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Original Research

Regional Differences and Evolution Trends of Zero Waste Performance in China

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Abstract

The "zero waste city" strategy is a visionary initiative to address the solid waste problem by minimizing landfill use and maximizing resource utilization. However, few studies have offered insights into the regional differences and evolution trends of the performance of zero waste in China at the city level. To address this gap, the present study assesses China's zero waste performance using entropy weight TOPSIS. Its regional differences and evolution trends are analyzed by employing the Dagum Gini coefficient, kernel density estimation, and spatial Markov chains. The results indicate that China's zero waste performance shows an upward trend. The overall regional difference in zero waste performance is narrowing and mainly derives from the inter-regional difference. The evolutionary characteristics of zero waste performance vary in each region. The polarization of zero waste performance in the eastern region diminishes, while the other three regions show an obvious aggravation of the polarization. China's zero waste performance presents a significant positive spatial correlation. It is also characterized by spatial agglomeration and club convergence. These findings offer a theoretical foundation for promoting the construction of a zero waste city in China and provide a valuable reference for waste management in other developing countries.

Keywords: zero waste, zero waste city, zero waste performance, regional difference, evolution trend

Introduction

Resource scarcity and waste siege are posing serious challenges to global municipal waste management and environmental governance [1, 2]. In the context of global low-carbon and green transformations, achieving sustainable waste management is a critical issue that urgently needs to be addressed [3, 4]. The zero waste (ZW) strategy was developed to alleviate the environmental burden and resource depletion caused by solid waste [5]. The core of ZW lies in promoting responsible production and consumption patterns, as well as resource reuse and efficient recycling, striving to avoid waste incineration and arbitrary discharge, thereby maximizing the efficiency of natural resource utilization and minimizing negative impacts on the ecological environment [6-8]. Looking back at history, Canberra, Australia, set an example in 1995 and became the world's first city to implement the ZW

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strategy, leading a global environmental trend. Since then, many countries, organizations, and enterprises have responded and devoted themselves to ZW practices [2, 9]. The zero waste city (ZWC), a cutting-edge concept of sustainable urban development, has become a goal pursued in many countries [10, 11]. ZWC is not only an important measure to promote collaborative efficiency in reducing pollution and carbon emissions but also the main way to achieve the high-quality development of a green economy. Therefore, to curb solid waste problems from the source and promote the construction of an environmentally friendly society, it is urgent to conduct a more in-depth exploration of ZWC.

As the second-largest economy in the world, China is facing serious waste pollution problems due to industrialization and urbanization in the past few decades [12]. It is estimated that China adds more than 10 billion tons of solid waste annually, with a total storage volume of about 70 billion tons [13]. The various problems caused by solid waste, such as high generation intensity, low resource utilization, and illegal dumping incidents, urgently need to be addressed [14]. The Ministry of Ecology and Environment of China issued the "Work Plan of the ZWC Pilot Program" in 2018, which marked the launch of the ZWC strategy. Sixteen local authorities and districts were identified as ZWC pilot areas in 2019 and were broadened to 113 cities in 2022 [15, 16]. These policy initiatives demonstrate China's strong commitment to ZW management. Exploring Chinese ZWC is of great importance to addressing the waste pollution problem in China and the implementation of ZW strategies in other developing countries.

Zero waste performance (ZWP) refers to the evaluation of the effectiveness achieved in reducing solid waste at the source, utilizing resources, and harmless disposal through the implementation of a series of measures and policies in the process of building a ZWC. Understanding ZWP is not only one of the main tasks of ZWC construction but also provides theoretical support for subsequent policy decisions [17]. The differences in economic structure and resource endowment may cause different demands for solid waste disposal, resulting in discrepancies in waste management [13]. Exploring the regional gaps in ZWP is of practical significance for the balanced promotion of ZWC construction. Moreover, capturing the evolutionary trends of ZWP is critical to the further expansion of ZWC pilots in the future. Therefore, it is necessary to evaluate ZWP in China and to analyze its regional differences and evolutionary trends.

Previous studies related to the measurement of ZWP can be divided into two categories. One is to measure the effectiveness of waste management through a series of specific indicators, such as per capita waste generation, diversion ratio, collection efficiency, and recovery rate, as a single quantitative standard [18]. Some scholars have criticized this outcome-oriented assessment approach for failing to adequately reflect the complexity and dynamics of the waste management process [19]. Zaman and Lehmann [20] pointed out that even achieving a 100% diversion rate does not necessarily mean achieving the goal of ZW. The second is to use comprehensive evaluation indicators to measure ZWP. For example, the "zero waste index" was proposed by Zaman and Lehmann [17]. This tool can measure ZWC performance based on the substitution potential of recycled, renewable resources for virgin resources and has been applied in several case studies [21]. Cong et al. [22] used the undesirable super-efficiency model to assess the efficiency of ZWC constructions. Zaman [23] constructed an evaluation index system for ZWP from four dimensions: socio-cultural, managerial, economic, and environmental.

