Chapter 10
Sustainability Risks of Resource-Exhausted Cities in China: A Principal Component Analysis

Huijuan Xiao, Long Zhang, and Jingzheng Ren

Abstract Resource-exhausted cities indicate the cities whose natural resources are exhausting, and whose accumulated exploitation reserves have reached more than 70% of the recoverable reserves. These types of cities could encounter many sustainability risks caused by the resource curse, such as slowing economic development, difficulty in economic transformation, sluggish in fostering new growth points, rising unemployment, insufficient innovation capacity, and deterioration of environmental and ecological systems. However, the status of sustainability of resource-exhausted cities is still unclear. To fill this research gap, the study constructs an evaluation framework covering economic, social, and environmental dimensions for the sustainability of resource-exhausted cities. The principal component analysis is used to evaluate the sustainability of resource-exhausted cities in China from 2005 to 2016. Results show that (1) the sustainability of resource-exhausted cities sees an increasing trend. However, the average sustainability of these cities is 64.297 in 2016 and there is still much room for improvement; (2) Shuangyashan, Fushun, Fuxin, Shizuishan, and Wuhai see the most significant risk in sustainability, at a mere 52.242, 52.447, 47.371, 34.062, and 4.113 in 2016, respectively; and (3) Panjin, Shuangyashan, and Yichun-HLJ are the only three cities whose sustainability sees a decreasing trend from 2005 to 2016. This indicates that Fuxin, Liaoyuan, and Shuangyashan face relatively significant sustainability risks and prompt actions should be taken to reverse this deterioration. The results obtained in this study can be a reference to take stock of where resource-exhausted cities stand in terms of sustainability, identify the potential risks, and further promote sustainable development.

Keywords Risk · Resource-exhausted cities · Sustainability · Principal component analysis · Resource curse

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10.1 Introduction

Sustainable development is the development that meets the needs of the present generation without compromising the ability of future generations to meet their own needs, which is defined by the Brundtland commission in 1987 (Brundtland et al. 1987). Here, we define sustainability risks as the factors that can pose risks to achieve a better and more sustainable future of a given system (e.g., an economy, a corporation, and a community). These sustainability risks can be related to economy, environment, and society. Resource-exhausted cities indicate the cities whose natural resources are exhausting and are in a later, late, or even end stages after continuous exploitation, and whose accumulated exploitation reserves have reached more than 70% of the recoverable reserves. China is not the only country that has resource-exhausted cities, in fact, these types of cities exist in many countries around the world. According to the National Development and Reform Commission of China, 69 resource-exhausted cities have been identified in this country (The Chinese Government 2011). These cities may encounter many sustainability risks caused by the resource curse, which have attracted great attention from many scholars and policy-makers (The Chinese Government 2008; Zhang et al. 2018).

The term 'curse of natural resource' is proposed by Auty et al. (1998) denoting the paradoxical situation that the development of resource-rich regions falls behind those with relatively poor natural resources. Some studies have found that the resource curse happens in China, especially in the central and western regions (Shao and Qi 2009; Zhang and Brouwer 2020). Shao and Qi (2009) suggested that there was a negative relationship between economic development and energy exploitation in Western China since the 1990s. The sustainability risks of resource-exhausted cities can be closely related to the negative impacts exerted by the resource curse. The transmission effects of the resource curse can be categorized into three main mechanisms (Shao et al. 2020; Szalai 2018), that is Dutch disease, crowding-out effect, and institutional weakening effect.

With China's economic restructuring and fundamental change of supply–demand in the resources market, resource-exhausted cities of China are faced with a series of dilemmas regarding the economy, society, and environment (Dong et al. 2007; He et al. 2017; Li et al. 2020). The dilemmas include slowing economic development, difficulty in economic transformation, sluggish in fostering new growth points, rising unemployment, insufficient innovation capacity, institutional issues, and deterioration of environmental and ecological systems. However, the sustainability risks of resource-exhausted cities are still unclear, even though numerous studies have examined these risks for Chinese resource-based cities (Lu et al. 2016; Qin et al. 2019).

To fill this research gap, the study constructs a framework covering economic, social, and environmental dimensions for the sustainability evaluation of resource-exhausted cities in China. The sustainability risks of resource-exhausted cities are multidimensional and complicated. The principal component analysis (PCA) is capable of summarizing the information of large dimensions to smaller dimensions while retaining the data information to a maximum degree (Liou et al. 2004; Vega et al.

1998). As such, the study uses the PCA method to evaluate the sustainability risks of resource-exhausted cities in China from 2005 to 2016. The results can be a reference to take stock of where resource-exhausted cities stand in terms of sustainability, identify the potential risks, and further promote sustainable development.

