Evaluation of city sustainability based on SPA method: The case of prefecture-level resources-exhausted cities in China

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Abstract. China's urbanization surge has exacerbated sustainability challenges in resource-exhausted cities. This study employs multi-criteria decision-making (MCDM) to assess 16 such cities against four regional hubs. We innovate a tri-dimensional (economic-social-environmental) framework with set pair analysis (SPA) weighting to address indicator interdependencies. Results show four cities surpassed average sustainability levels, with Zaozhuang, Jingdezhen, Jiaozuo, Liaoyuan, and Shizuishan performing poorest. Eastern/central regions outperformed northeastern/northwestern counterparts, while Shizuishan achieved optimal dimensional equilibrium. Critical barriers include foreign investment deficits and green infrastructure gaps, with social factors constraining 12 cities versus environmental limitations in Shizuishan and Wuhai. Data-driven policy pathways are proposed for sustainable transitions.

Keywords: City sustainability; Sustainability assessment; Key factor identification; Set pair analysis; prefecture-level resource- exhausted cities

1. Introduction

Urban sustainability constitutes a global priority as 55% (projected 68% by 2050) of humanity resides in cities [1], confronting interconnected crises from ecological degradation to social inequity [2]. These challenges demand integrated governance frameworks [3]. China's economic ascent (GDP: 5.2%→17%, 1952-2020) [8] relied on 262 resource cities [4], where unmanaged extraction created 69 "resource-exhausted" cities (≥70% reserve depletion) [5], requiring specialized fiscal strategies [6].

Multi-criteria decision-making (MCDM) emerges as a vital tool for tri-dimensional sustainability assessment [7], systematically processing data through normalization, weighting, and aggregation [8] to inform policy formulation [9]. Zhang et al. [10] (Jiangsu’s 30-subindicator system) exemplify diversified frameworks, while Li et al. [11] developed 21-indicator models for Chinese regions.

This study proposes a novel set pair analysis (SPA)-based weighting method for urban sustainability evaluation, integrating deterministic and uncertain indicator relationships to improve methodological frameworks and practical relevance. Using this approach, we assess 16 prefecture-level resource-exhausted cities, benchmarking against four regional hub cities (northeast, northwest, central, eastern China). Evaluation results are analyzed across comprehensive, dimensional, indicator, and factor levels to identify performance gaps and key constraints.

2. Case Study

China’s 16 prefecture-level resource-exhausted cities included in this study are Liaoyuan, Fushun, Hegang, Yichun, Baishan, Shizuishan, Baiyin, Wuhai, Huangshi, Jiaozuo, Pingxiang, Jingdezhen, Zaozhuang, Shaoguan, Luzhou, and Huaibei. Geographically, Liaoyuan, Fushun, Hegang, Yichun, and Baishan are situated in Northeast China; Shizuishan, Baiyin, and Wuhai in Northwest China; Zaozhuang, Shaoguan, Luzhou, and Huaibei in Eastern China; and Huangshi, Jiaozuo, Pingxiang, and Jingdezhen in Central China[12]. For comparative analysis, four regional central cities—Shenyang (Northeast), Xi’an (Northwest), Zhengzhou (Central), and Guangzhou (South)—were also evaluated to benchmark sustainability performance across different development contexts. Figure 1 illustrates the geographical distribution of the 20 study cities.