There are two types of studies related to ZWP evaluation objects. One type of study evaluated ZWP at the regional level. For example, Han et al. [13] investigated the performance of ZWC in 31 provinces in China from 2010 to 2019 and explored influencing factors in terms of economy, technology, resource endowment, and education. Peng et al. [24] studied the influence of environmental protection investment and green innovation on solid waste management capacity in 30 provinces in China. The other type of study looked at the city level. From the perspective of the "water-energy-food" system, a framework for the assessment of ZWC was constructed by Zhang et al. [25], and the similarities and differences between China (Beijing, Shanghai, and the Greater Bay Area city cluster) and other countries (San Francisco, New York, and Tokyo) were compared. Taking Xuzhou City as an example, Wen et al. [26] explored the construction status and barrier factors of mining-based ZWCs in China.

Although a number of studies have examined ZWP, there are still some shortcomings. First, previous studies mainly focused on ZWP evaluation at the provincial level, while few assessed ZWP at the city level in China. The rare studies focusing on ZW at the city level are limited to qualitative analysis and lack quantitative analysis, which prevents an overall understanding of China's city ZWP. Since the construction of a ZWC is city-based, measuring ZWP at the city level can offer a more intuitive understanding of ZWC construction. Second, there is a lack of studies analyzing regional differences in China's city ZWP and even fewer studies on its evolution trends. That is, the existing studies failed to provide information on the differences and evolution of ZWP in Chinese cities. Exploring regional differences and evolution trends is significant, not only for narrowing the disparity in ZWP but also for further promoting ZWC construction in China and other developing countries.

Based on the above considerations, this paper aims to fill the above research gap by answering the following three questions. (1) What is ZWP at the city level in China? (2) What are the differences among regions? (3) What are the evolution trends of ZWP? Compared with previous works, the present study has two potential innovations: First, different from previous studies on the evaluation of ZWP at the provincial level, this paper achieves a horizontal comparison at the city level and provides a comprehensive understanding of ZWC construction in China. Second, this study attempts to explore the dynamic evolution and shifting trends of ZWP at the city level in China. This study is one of the first batches of literature to examine the regional differences and dynamic evolution of China's ZWP. The findings in this paper offer theoretical support and decision-making reference for further expansion of the ZWC pilot. It is of great significance for narrowing the regional differences in China's ZWP and promoting the construction of ZWC in a balanced manner.

Materials and Methods

Entropy Weight TOPSIS

This paper uses entropy weight TOPSIS to evaluate the ZWP at the city level in China. Table 1 shows the evaluation index system of ZWP. ZW pursues reducing the amount of waste generated, improving resource utilization, and guaranteeing capability. Therefore, the indicators related to waste generation (X1-X4) are set as negative indicators, and the indicators related to resource utilization (X5-X8) and development of security capacity (X14-X20) are positive. The two indicators on waste storage rates (X9, X10) are considered negative indicators due to the potential adverse effects of waste storage on soil, air, and water. The proportion of waste disposal (such as waste incineration, sewage, and dry sludge disposal) represents the construction and treatment capacity of a waste treatment infrastructure. Therefore, referring to the studies of Hao et al. [2] and Han et al. [13], X11-X13 are regarded as positive indicators.

Regional Difference Decomposition Model

The Dagum Gini coefficient not only responds to regional differences and their sources but also addresses the issue of cross-overlapping between sample data. The larger the Gini coefficient, the more uneven the ZWP. The specific calculations are as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2n^2\mu} \quad (1)$$

$$G = G_\omega + G_b + G_t \quad (2)$$

Where k denotes the count of regions, n is the count of sample cities, $y_{ji}(y_{hr})$ is the ZWP of city $i(r)$ in region $j(h)$,

Table 1. Evaluation indicator system for ZWP.

Target layer	Criterion layer	Indicator layer	Attribution
ZWP	Reduction at source	X1: General industrial solid waste generation intensity	-
		X2: Industrial hazardous waste generation intensity	-
		X3: Quantity of domestic waste collected and transported	-
		X4: Domestic waste generation per capita	-
	Resource utilization	X5: Integrated utilization rate of general industrial solid waste	+
		X6: Integrated utilization rate of industrial hazardous waste	+
		X7: Resource recovery of domestic waste	+
		X8: Harmless rate of domestic waste	+
	Final disposal	X9: Storage rate of general industrial solid waste	-
		X10: Storage rate of industrial hazardous waste	-
		X11: Share of domestic waste incineration capacity	+
		X12: Sewage disposal rate	+
		X13: Dry sludge disposal rate	+
	Development of security capacity	X14: Fixed assets investment in urban service facilities	+
		X15: Total number of vehicles and equipment dedicated to amenities and sanitation	+
		X16: Number of Harmless treatment plants	+
		X17: Number of sewage treatment plants	+
		X18: Harmless treatment capacity of domestic waste	+
		X19: Number of operatives in environmental protection management system	+
		X20: Number of relevant laws and regulations	+

and μ represents the average ZWP of all cities. G represents the overall Gini coefficient (that is, overall difference), which is divided into intra-regional difference (G_ω), inter-regional difference (G_b), and the intensity of transvariation (G_t). The intra-regional difference is the difference in a city's ZWP within the four regions of China. Interregional difference refers to the difference in a city's ZWP between two regions. The intensity of transvariation means the difference due to sample crossover.

