshold projection. While Shi et al. (2013b) documented dry-weight biomass equivalents for 2004–2008 through field-calibrated literature synthesis, our moisture-adjusted calculations demonstrate temporal consistency with their baseline data, though offering superior temporal resolution and contemporary relevance.

Spatiotemporal analysis identifies distinct geographic disparities, mirroring regional economic gradients. Southeastern provinces exhibit disproportionately high waste generation (58.7% national total), attributable to their advanced urbanization, substantial green space investments, and favorable subtropical climates that accelerate plant metabolism. This spatial pattern corroborates regional studies (Shu et al., 2021), yet our longitudinal analysis reveals previously unquantified dynamics in growth trajectories.

Notably, the southwestern region emerged as an accelerated growth pole post-2015, its national contribution rising from 8.2% to

13.6% within the study period. This surge correlates with western development initiatives (Go West Policy) and parallel increases in municipal greening budgets (+214% 2015–2020). Conversely, northeastern provinces displayed cyclical fluctuations—rapid early growth (2003–2007: +12.8% p. a.) followed by recessionary declines (2008–2012: 3.1% p. a.) and subsequent recovery (2013–2022: +5.4% p. a.). These oscillations mirror regional economic restructuring phases, where industrial slowdowns precipitated reduced green space maintenance, later counterbalanced by ecological restoration mandates under the Northeast Revitalization Strategy.

4.1.2 Discussion on influencing factors of green waste generation

The IPAT-LMDI model was employed to decompose the driving factors behind changes in green waste generation. The findings indicated that economic development, environmental pressure, and population size exerted positive influences on green waste generation, whereas urban development acted as a restraining factor, inhibiting the increase in green waste generation. These results align with the study by Shu et al. (2021), but this research further elucidates the temporal variations in the degree of influence exerted by different factors.

The scale of the population has a positive driving effect on the resource utilization of green waste, which is consistent with the findings of Han et al. (2018) in developing countries. However, this study further reveals that over time, the impact of population size on green waste resource utilization exhibits an inverted U-shaped trend, with a turning point identified in 2011. This phenomenon can be attributed to the relatively rapid population growth prior to 2011, where the annual growth rate was approximately 6%. To meet the production and living needs of urban residents, built-up areas gradually expanded and green space increased, resulting in greater amounts of green waste generated. After 2011, influenced by changes in fertility concepts and awareness, national population growth rates slowed down to an average annual rate of 4%; nevertheless, residents' demand for urban green spaces continued to rise alongside increasing urban greenery area. Consequently, despite slow population growth during this period still exerting a positive influence on green waste resources. However, as urban space became increasingly saturated and population numbers declined by 2022, changes in population size began to exert a negative driving effect on variations in green waste resources.

Economic development serves as the most significant driving force behind increases in green waste generation (Wang Z. et al., 2022). As GDP *per capita* rises, residents' expectations regarding environmental quality also increase—prompting governments to enhance investments in urban landscaping—which subsequently leads to higher volumes of generated green waste. For instance, between 2008 and 2012 China actively responded to economic crises by promoting technological innovation and ecological construction; during this period there were notable improvements in urban greening infrastructure and management levels leading economic development's impact on green waste output to reach its peak value. Nonetheless, current challenges facing resource utilization from organic wastes include poor product sales performance and high costs among others. Future research should focus on optimizing industrial chains related to organic waste recycling while improving resource efficiency through cost reduction strategies aimed at