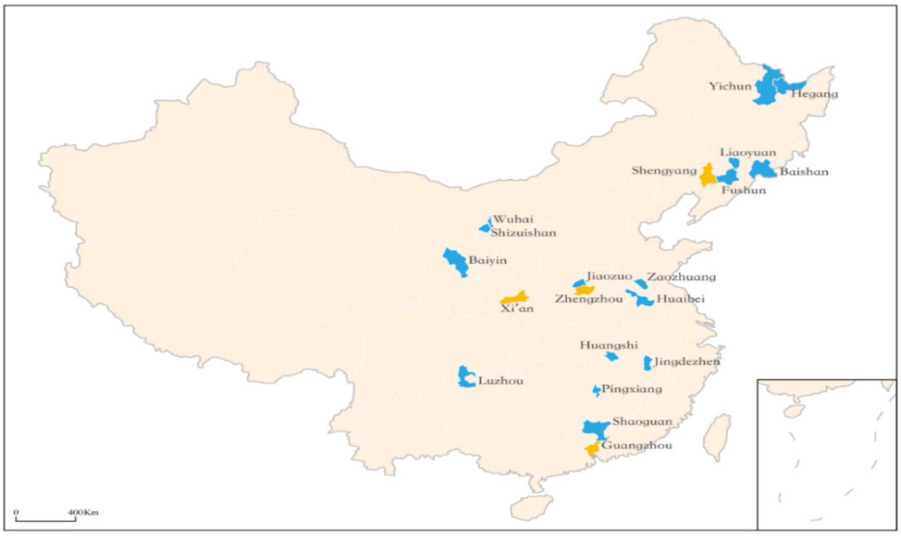

Fig. 1 Locations of the 20 cities in China

3. Methodology

As a robust methodology for multi-attribute decision integration [13], MCDM operationalizes sustainability assessment through five systematic phases: objective definition, framework construction, weighting calculation, data aggregation, and alternative ranking [14]. Our implementation (Fig. 2) comprises: (1) Construct a sustainability evaluation indicator system and select appropriate indicators; (2) Collect and normalise the data; (3) Constitute indicators into a set pair system, and calculate the weighting.

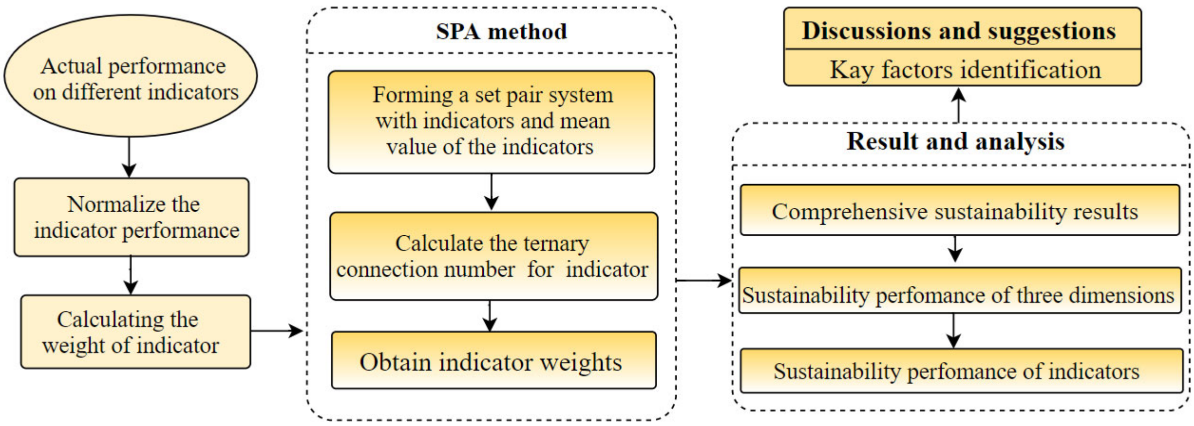

Fig. 2 Evaluation framework

3.1 Indicator System

Indicators were selected based on criteria of comprehensiveness, objectivity, comparability, and data availability, drawing on data from China's national statistical yearbooks, urban statistical yearbooks, academic literature, and the unique developmental characteristics of prefecture-level resource-exhausted cities. The final framework comprises 18 indicators organized into three dimensions (Table 1).

Table 1. Indicator system for the assessment.