Kernel Density Estimation

Kernel density estimation was employed to analyze the dynamic evolution of ZWP at the city level in China by observing the location, main peak, extension, and waves in the kernel density curve. Specifically, the kernel density curve of the ZWP for cities in region j is generated by the following function:

$$f_j(y) = \frac{1}{n_j H} \sum_{i=1}^{n_j} K\left(\frac{y_{ji} - y}{H}\right) \tag{3}$$

Where K is the Gaussian kernel function, $K(x) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{x^2}{2})$. n_j is the number of cities in region j. H denotes the bandwidth that reflects the estimation accuracy and curve smoothness. y_{ji} refers to the observations and y is the average of y_{ji}.

Spatial Markov Chain

The state and evolutionary trends of ZWP were measured by constructing the transfer probability matrix using Markov chains. The method assumes that the probability of the state of the random variable X in period $t+1$ depends only on the state of X in period t. This can be expressed by the following formula:

$$P\{X_{t+1} = j | X_t = i_t, X_{t-1} = i_{t-1}, \ldots, X_0 = i_0\} = P\{X_{t+1} = j | X_t = i_t\} = P_{ij} \tag{4}$$

Where P_{ij} denotes the probability of the city's ZWP transferred from state i in period t to state j in period $t+1$. If there are m_i cities belonging to state i, and m_{ij} equals the number of cities that transferred from state i to state j, then $P_{ij} = \frac{m_{ij}}{m_i}$.

The Markov first-order transfer matrix of the city's ZWP can be obtained by integrating all shifting probabilities. If the ZWP at the city level is classified into N types, the Markov transfer matrix is an $N \times N$ matrix.

The spatial Markov chain can examine the impact of adjacent cities on the state transfer of the city. Under the condition of considering spatial effects, the conventional Markov transfer matrix $N \times N$ can be divided into the transfer matrix of $N \times N \times N$. The adjacency principle is employed to define the spatial relationships of the sample cities. The relationship between transition probability and adjacent city types can be understood by comparing the values of the corresponding elements in the traditional and spatial Markovian transfer matrix. Based on the above considerations, spatial Markov chains were employed to analyze the dynamic evolutionary trends of China's city ZWP.

Index Selection and Data Source

Given the differences in the statistical caliber of relevant data, as well as the availability and comparability of data, this study was conducted based on the data of 173 prefecture-level and above cities in China from 2010 to 2020. Data related to the generation, utilization, and disposal of solid waste are obtained from the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, and the Information Notice on the Prevention and Control of Environmental Pollution by Solid Waste. Data on the development of security capacity is mainly from the China Urban Construction Statistical Yearbook. The number of relevant laws and regulations is obtained from the Peking University Law Website. Linear interpolation and mean interpolation were used to correct and refine individual abnormal and missing data.

Results and Discussion

Overall Evaluation of the ZWP

Fig. 1 reports the trends of ZWP at the city level in China and four major regions from 2010 to 2020. Overall, China's city ZWP at the city level improved from 0.0892 to 0.2358 during the observation period, with an increase of 10.21% per year on average. From a regional perspective, only the average of waste management in the eastern region is larger than the national mean, while the other three regions have a lower average than that of the country. The results indicated that China's city ZWP is gradually increasing.

China's city ZWP gradually increased, which agrees with the result of Han et al. [13]. The improvement in ZWP may be attributed to the Chinese government's high emphasis on solid waste management. On the one hand, a series of environmental regulatory instruments have been adopted for solid waste pollution prevention and control, with remarkable results. For instance, the extended producer responsibility system has been adopted, and mandatory domestic waste separation has been promoted [27]. On the other hand, residents and enterprises have become aware of environmental protection and actively participate in waste management, promoting waste recycling and resource utilization [28, 29]. Despite the increase in China's city ZWP, there is still significant room for improvement. This finding is consistent with the opinion of Wen et al. [30]. The construction of ZWC in China is at a preliminary stage and has not yet been implemented nationwide [13], which may be a potential explanation for the relatively low level of China's city ZWP.