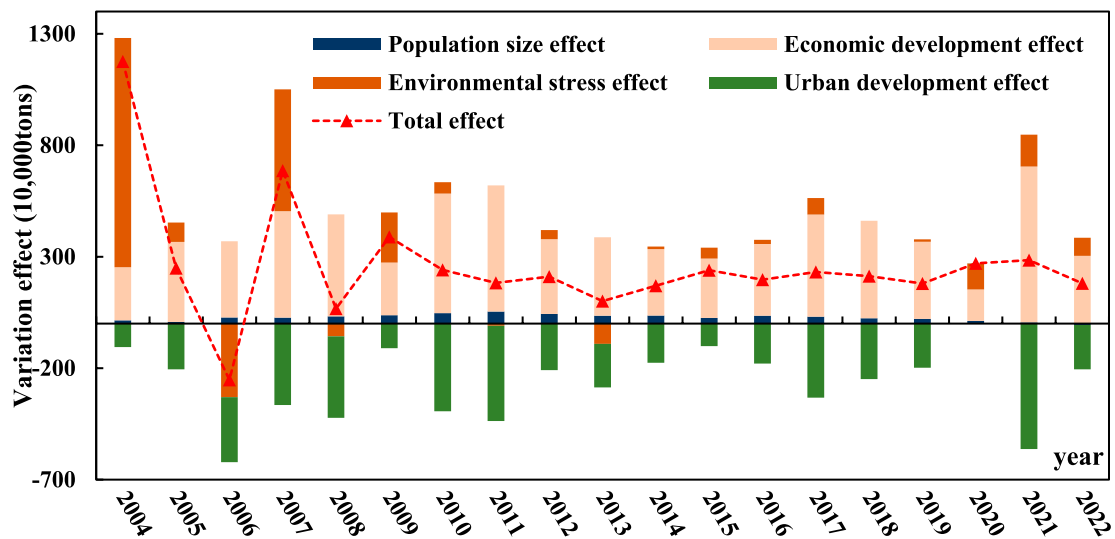


FIGURE 6
Decomposition of driving factors for changes in green waste resources.

enhancing market competitiveness for products derived from such processes.

The relationship between environmental pressure and quantities of generated organic wastes is complex. Previous studies have indicated that increased vegetation cover can suppress overall refuse generation (Wang et al., 2020a), whereas most research concerning organic wastes suggests a significant positive correlation between their volume produced relative expansion within vegetative areas (Shu et al., 2021). During periods characterized by rapid city expansion (2003–2013), contributions made towards generating organic refuse fluctuated considerably due largely because when built-up zones expand faster than new greenspace developments do then temporary reductions occur; conversely increases arise under opposite conditions instead. From years spanning across both intervals ranging from year fourteen until twenty-two however, with limited available spatial capacity now existing, urban greening efforts shifted focus onto upgrading pre-existing landscapes thus creating sustained positive influences stemming forth via heightened pressures upon environment impacting total outputs seen here. This indicates how shifts occurring within developmental models along with respective greening strategies significantly affect relationships observed amongst these variables moving forward into future investigations exploring dynamic interactions present amidst differing forms taken up throughout various cities providing more targeted recommendations applicable towards planning initiatives surrounding both aspects mentioned earlier.

Urban development levels negatively influence quantities associated with produced organics (Yu et al., 2024; Wang et al., 2020b), meaning improved efficiencies achieved through advancements made will ultimately lead lessened outputs being recorded overall. As land-use effectiveness improves across metropolitan regions available spaces become increasingly allocated toward commercial/residential purposes thereby indirectly constraining expansions witnessed previously around public parks reducing resultant figures accordingly too.

Simultaneously though emphasis placed upon maintaining balance found amid ecological/economic pursuits encourages innovations emerging within greener industries fostering betterment seen throughout landscape management practices influencing outcomes experienced here once again yet another layer needing exploration remains evident going forward whereby effective controls could potentially emerge allowing rationalized utilizations taking place concurrently alongside enhanced operational efficacies realized thereafter.

In addition beyond four factors analyzed herein other studies indicate natural elements including temperature fluctuations types exhibited among local flora precipitation patterns extreme weather events policy guidance resident awareness pertaining eco-friendly practices all contribute likewise affecting totals reported concerning organics produced (Lu et al., 2022; Shi et al., 2021). Therefore when formulating policies directed towards managing said materials sustainably implementing interventions necessitates comprehensive considerations encompassing multiple interacting influences ensuring scientific efficient governance achieved effectively overall.

4.1.3 Scenarios for variations in green waste generation factor

The Intergovernmental Panel on Climate Change (IPCC, 2023)'s Sixth Assessment Report (AR6), "Climate Change 2023," highlights a 1.1°C increase in global mean temperature compared to pre-industrial levels, emphasizing the severity of climate change. This is accompanied by a rise in extreme weather events. Research by Lin et al. (2010) shows that global warming has led to an 8.4%–16.3% increase in terrestrial plant biomass, suggesting a corresponding rise in green waste yield per unit area. This indicates that current estimates of green waste production may be conservative. Moreover, with economic development and growing environmental awareness, the management and maintenance of urban green spaces are expected to improve. Optimized urban greening strategies, with intensified

maintenance and higher vegetation densities, could lead to increased green waste yields.

Considering the changes in plant biomass, the production of green waste per square meter of green space is likely to rise to 1.84–1.98 kg in the near future. For example, in 2022, the recalculated amount of green waste generated in China was estimated to be between 65.96 million and 70.876 million tons, with the production density in urban built-up areas rising to 1.01–1.09 kg per square meter. These shifts pose new challenges for managing green waste but also provide opportunities for more efficient and sustainable practices, contributing to the circular economy and reducing carbon emissions.