Dimension	Indicator	Code	Unit	Property	References
Economy (EC)	Per capita GDP	C_1	Yuan	Benefit	[14, 17, 26]
	GDP growth rate	C_2	%	Benefit	[4, 45, 46]
	Added value of service industry	C_3	Yuan	Benefit	[47-49]
	Proportion of increase in fixed asset investment	C_4	%	Benefit	[14, 50]
	Per capita retail sales of consumer goods	C_5	Yuan	Benefit	[27, 51]
	Per capita foreign investment	C_6	USD	Benefit	[16, 45]
Society (SO)	Population density	C_7	%	Benefit	[14, 26, 52]
	Education and technology accounted for the proportion of fiscal expenditure	C_8	%	Benefit	[14, 50]
	Number of college student per 10,000 People	C_9	Person	Benefit	[16, 25]
	Number of doctors per 10,000 people	C_{10}	Person	Benefit	[4, 31]
	Number of Internet broadband households	C_{11}	unit	Benefit	[4, 53]
	Per capita urban road area	C_{12}	People/m^2	Benefit	[4, 54, 55]
Environment (EN)	SO_2 emissions as a percentage of GDP	C_{13}	10000 tons	Cost	[17, 26]
	Ammonia nitrogen emission	C_{14}	10000 tons	Cost	[15, 30, 36]
	Industrial Soot and Dust Emissions	C_{15}	10000 tons	Cost	[2, 4, 56]
	Comprehensive utilisation rate of industrial solid waste	C_{16}	%	Cost	[17, 26, 45]
	Harmless treatment rate of household garbage	C_{17}	%	Cost	[16, 17]
	Per capita green park area	C_{18}	m^2	Benefit	[14, 16, 17, 30]

3.2 SPA Weighting Method

Traditional sustainability assessment methods often assume indicator independence, which fails to capture complex interrelationships inherent in urban systems. To address this limitation, a novel set pair analysis (SPA)-based weighting approach was developed, explicitly accounting for deterministic and uncertain inter-indicator relationships to enhance weighting accuracy.

The sustainability assessment in this study involved 20 cities denoted as o_i, 18 indicators denoted as e_j, and 10 years denoted as t_k. $x_{ij}(t_k)$ represents the initial values of an alternative (city) with respect to indicators from 2010 to 2019, where $i=1,2,\ldots,20; j=1,2,\ldots,18; k=1,2,\ldots,10$. The specific weighting procedure for sustainability evaluation is as follows:

Step 1. Normalise the values of performance.

$$x'_{ij}(t_k)=\frac{x_{ij}(t_k)-\min_i \min_k x_{ij}}{\max_i \max_k x_{ij}-\min_i \min_k x_{ij}}, e_j \text{ is a benefit indicator} \quad (1)$$

$$x'_{ij}(t_k)=\frac{\max_i \max_k x_{ij}-x_{ij}(t_k)}{\max_i \max_k x_{ij}-\min_i \min_k x_{ij}}, e_j \text{ is a cost indicator} \quad (2)$$

where $x'_{ij}(t_k)\in[0,1]$ is the normalised value, $\max_i \max_k x_{ij}(t_k)$ and $\min_i \min_k x_{ij}(t_k)$ are the largest and smallest indicator values of cities in different periods.

Step 2. Calculate the average value of indicators.

$$a_j=\frac{1}{200}\sum_{i=1}^{20}\sum_{k=1}^{10}x'_{ij}(t_k) \quad (3)$$

where $a_j\in[0,1]$ reflects the overall level of the same indicator relative to different cities O_i and period t_k. The larger the a_j, the higher the overall level.

Step 3. The indicator and the average value of the indicator are combined into a set pair system to calculate the connection number.