The spatial distribution of ZWP at the city level in China displays the characteristics of "East > Central >

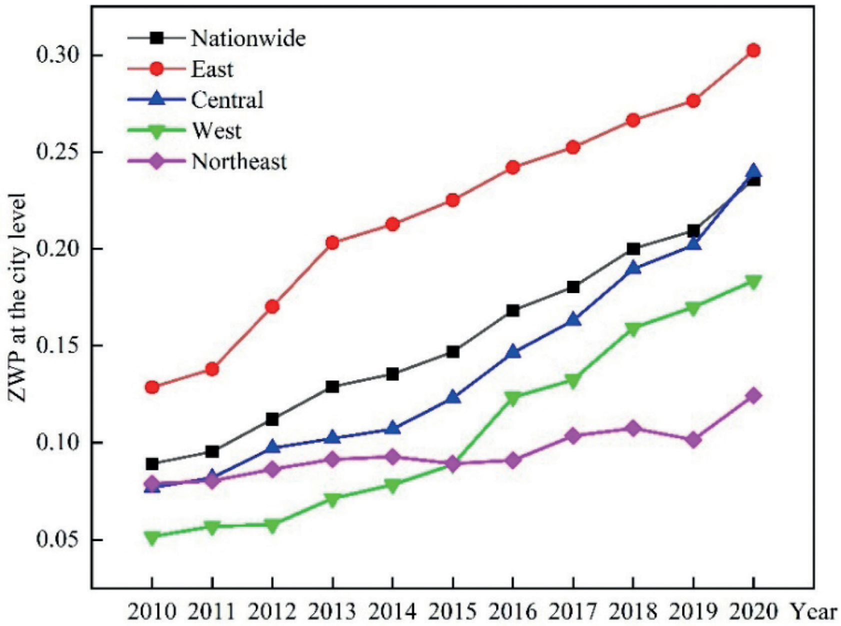

Fig. 1. ZWP at the city level in China and four regions from 2010 to 2020.

West > Northeast". The eastern region takes the lead in ZWP, which echoes the findings of existing literature [13, 30]. The possible reasons are as follows: First, the eastern region has more efficient solid waste management than other regions and can efficiently convert resource inputs into outputs [31]. Second, the eastern region is economically developed and has invested heavily in waste management (e.g., sanitation vehicles and waste incineration plants), which offers the fundamental guarantee for ZWC construction. The ZWP of the central region gradually approaches the national average, second only to the eastern region, showing a significant catching-up effect. This may be attributed to the "Rise of Central China" strategy, which has led to industrial structure optimization in the central region [32], reduced dependence on natural resources, and curbed solid waste emissions [33, 34]. The western region is prone to solid waste hoarding due to its fragile ecology [13]. In addition, there are many obstacles to solid waste management in the western region, such as more illegal solid waste disposal practices, lower utilization rates, and backward construction of management institutions and teams [35]. In the northeast region, shrinking cities and severe population exodus have led to increased operating share costs for urban infrastructure and a lack of waste collection and transportation facilities [36]. This may hinder the development of ZW management.

Decomposition of the Regional Difference in ZWP

Intra-regional Difference

The results of the Gini coefficient are presented in Table 2. The overall differences in ZWP tend to increase slightly first and then decrease, showing that the regional gaps are narrowing.

The intra-regional disparities in the eastern region tended to go downward from 0.4559 in 2010 to 0.1589 in 2020. The intra-regional gaps in the central region increased from 2010 to 2014 and decreased after 2014, showing a general downward trend. For the western region, intra-regional disparities slightly decrease, varying between 0.4267 and 0.4982. Unlike the other three regions, the northeast region shows an upward trend with an average annual increase of 2.94%.

Inter-regional Difference

The trends of inter-regional differences in China's city ZWP are illustrated in Table 2. The inter-regional difference between the central and eastern regions shows a narrowing trend. The catching-up effect of the central region in ZWP was confirmed. The gaps between the eastern and western regions showed little variation from 2010 to 2015 and decreased after 2015. The differences between the central and western regions first increased and then decreased, showing a general downward trend.

The gaps between the eastern and northeastern regions ranged from 0.4561 to 0.5877 during the sample period. The discrepancy between the central and northeastern regions is between 0.434 and 0.5191, and the discrepancy between the western and northeastern regions ranges from 0.4395 to 0.5085. In terms of the gaps between the Northeast and other regions, the inter-regional Gini coefficients have been relatively large (> 0.4), indicating that the gaps between the Northeast and the other regions are the largest.

Table 2. Gini coefficient of city-level ZWP in China and the four regions.