Globally, green waste, as a significant biomass resource, exhibits distinct generation patterns across nations and regions, closely tied to socioeconomic structures, environmental policies, and statistical frameworks. In China, green waste mainly comes from urban public areas and is collected by municipal departments. Based on this, the output per unit of green area becomes a reasonable measurement parameter. However, in other countries, part of the green waste originates from privately - owned areas, making it difficult to accurately calculate the green area. Thus, the per - capita green waste output has become a commonly used calculation parameter. This difference makes it challenging to directly compare green waste data among different countries and also reflects the necessity of unifying the definition and statistical methods of green waste at the global level.

In terms of per - capita green waste output, there are obvious imbalances among different countries and regions. The calculation by Lu et al. (2022) shows that the global green waste generation ranges from 1 to 336 kg/cap/year, with a weighted average of 47 kg/cap/year. Maldives, Puerto Rico, and Denmark rank among the top three in per - capita green waste output, reaching 336, 246, and 240 kg/cap/year respectively. Western Europe and the United States have relatively high per - capita green waste output, while Asia and South America have relatively low per - capita green waste output. For example, the per - capita green waste output in the United States increased from 74 kg/cap/year in 2008 to 97.8 kg/cap/year in 2014 (EPA, 2016; MacFarlane, 2009). The average generation rate of per - capita green waste in the European Union is estimated to be between 61.5–77.0 kg/cap/year, while in India it is only 20 kg/cap/year, which is much lower than that in Europe and the United States.

Green waste generation also has obvious seasonal characteristics. Taking Denmark as an example, the study by Boldrin and Christensen (2010) distinguished the green waste generation coefficients in winter and summer in Denmark. The summer coefficient can reach 19.4 kg/cap/month, much higher than 2.5 kg/cap/month in winter. In addition, there are differences in green waste output between rural and urban households. The study by Eades et al. (2020) found that rural households produce 1.96 ± 1.35 kg per day, while urban households produce 0.64 ± 0.46 kg per day. This is mainly because rural households usually have larger yards and more private green spaces and may engage in certain agricultural production activities, all of which lead to higher green waste generation in rural households than in urban households.

Overall, the global green waste generation situation is complex and diverse, affected by a combination of various factors. In future research and practice, on the one hand, it is necessary to further clarify a unified definition and statistical standard for green waste to

enable more accurate international comparison and analysis. On the other hand, it is necessary to fully consider the actual situations of different countries and regions, formulate local - specific green waste management strategies, improve the resource utilization efficiency of green waste, and achieve sustainable development.

4.1.4 Projected trends in green waste generation in the future

While urban territories occupy merely 3% of the Earth's total land area, they accommodate over half of the global population (Nations, 2018), positioning them as pivotal drivers of numerous environmental and societal transformations (Gao and O'Neill, 2020). Numerous scholars have ventured predictions on the expansion trajectory of urban built-up areas under diverse socioeconomic scenarios and varying modes of spatial growth.

Urban green spaces constitute a vital component of urban ecological environments, playing a pivotal role in beautifying city landscapes, providing leisure spaces for residents, and maintaining ecological balance (Chen et al., 2021). As outlined in the "National Land Greening Plan Outline (2022–2030)" issued by the National Greening Committee of China (2022), China aims to significantly enhance urban greening by 2030, targeting a 43% green coverage rate in urban constructed areas. This goal underscores the nation's steadfast commitment to fostering green and livable urban environments.

According to in-depth projections by Huang et al. (2022b), in tandem with accelerating urbanization, China's urban built-up areas are projected to expand to a range of 105,500 to 107,500 square kilometers by 2030 (Huang et al., 2022a). Consequently, urban green space is anticipated to witness a remarkable increase, spanning an area of 45,300 to 46,200 square kilometers. While this expansion symbolizes progress towards sustainable urban development, it also forecasts a substantial rise in green waste generation, estimated to reach between 83.35 million and 91.48 million tons. This anticipated upsurge in green waste not only imposes heightened demands on municipal solid waste management systems but also opens avenues for resource recovery and utilization.

4.2 Policy recommendations

To effectively address the challenges faced by China's green waste management and achieve scientific treatment and resource utilization of green waste, it is imperative to establish a comprehensive and targeted policy framework. This should involve fully leveraging international best practices while adapting them to domestic conditions through innovative implementation, thereby overcoming obstacles in policy execution.