The average value divided the indicator into two grades, the first grade was $\left[u_{j0}, a_j\right)$, and the second was $\left[a_j, u_{j2}\right]$. u_{j0} takes 0 and u_{j2} takes 1 due to $x'_{ij}\left(t_k\right) \in [0,1]$, when $u_{j0} \le x'_{ij}\left(t_k\right) < a_j$ such as

$$\begin{cases} u_{ij1}\left(t_k\right) = -1 \\ u_{ij2}\left(t_k\right) = 1 - 2\left(a_j - x_{ij}{}'\left(t_k\right)\right) / \left(a_j - u_{j0}\right) \\ u_{ij3}\left(t_k\right) = 1 \end{cases} \tag{4}$$

Similarly, when $a_j \le x'_{ij}\left(t_k\right) \le 1$, then

$$\begin{cases} u_{ij1}\left(t_k\right) = 1 \\ u_{ij2}\left(t_k\right) = 1 - 2\left(x_{ij}{}'\left(t_k\right) - a_j\right) / \left(u_{j2} - u_{j0}\right) \\ u_{ij3}\left(t_k\right) = -1 \end{cases} \tag{5}$$

where $u_{ijr}\left(t_k\right) \in [0,1]$ and $u_{ijr}\left(t_k\right)$ values depend on the grade to which the indicator value belongs. The values of $u_{ijr}\left(t_k\right)$ and $x'_{ij}\left(t_k\right)$ are positively correlated. $u_{ijr}\left(t_k\right)$ can be used as a function to distinguish the relationship between the indicators and the grade. $v_{ijr}\left(t_k\right)$ is the corresponding relative membership degree:

$$v_{ijr}\left(t_k\right) = 0.5 + 0.5 u_{ijr}\left(t_k\right) \tag{6}$$

$V_{ij1}\left(t_k\right)$, $V_{ij2}\left(t_k\right)$, and $V_{ij3}\left(t_k\right)$ represent the identity, difference, and opposite in the set pair system, respectively. The identity degree and opposite degree reflect relatively definite fuzzy relations, whereas the difference degree is a relatively uncertain fuzzy relation $V_{ij1}\left(t_k\right) + V_{ij2}\left(t_k\right) + V_{ij3}\left(t_k\right) = 1$. The calculation formulas are as follows:

$$\begin{cases} V_{ij1}\left(t_k\right) = v_{ij1}\left(t_k\right) \Big/ \sum_{r=1}^{3} v_{ijr}\left(t_k\right) \\ V_{ij2}\left(t_k\right) = v_{ij2}\left(t_k\right) \Big/ \sum_{r=1}^{3} v_{ijr}\left(t_k\right) \\ V_{ij3}\left(t_k\right) = v_{ij3}\left(t_k\right) \Big/ \sum_{r=1}^{3} v_{ijr}\left(t_k\right) \end{cases} \tag{7}$$

$U_{ij}\left(t_k\right)$ denotes the connection numbers, calculated using the following:

$$U_{ij}\left(t_k\right) = V_{ij1}\left(t_k\right) + V_{ij2}\left(t_k\right) I + V_{ij3}\left(t_k\right) \tag{8}$$

where $I \in [-1,1]$ is the difference coefficient and $J \in [-1,0]$ is the opposite coefficient [33, 57].

Step 4. Obtain the indicator weight.

$$w_j = \sum_{i=1}^{20} \sum_{k=1}^{10} U_{ij}\left(t_k\right) \Big/ \sum_{i=1}^{20} \sum_{j=1}^{18} \sum_{k=1}^{10} U_{ij}\left(t_k\right) \tag{9}$$

4. Results

4.1 Overall Sustainable Results

Indicator values were first standardized to eliminate dimensional disparities, followed by weight calculation using the proposed set pair analysis (SPA) methodology. The aggregation model is expressed as:

$$S_i\left(t_k\right) = \alpha \sum_{j=1}^{m} w_j x'_{ij}\left(t_k\right) + \beta \sum_{j=1}^{m} w_j \hat{x}_{ij}\left(t_k\right) \tag{10}$$

where $S_i\left(t_k\right)$ is the overall state-trend sustainability value. $\hat{x}_{ij}\left(t_k\right) = x'_{ij}\left(t_{k+1}\right) - x'_{ij}\left(t_k\right)$ is the gain value. α, β are the adjusting parameters while $\alpha \in [0,1]$, $\beta \in [0,1]$, and $\alpha + \beta = 1$. In the absence of special needs, $\alpha = \beta = 0.5$.