Year	Overall differences	Intra-regional differences				Inter-regional differences					
		East	Central	West	Northeast	East-Central	East-West	East-Northeast	Central-West	Central-Northeast	West-Northeast
2010	0.4864	0.4559	0.4598	0.4764	0.3417	0.5073	0.5161	0.5424	0.4728	0.4383	0.4395
2011	0.4897	0.4282	0.4887	0.4633	0.3928	0.5145	0.5079	0.5535	0.4824	0.4674	0.4524
2012	0.4941	0.3925	0.5083	0.4641	0.371	0.5134	0.5166	0.5877	0.497	0.4934	0.4557
2013	0.483	0.3163	0.513	0.4781	0.4558	0.5085	0.5171	0.5829	0.5024	0.5102	0.4818
2014	0.4754	0.2958	0.5134	0.4795	0.4763	0.4969	0.5164	0.5691	0.5034	0.515	0.4884
2015	0.4571	0.2694	0.5005	0.4634	0.492	0.4581	0.5234	0.5424	0.5049	0.5191	0.4824
2016	0.4189	0.2229	0.4732	0.4982	0.4667	0.404	0.4528	0.5197	0.4924	0.5178	0.5053
2017	0.3854	0.2154	0.4029	0.4851	0.452	0.3496	0.4334	0.4853	0.4558	0.4685	0.4861
2018	0.3579	0.2023	0.3549	0.4601	0.4732	0.3033	0.3865	0.4974	0.4175	0.4823	0.5046
2019	0.3388	0.1905	0.3174	0.4425	0.483	0.2736	0.3679	0.5074	0.3926	0.4863	0.5085
2020	0.2914	0.1589	0.2258	0.4267	0.4566	0.2038	0.3472	0.4561	0.3516	0.434	0.4755

Note: Overall differences represent regional differences across the country.

Table 3. Contribution value and contribution rate of regional difference in China's city ZWP.

Year	Intra-regional difference		Inter-regional difference		Intensity of transvariation	
	Contribution value	Contribution rate (%)	Contribution value	Contribution rate (%)	Contribution value	Contribution rate (%)
2010	0.1346	27.67	0.1825	37.52	0.1693	34.81
2011	0.1326	27.09	0.1806	36.88	0.1764	36.03
2012	0.1290	26.11	0.2145	43.41	0.1506	30.48
2013	0.1172	24.26	0.2242	46.41	0.1417	29.33
2014	0.1141	23.99	0.2192	46.12	0.1421	29.89
2015	0.1099	24.04	0.2100	45.94	0.1372	30.03
2016	0.1013	24.19	0.1784	42.6	0.1391	33.22
2017	0.0939	24.36	0.1659	43.05	0.1256	32.58
2018	0.0878	24.52	0.1463	40.87	0.1239	34.61
2019	0.0821	24.23	0.1470	43.37	0.1098	32.40
2020	0.0675	23.18	0.1383	47.45	0.0856	29.37
Mean	0.1064	24.88	0.1824	43.06	0.1365	32.07

Source of Regional Difference

The overall difference in China's city ZWP is decomposed using the Dagum Gini coefficient method to understand the source of regional differences. The results are demonstrated in Table 3. The proportion of intra-regional difference to the overall gap was stable, ranging between 23.18% and 27.67% from 2010 to 2020. The contribution of inter-regional gaps increased from 37.52% to 47.45%, while the contribution of the intensity of transvariation decreased from 34.81% to 29.37%. The average contribution of intra- and inter-regional gaps and the intensity of transvariation were 24.88%, 43.06%, and 32.07%, respectively. Meanwhile, the contribution of inter-regional differences is always larger than that of the other two components, suggesting that inter-regional differences are the main source of regional differences in China's city ZWP.

Regional differences in China's city ZWP decreased from 2010 to 2020, and its main source was the inter-regional difference. It has been argued that economic activities are the direct cause of solid waste generation [30]. Due to differences in external conditions and resource endowments, there is uneven economic distribution and environmental carrying capacity in each region [37], which might be the critical reason for the inter-regional difference in ZWP. It is worth noting that the intra-regional difference in the northeast region shows a rising trend. During the observation period, some cities in the northeast region (e.g., Dalian, Shenyang, and Fuxin) show remarkable growth in ZWP. However, some cities (e.g., Jinzhou and Tieling) display little change in ZWP, and individual cities (e.g., Jilin and Yichun) even show a decreasing trend. This phenomenon has led to a rise in intra-regional differences in the northeast region. In addition, the largest inter-regional gaps are found between the northeast and other regions. Due to shrinking cities and economic downturn, the mean annual growth rate of ZWP was only 4.66% in the northeast region, lower than the national average (10.21%). This is a potential reason why the northeast region lags behind other regions.

The Evolution Trend of ZWP

Time Evolution Trend

Fig. 2 portrays the kernel density curves of China's city ZWP in 2010, 2013, 2017, and 2020. It can be found that the curve shifted to the right, indicating that China's city ZWP has improved. The main peak of the curve increased in height and narrowed in width from 2010 to 2020, which means that the aggregation of China's city ZWP has improved, and its absolute difference has decreased. The obvious right trailing feature was found on the curve in 2010, which weakened in 2020, showing that the difference in China's city ZWP decreases. The kernel density curves exhibit a double-peaked curve throughout the observation period; that is, the ZWP of most Chinese cities is distributed around two different scores (0.05 and 0.3). This phenomenon can be referred to as the polarization of ZWP in Chinese cities.