- (1) Differentiated regional governance frameworks will be constructed to enhance local adaptation of international experiences.

Given China's vast territory and significant regional development disparities, multi-level green waste management strategies must be designed according to regional development gradients. In highly urbanized eastern coastal areas, characterized by developed economies, dense populations, and large volumes of

green waste, an urban agglomeration green waste (GW) metabolism network can be established by emulating Germany's Rhine-Ruhr region cross-city collaborative model. For instance, within the Guangdong-Hong Kong-Macao Greater Bay Area, leveraging the existing carbon trading mechanism, cities with strong processing capabilities like Shenzhen can treat green waste generated in Dongguan and convert it into local carbon allowances for Shenzhen. This approach not only alleviates disposal pressures on individual cities but also optimizes resource allocation via market mechanisms, promoting coordinated regional green waste treatment.

In ecologically fragile western regions, greater emphasis should be placed on ecological protection during green waste treatment. Drawing from Japan's Kanto Plain urban-rural complementarity mechanism, green waste treatment and ecological restoration can be closely integrated. For example, following Inner Mongolia's Kubuqi model, enterprises could receive management rights to 1 mu of desertified land for every 10 tons of green waste resources processed, attracting social capital to participate in ecological construction and green waste treatment in the west. To ensure smooth implementation of these regional-specific policies and support corresponding financial incentives, it is recommended that the central government establish a "Western GW Governance Transfer Payment Fund" for equipment procurement, sharing local financial burdens.

- (2) Innovative cost control mechanisms across the entire chain are essential to address financing and benefit coordination issues.

High costs remain a key bottleneck in green waste management. By integrating Singapore's DBO model with California's SB 1383 act experience, a "risk-sharing - pollution payment" strategy can be implemented. In financially robust regions such as the Yangtze River Delta, adopting the design-construction-operation (DBO) integrated bidding model would require successful bidders to bear 50% of investment and financing risks, thus leveraging corporate expertise while reducing initial government investment. Considering the lagging infrastructure in county areas, promoting simple composting and other low-cost green waste recycling models can effectively meet local treatment needs. Additionally, improving reward and punishment mechanisms, including implementing "waste reduction performance rewards," can resolve conflicts of interest among stakeholders in green waste management.

- (3) A dynamic regulatory system will be enhanced to lay the foundation for efficient use.

Based on the EU Circularity Check and New York's Local Law 77 mandatory disclosure principle, a multi-level monitoring network will be established. Cities at or above the municipal level will be required to publish a biennial green waste metabolism audit report, with non-compliant areas losing eligibility for ecological compensation funds. Data sharing and collaboration among various regulatory links will be strengthened. A unified green waste management information platform will integrate data on green waste sources, transportation processes, and treatment facility operations, enabling real-time access to accurate information for

government departments, enterprises, and the public, ensuring transparent supervision throughout the process. Combining this with green waste production prediction models will forecast trends in different regions and seasons, providing a scientific basis for planning treatment capacity and resource allocation in advance.

5 Conclusion and prospect

5.1 Conclusion

This study employed the yield factor method to quantify and analyze the spatiotemporal characteristics of green waste across 30 provinces in Chinese mainland (excluding Tibe) from 2003 to 2022. Quantify the actual impact of population size, economic development, environmental pressure, and urbanization on the total amount of green waste based on the IPAT-LMDI model framework. The main conclusions are as follows.

- (1) From 2003 to 2022, China's total green waste resources exhibited an overall upward trend, with an initial production total of 10.71 million tons in 2003, escalating to 608.53 million tons by 2022, marking a nearly five-fold increase. Presently, the annual growth rate of total green waste hovers stably between 3% and 5%.
- (2) The distribution of green waste resources shows a clear pattern of higher volumes in the southeast and lower in the northwest, with a faster growth rate observed in western regions compared to slower growth in eastern and northern parts. Provincially, from 2018 to 2022, the top six provinces in terms of annual average resource volume—Guangdong, Jiangsu, Shandong, Zhejiang, Shanghai, and Liaoning—were all coastal provinces.
- (3) The production density of green waste resources has demonstrated an overall fluctuating yet ascending trend, reaching 935.91 tons per square kilometer in built-up areas nationally by 2022. Spatially, the resource density is characterized by higher values in the east and lower in the west, with southern regions experiencing a more rapid increase over time, leading to a gradient of higher densities in the southeastern regions and lower in the northwest.
- (4) The LMDI analysis revealed that, collectively, population size, economic development, and environmental pressures exert positive influences on the increment of green waste resources. Conversely, the urbanization effect (operating negatively) serves to mitigate the increase in green waste quantities to some extent.
- (5) Anticipated against the backdrop of global warming, urban sprawl, and improving urban green space management standards, China's green waste production is projected to persistently rise, with estimates forecasting an increase to between 83.35 million and 91.48 million tons by 2030.