Table 2 shows four central cities had the highest sustainability scores, with Shizuishan ranking lowest—Guangzhou's score nearly double Shizuishan's, highlighting significant disparities. Eight cities exceeded the mean: four central hubs and four resource-exhausted cities (Zaozhuang, Jingdezhen, Jiaozuo, Liaoyuan). Fourteen resource-exhausted cities (excluding Shaoguan/Fushun) showed positive growth rates, indicating sustained momentum, though gaps persisted in both scores and trajectories compared to central cities.

From 2010 to 2019, sustainability scores of the 20 cities exhibited an overall upward trajectory with varying degrees of volatility (Fig. 3). Pingxiang recorded the highest score fluctuations, followed by Huangshi and Baishan, while Shaoguan showed the steadiest performance. Notably, four Northeastern cities—Liaoyuan, Fushun, Baishan, and Hegang—experienced a trough in 2014, followed by consistent growth culminating in peak scores in 2018. At the regional level, only Shenyang—a central benchmark city—consistently exceeded the Northeastern regional average in annual sustainability scores during 2010–2019.

Table 2. Comprehensive sustainability performance score of 20 cities

City	Ranking	Measurement score	Growth rate*	Region
Guangzhou	1	0.404	2.087%	Eastern
Shenyang	2	0.350	0.382%	Northeastern
Zhengzhou	3	0.316	2.972%	Central
Xi'an	4	0.311	3.134%	Northwest
Zaozhuang	5	0.291	1.163%	Eastern
Jingdezhen	6	0.283	0.916%	Central
Jiaozuo	7	0.282	1.885%	Central
Liaoyuan	8	0.278	0.401%	Northeastern
Huangshi	9	0.266	1.729%	Central
Shaoguan	10	0.265	-0.877%	Eastern
Pingxiang	11	0.262	1.128%	Central
Huaibei	12	0.259	1.144%	Eastern
Luzhou	13	0.255	1.305%	Western
Baiyin	14	0.249	0.518%	Northwest
Wuhai	15	0.248	0.561%	Northwest
Baishan	16	0.241	1.697%	Northeastern
Yichun	17	0.227	0.025%	Northeastern
Hegang	18	0.226	0.141%	Northeastern
Fushun	19	0.217	-0.484%	Northeastern
Shizuishan	20	0.212	1.566%	Northwest