The kernel density curves of the four regions in 2010, 2013, 2017, and 2020 are reported, which shows the evolutionary trend of city ZWP in four regions (Fig. 3). For the eastern region, the main peak height rises, and the peak width narrows from 2010 to 2020, illustrating

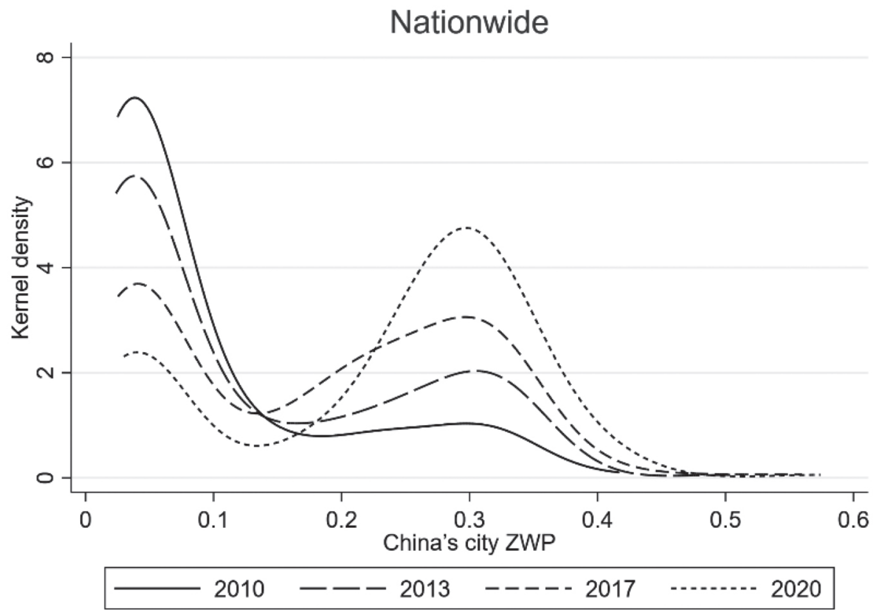

Fig. 2. Kernel density curve of China's city ZWP.