These conclusions underscore the imperative for strategic planning and adaptive management strategies to address the growing challenge of green waste amidst ongoing urbanization and climate change.

5.2 Limitations and future perspectives

While this study advances the quantification of China's green waste dynamics, several limitations must be acknowledged to guide future research.

- (1) The estimation of green waste production in this study is based on municipal statistical reports and relatively stable production factors. However, this approach may overlook the heterogeneity among different cities within the province as well as the green waste generated from private areas. Future research should aim to enhance measurement accuracy by incorporating remote sensing technology to develop a more precise model for estimating green waste output.
- (2) The generation of green waste is influenced by a multitude of factors. While this study quantitatively decomposed the social and economic factors impacting green waste production, it did not account for natural factors such as climate, temperature, and vegetation type, which also significantly influence green waste output, nor did it consider human factors like construction frequency. Future research should delve deeper into the complex mechanisms affecting green waste production and develop a more robust predictive model for green waste yield by integrating machine learning methodologies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

BS: Data curation, Software, Visualization, Writing – original draft, Writing – review and editing. XH: Data curation, Methodology, Writing – original draft. YL: Formal Analysis,

Software, Writing – original draft. WH: Software, Visualization, Writing – review and editing. XR: Conceptualization, Writing – review and editing. HL: Conceptualization, Writing – review and editing. QF: Methodology, Formal analysis, Validation, Writing – review & editing

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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TABLE A1 Contribution of driving factors for changes in green waste resource quantity.

Annual interval	Changes in green waste production (10,000 tons)	Population size effect		Economic development effect		Environmental stress effect		Urban development effect	
		Value (10,000 tons)	Rate (%)	Value (10,000 tons)	Rate (%)	Value (10,000 tons)	Rate (%)	Value (10,000 tons)	Rate (%)
2003–2004	1175.72	14.41	1.23	238.86	20.32	1027.64	87.40	–105.19	–8.95
2004–2005	248.71	7.29	2.93	359.15	144.40	87.08	35.01	–204.81	–82.35
2005–2006	–252.26	27.85	–11.04	341.75	–135.47	–330.10	130.86	–291.76	115.66
2006–2007	685.76	26.49	3.86	477.97	69.70	546.62	79.71	–365.32	–53.27
2007–2008	66.81	32.39	48.48	457.22	684.36	–57.23	–85.66	–365.58	–547.19
2008–2009	388.64	37.49	9.65	236.08	60.74	225.30	57.97	–110.22	–28.36
2009–2010	240.53	46.73	19.43	536.46	223.03	50.94	21.18	–393.59	–163.64
2010–2011	182.92	53.78	29.40	566.44	309.66	–10.09	–5.52	–427.21	–233.55
2011–2012	210.97	43.08	20.42	335.29	158.93	41.03	19.45	–208.43	–98.80
2012–2013	100.81	35.10	34.82	352.24	349.41	–91.31	–90.58	–195.22	–193.65
2013–2014	170.01	36.34	21.38	297.46	174.96	11.69	6.88	–175.47	–103.21
2014–2015	239.18	25.48	10.65	266.16	111.28	48.71	20.37	–101.17	–42.30
2015–2016	197.03	35.77	18.15	321.32	163.08	18.89	9.59	–178.95	–90.82
2016–2017	231.38	31.30	13.53	458.09	197.98	73.88	31.93	–331.88	–143.44
2017–2018	212.5	24.06	11.32	437.45	205.86	–0.43	–0.20	–248.58	–116.98
2018–2019	179.51	21.21	11.82	345.84	192.66	10.65	5.93	–198.19	–110.41
2019–2020	270.48	11.68	4.32	141.32	52.25	116.19	42.96	1.29	0.48
2020–2021	284.92	5.24	1.84	699.50	245.51	142.65	50.07	–562.46	–197.41
2021–2022	180.36	–6.17	–3.42	304.14	168.63	81.11	44.97	–198.73	–110.18
Total	5013.98	509.53	10.16	7172.71	143.05	1993.21	39.75	–4661.47	–92.97