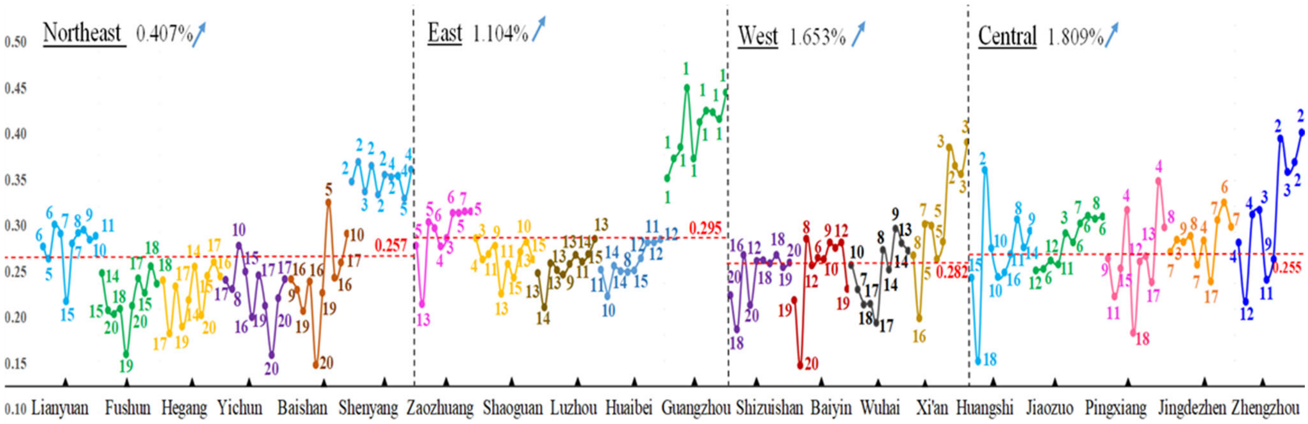

Fig. 3 Comprehensive sustainability scores of 20 cities in 2010-2019

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4.2 Dimensional-Level Results

This section focuses on analyzing the coordination of sustainability across economic (EC), social (SO), and environmental (EN) dimensions. The formula for deriving performance scores of the three dimensions is expressed as:

$$\begin{cases} S_i^{EC}(t_k) = \alpha \sum_{j=1}^{6} w_j x'_{ij}(t_k) + \beta \sum_{j=1}^{6} w_j \hat{x}_{ij}(t_k) \\ S_i^{SO}(t_k) = \alpha \sum_{j=7}^{12} w_j x'_{ij}(t_k) + \beta \sum_{j=7}^{12} w_j \hat{x}_{ij}(t_k) \\ S_i^{EN}(t_k) = \alpha \sum_{j=13}^{18} w_j x'_{ij}(t_k) + \beta \sum_{j=13}^{18} w_j \hat{x}_{ij}(t_k) \end{cases} \quad (11)$$

Table 3 shows Shizuishan has the most balanced economic (EC), social (SO), and environmental (EN) performance, followed by Zhengzhou, Xi'an, and Guangzhou. Central cities (Zhengzhou, Xi'an, Guangzhou, Shenyang) have mean dimensional scores >0.1—significantly higher than resource-exhausted cities' sub-0.1 averages—and lower variances, indicating more balanced development. Despite leading in dimension balance, Shizuishan has the lowest overall score and dimensional averages, reflecting a balance-performance trade-off. Cities like Jingdezhen, Huaibei, Luzhou, and Liaoyuan show poor coordination with dimensional variances ~0.01, signaling significant economic-social-environmental imbalances.

Table 3. The 20 cities' sustainability scored on three dimensions

City	Ranking	EC	SO	EN	Mean*	Var*	EC Growth rate*	SO Growth rate *	EN Growth rate *
Shizuishan	1	0.034	0.050	0.128	0.071	0.0025	-1.428	1.938	0.421
Zhengzhou	2	0.070	0.074	0.173	0.105	0.0034	-15.840	2.351	0.496
Xi'an	3	0.071	0.067	0.172	0.104	0.0036	-0.462	-5.041	0.787
Guangzhou	4	0.094	0.103	0.26	0.135	0.0039	-0.390	-0.503	0.171
Wuhai	5	0.044	0.044	0.161	0.083	0.0045	2.398	-0.302	1.753
Fushun	6	0.032	0.029	0.156	0.072	0.0052	-0.312	1.250	0.282
Huangshi	7	0.039	0.049	0.178	0.089	0.0060	-2.180	4.236	1.341
Shenyang	8	0.062	0.081	0.207	0.117	0.0061	0.200	1.668	0.324
Jiaozuo	9	0.040	0.057	0.186	0.094	0.0064	-1.221	3.533	0.081
Baishan	10	0.038	0.026	0.178	0.080	0.0072	3.011	4.256	2.756
Pingxiang	11	0.039	0.038	0.186	0.087	0.0072	2.343	2.934	1.210
Shaoguan	12	0.042	0.035	0.188	0.088	0.0075	4.121	0.747	1.604
Zaozhuang	13	0.039	0.055	0.197	0.097	0.0075	1.626	3.967	0.462
Baiyin	14	0.034	0.032	0.184	0.083	0.0076	2.089	4.591	-0.100
Hegang	15	0.023	0.027	0.176	0.075	0.0077	4.069	2.458	2.764
Yichun	16	0.026	0.019	0.183	0.076	0.0086	0.466	2.277	0.960
Jingdezhen	17	0.038	0.038	0.207	0.094	0.0095	-0.385	0.324	-1.201
Huaibei	18	0.034	0.026	0.199	0.086	0.0096	2.646	3.948	0.718
Luzhou	19	0.037	0.019	0.200	0.085	0.0099	0.020	2.000	1.203
Liaoyuan	20	0.036	0.033	0.209	0.093	0.0102	2.678	3.642	0.931