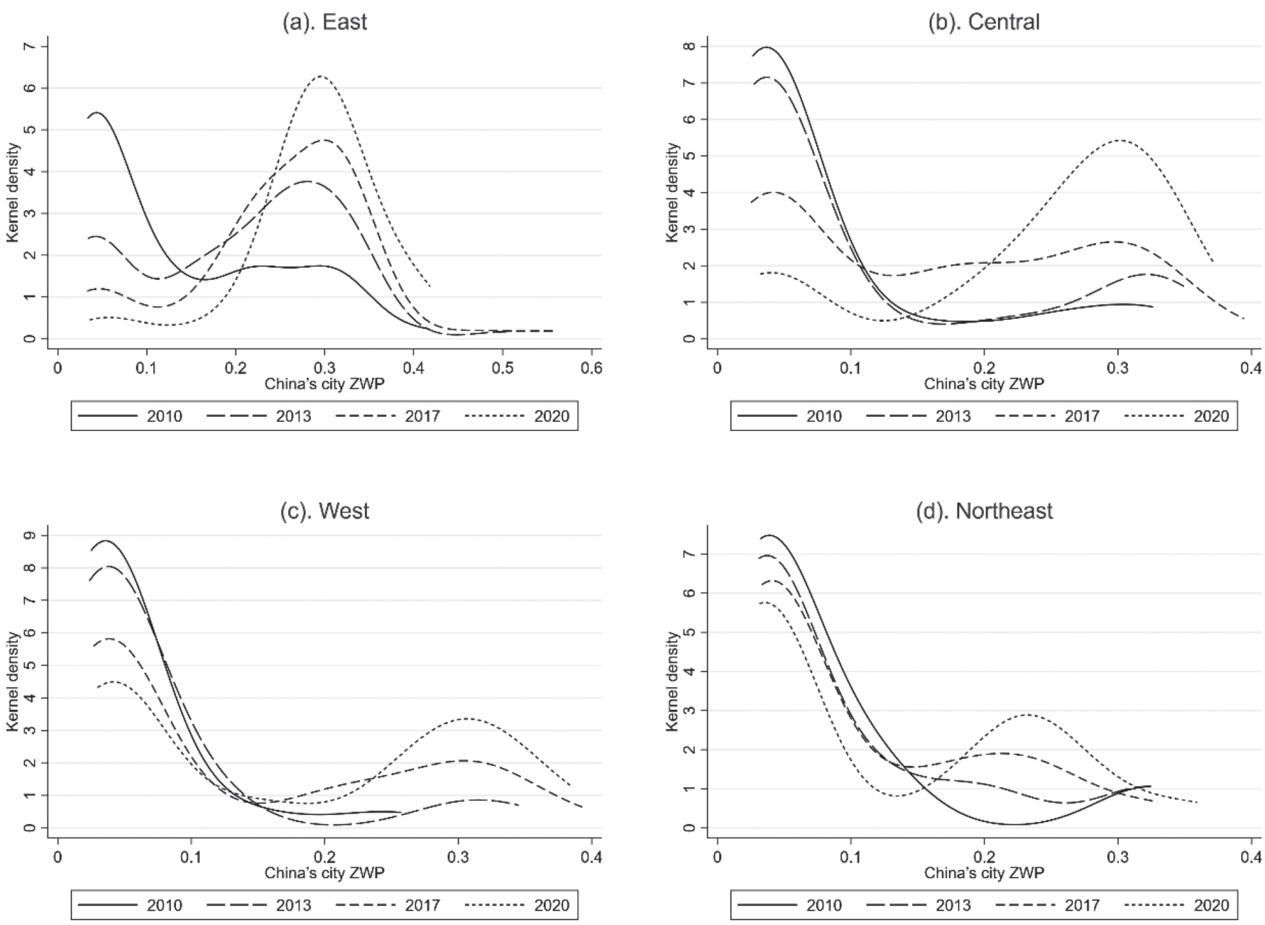

Fig. 3. Kernel density curve of city ZWP in the four regions.

Table 4. Global Moran's I of China's city ZWP.

Year	Moran's *I*	E(I)	Sd(I)	Z-vale	P-value
2010	0.132	-0.006	0.064	2.151	0.032
2011	0.122	-0.006	0.064	1.986	0.047
2012	0.167	-0.006	0.064	2.692	0.007
2013	0.222	-0.006	0.064	3.532	0.000
2014	0.231	-0.006	0.065	3.676	0.000
2015	0.235	-0.006	0.065	3.737	0.000
2016	0.268	-0.006	0.065	4.251	0.000
2017	0.277	-0.006	0.065	4.392	0.000
2018	0.247	-0.006	0.064	3.923	0.000
2019	0.247	-0.006	0.064	3.928	0.000
2020	0.215	-0.006	0.064	3.449	0.001

a downward trend in the absolute gap of ZWP in the eastern region. The right trailing feature gradually weakened, indicating a decrease in the difference in the eastern region. The double peak evolved into a single peak, implying a weakening polarization in the eastern region.

Unlike the eastern region, the other three regions have been showing an obvious double-peak feature, which indicates that there has been a polarization of ZWP in the other three regions from 2010 to 2020. In the western region, for example, the ZWP of Chongqing, Chengdu, and Xi'an reached 0.37 or above in 2020, while 18 cities have not yet reached 0.07. It can be seen that there is a huge difference in ZWP. The cities with higher ZWP usually belong to provincial capitals or municipalities directly under the central government. This finding coincides with the result of Zhao et al. [38], who found that Taiyuan, the capital city in Shanxi Province, had a higher level of ZWP than other non-capital cities.

Spatial Evolution Trend

The spatial correlation of ZWP at the city level in China was verified, and the results are shown in Table 4. Moran's I was significant ($p<0.05$) and fluctuated between 0.122 and 0.277, which means that the spatial correlation of China's city ZWP is significantly positive.

Based on the quartiles of the level of ZWP, all sample cities were classified into four states, namely, S1, S2, S3, and S4, which represent the city's ZWP from poor to good. The transfer probability matrices are shown in Table 5. The results of the conventional Markov chain show that the likelihood that S1, S2, S3, and S4 will remain the same in the next year is 72.81%, 67.27%, 78.22%, and 90.84%, respectively. The relatively high probabilities on the diagonal of the transfer matrix demonstrate the strong stability of ZWP at the city level in China under the condition that the sample city is seen as an independent unit. The probabilities of S1, S2, and S3 shifting upward are 27.19%, 17.38%, and 19.2%, respectively. The probabilities of a downward shift for S2, S3, and S4 are 15.25%, 2.58%, and 9.16%, respectively. It can be seen that the likelihood of upward transfer is generally higher than the likelihood of downward transfer, suggesting that the ZWP at the city level in China displays an improving trend.

Table 5 indicates that the spatial Markov transfer matrix has the following features: First, the probabilities on the diagonal are higher than the probabilities on the non-diagonal, which means China's city ZWP remains stable when considering the effect of adjacent cities. Second, the shifting probabilities are concentrated near the diagonal, indicating that the shift of ZWP occurs mainly in adjacent states, and it is hard to make the jump to transition in a short time. Third, the state transfer of China's city ZWP has a spatial spillover effect. That is, the lower the ZWP in the neighboring cities, the greater the transferring probability of the city to a lower state; the higher the ZWP in the neighboring cities, the greater the transferring probability of the city to a better state. For instance, the transfer likelihood of S3 to S2 is 2.11%, while the corresponding transfer probability increases to 10.34% when adjacent to S1. The probability of S1 shifting to S2 is 22.27%, but the corresponding transfer probability increases to 26.67% when adjacent to S4.