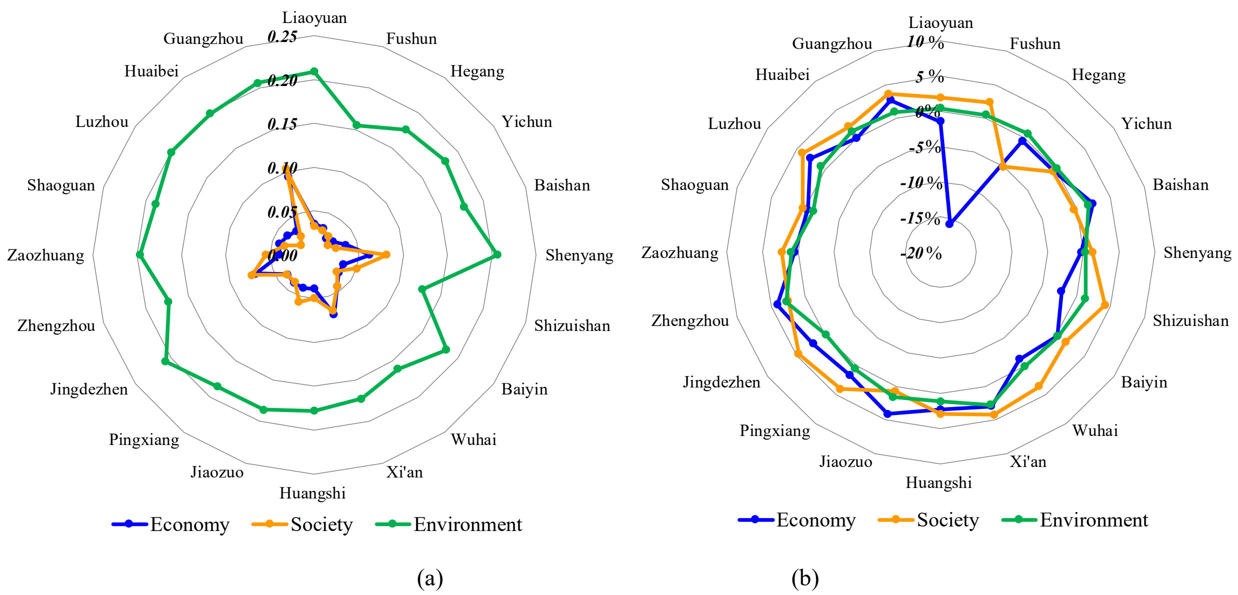

Fig. 4. a Average value in the three dimensions, b Average growth rates in the three dimensions

Table 3 and Figure 4 show environmental sustainability outperformed economic/social dimensions on average, particularly in Hegang, Yichun, and Baishan. Five resource-exhausted cities had negative economic growth, while only Wuhai saw declining social growth. Environmental growth was mostly positive, except in Baiyin and Jingdezhen. Among central cities, Zhengzhou, Xi'an, and Guangzhou had negative economic growth; Xi'an and Guangzhou showed social declines, but all central cities maintained positive environmental growth.

4.3 Indicator Level Results

In this section, we analysed the relationship between indicators and their sustainable evaluation scores to determine the driving factors of sustainable development. Figure 5 shows the top 5 indicators of the advantages and disadvantages of the 20 cities. As shown in Figure 5, the top five indicators in the 20 cities were primarily environmental dimension indicators, C_{13}, C_{14}, C_{15}, C_{16}, and C_{17}. However, C_2 was included in the top five indicators of resource-exhausted cities, Fushun, Baishan, Baiyin, and Luzhou. C_4, C_5, C_6, C_7, C_9, and C_{11} showed a high frequency in the bottom 5 indicators of resource-exhausted cities. There was a significant difference between the sum of the top five indicators and the bottom five indicators in resource-exhausted cities. Huaibei showed the smallest difference between the sum of the top and bottom five indicators (5.77 times).

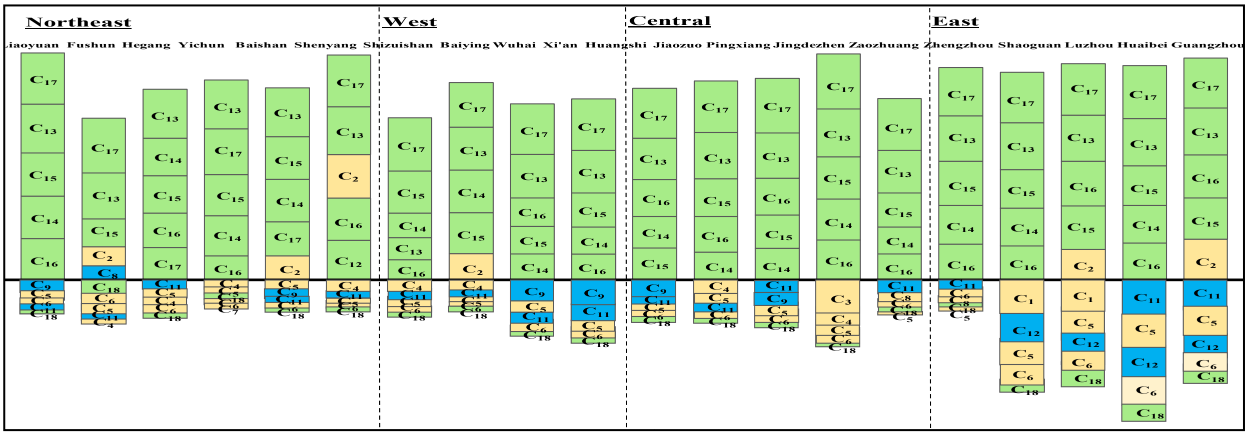

Fig. 5 Top 5 advantage and disadvantage indicators of 20 cities in China.

5. Conclusion

This study employs a multi-criteria decision-making (MCDM) framework to assess the sustainability of 16 prefecture-level resource-exhausted cities, introducing a novel subjective-objective hybrid weighting method based on the standard deviation preference approach (SPA). This methodological innovation contributes to advancing urban sustainability evaluation research by addressing indicator interaction complexities. The findings offer empirical insights for policymakers to refine sustainable development strategies and urban planning frameworks. Results revealed that four central cities dominated the top sustainability rankings, with Guangzhou scoring highest (0.404). Among resource-exhausted prefecture-level cities, Zaozhuang led (0.291) and Shizuishan ranked lowest (0.212), with only 20% (4 cities) exceeding the average. Most such cities (excluding Shaoguan and Fushun) showed positive growth trends, indicating sustained development over the decade. Regional disparities were evident: southern/eastern cities outperformed northern/western counterparts. While resource-exhausted cities lagged central cities across all three dimensions, growth rate gaps narrowed. Underperforming indicators focused on green space, broadband access, population density, and foreign investment.

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