In terms of spatial evolution, the state of China's city ZWP is relatively stable and usually shifts between adjacent states. As mentioned by Li and Li [39], realizing a "Zero Waste Society" requires long-term and arduous efforts. Moreover, the evolution of China's city ZWP has spatial spillover effects. The probability of the city transforming to higher levels of ZWP increases when neighboring cities have higher levels. The probability of the city evolving to lower levels of ZWP increases when adjacent to cities with

Table 5. The Markov transfer probability matrix of China's city ZWP.

Type of space	Status at year t	Status at year t+1			
		S1	S2	S3	S4
No lag	S1	0.7281	0.2227	0.0364	0.0128
	S2	0.1535	0.6727	0.1445	0.0293
	S3	0.0047	0.0211	0.7822	0.192
	S4	0	0.0051	0.0865	0.9084
S1	S1	0.8261	0.1304	0.029	0.0145
	S2	0.1765	0.6471	0.1569	0.0196
	S3	0	0.1034	0.7241	0.1724
	S4	0	0	0.0435	0.9565
S2	S1	0.721	0.2403	0.0386	0
	S2	0.1696	0.6784	0.1345	0.0175
	S3	0.0244	0.0488	0.7805	0.1463
	S4	0	0.0175	0.0877	0.8947
S3	S1	0.7067	0.2333	0.04	0.02
	S2	0.1263	0.6684	0.1579	0.0474
	S3	0	0.004	0.7968	0.1992
	S4	0	0.0044	0.1135	0.8821
S4	S1	0.6	0.2667	0	0.1333
	S2	0.1935	0.7097	0.0968	0
	S3	0	0.0154	0.7538	0.2308
	S4	0	0	0.0238	0.9762

lower levels. This finding is similar to the results of previous studies. The positive spatial correlation of solid waste emissions was revealed in the study of Guo and Liu [21]. Peng et al. [24] found that the spatial correlation of solid waste management capacity is significant, and the impact of green innovation and environmental investment on solid waste management capacity has a positive spatial spillover effect. The cities with high levels of ZWP may play a demonstration role by transmitting advanced solid waste disposal technologies and management models to surrounding areas, which in turn will lead to ZWP in neighboring cities.

Conclusions

This paper evaluates China's city ZWP from 2010 to 2020 and explores its regional differences, sources of differences, and dynamic evolution. The results indicate that China's city ZWP shows an upward trend from 0.0892 in 2010 to 0.2358 in 2020, but currently, China's city ZWP is still relatively low. From the regional perspective, China's city ZWP has the feature of "East>Central>West>Northeast". The overall regional disparity of ZWP at the city level in China tends to decrease. The overall difference in China's city ZWP mainly originated from inter-regional differences. The aggregation degree of China's city ZWP increases, and the absolute difference tends to diminish. The evolutionary characteristics of city ZWP vary in each region. The polarization of ZWP in the eastern region diminishes. On the contrary, the polarization phenomenon becomes severe in the other three regions. There is the club convergence characteristic in China's city ZWP. Most transfers of China's city ZWP occur at adjacent types, and it is hard to make the jump shift in the short term. The shifting trends of China's city ZWP show the spatial spillover effect.

Combining the conclusions derived from this paper, the following policy recommendations are proposed. ZWP can be improved by reducing regional differences, avoiding polarization, and outlining the role of demonstrators. First, regional differences brought about by resource endowment and economic level should be fully recognized. It is important to focus on implementing a diversified, graded, and dynamic ZWC strategy. The urban characteristics of each region can be taken into account to formulate targeted fiscal measures to attract the inflow of talent and high-tech enterprises, stimulate market vitality, and thus promote sustainable waste management. Second, improving ZW construction in third- and fourth-tier cities is crucial to alleviating the polarization phenomenon. The first batch of ZWC pilot cities in China represent different prefecture-level cities. For example, Panjin represents a resource-depleted city; Xining is a representative of an ecologically fragile and economically backward city. Summarizing and disseminating the experience of these pilots may be a good way to improve ZWP in third- and fourth-tier cities in China. Third, the role of high-level cities in leading the surrounding cities should be given full play. The ZWC cluster can be created to achieve contiguous development by publicizing and sharing the lessons learned from waste treatment technologies and management models. Cities with low levels of ZWP should actively introduce advanced waste treatment technologies and break down technical barriers. Industrial cooperation and structure optimization should be strengthened to promote deep integration between industries.

Although this paper provides some insights into promoting ZWP at the city level in China, it still has certain shortcomings. First, due to the limitation of data disclosure and lags in the effects of pilot policies, the study sample only covers 173 cities from 2010 to 2020. Subsequent studies could explore the evolutionary trends in ZWP after 2020, as well as comparative analyses of ZWP before and after the implementation of the pilot policy. Other indicators or alternative data can also be considered to expand the scope of the study sample in the future. Secondly, the regional differences and evolutionary trends of ZWP are focused on in this paper, and there are many other worthy research directions in related fields, such as the relationship between technological innovation and ZWP and spatial spillover effects.

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Conflict of Interest

The authors declare no conflict of interest.

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