10.2 Methodology and Data

10.2.1 The Principal Component Analysis

The PCA conducts dimension reduction by discarding the highly correlated data information and generates irrelevant components. Thus, PCA can be regarded as one of the most widely adopted statistical tools to reduce dimensions and improve working efficiency for the dataset with many indicators. Considering these advantages of PCA, it has been widely applied in many study areas for performance evaluation and ranking (Omrani et al. 2019; Zhu 1998). In this study, PCA is used to extract information from the dataset with 14 indicators and reduce the dimensions to 7. The procedure of PCA used to evaluate the sustainability risk is provided and some steps are based on Zhu (1998).

Step 1 (Constructing the origin matrix $X = \left[x_{ij}\right]_{n\times p}$). Suppose the dataset has n decision-making unit (DMU) and p indicators. The origin matrix can be constructed as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix} \tag{10.1}$$

where x_{ij} is the value of indicator j under DMU i.

Step 2 (Transform all indicators to positive dimension indicator and obtain $Y = \left[y_{ij}\right]_{n\times p}$). The indicators in negative dimension mean the increase of the value of these indicators could deteriorate the performance of DMUs. For consistency, we need to transform the indicators in negative dimension to positive dimension, as follows.

$$y_{ij} = \begin{cases} x_{ij}, & \text{for indicators in positive dimension} \\ -x_{ij}, & \text{for indicators in negative dimension} \end{cases} \tag{10.2}$$

Step 3 (Standardize the matrix Y and obtain standardized matrix $Z = \left[z_{ij}\right]_{n\times p}$). Without loss of generality, all the variables should be standardized to ensure each of them has sample mean 0 and variance of 1. The standardization formula is as follows.

$$z_{ij} = \frac{y_{ij} - \overline{y}_j}{s_j} \quad i = 1, 2, ..., n \quad and \quad j = 1, 2, ..., p \tag{10.3}$$

$$Z = \left[z_{ij}\right]_{n\times p} = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1p} \\ z_{21} & z_{22} & \cdots & z_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{np} \end{bmatrix} \tag{10.4}$$

$\overline{y}$ and s_j indicate the average value $\left(\frac{\sum_{i=1}^{n} y_{ij}}{n}\right)$ and standard deviation $\left(\sqrt{\frac{\sum_{i=1}^{n}(y_{ij}-\overline{y}_j)^2}{n-1}}\right)$ of indicator j.

Step 4 (Construct the covariance matrix $R = \left[r_{ij}\right]_{p\times p}$). The covariance matrix among the p indicators can be expressed as follows:

$$R = \left[r_{ij}\right]_{p\times p} = \frac{Z^T Z}{n-1} = \begin{bmatrix} \frac{1}{n-1}\sum_{i=1}^{p}(z_{i1})^2 & \frac{1}{n-1}\sum_{i=1}^{p} z_{i1}z_{i2} & \cdots & \frac{1}{n-1}\sum_{i=1}^{p} z_{i1}z_{ip} \\ \frac{1}{n-1}\sum_{i=1}^{p} z_{i2}z_{i1} & \frac{1}{n-1}\sum_{i=1}^{p}(z_{i2})^2 & \cdots & \frac{1}{n-1}\sum_{i=1}^{p} z_{i2}z_{ip} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{n-1}\sum_{i=1}^{p} z_{ip}z_{i1} & \frac{1}{n-1}\sum_{i=1}^{p} z_{ip}z_{i2} & \cdots & \frac{1}{n-1}\sum_{i=1}^{p}\left(z_{ip}\right)^2 \end{bmatrix} \tag{10.5}$$

Matrix Z^T is the transpose of the matrix Z. The diagonal elements of the matrix Z indicate the variance of a specific indicator, while other elements mean the covariance between two indicators. If the covariance between indicators is high, this dataset is more suitable for conducting PCA. To be noticed, the covariance matrix Z is equal to its correlation matrix using the Pearson correlation method since the matrix Z has been standardized in step 3. To be specific, the formula of correlation between indicator a and indicator b is $\rho_{a,b} = \frac{COV(a,b)}{\sigma_a\sigma_b}$ where $\sigma_a = 1$ and $\sigma_b = 1$. Therefore, $\rho_{a,b} = \frac{COV(a,b)}{\sigma_a\sigma_b} = COV(a, b)$.

Step 5 (Calculate the eigenvalue (λ_k) and eigenvector ($\vec{b_k}$)). k indicates the newly constructed components. The number of the components is the same as the number of indicator j. The eigenvalue of the component k is denoted as λ_k, while the eigenvector is denoted as b_k. According to the properties of the matrix, the number of eigenvalues of a matrix is the same as its order. The eigenvalues can be the same (the multiple roots). As such, we can obtain p eigenvalues and $\lambda_1 \geq \lambda_1 \geq \cdots \geq \lambda_p \geq 0$, the calculation process of the eigenvalue is as follows.

$$\left|R - \lambda I_p\right| = 0 \tag{10.6}$$

where I_p is the identity matrix of size p. The eigenvector ($\vec{b}_k$) corresponding to the kth eigenvalue (λ_k) can be obtained as follows.

$$R\vec{b}_k = \lambda_k \vec{b}_k, \quad \vec{b}_k = \begin{bmatrix} b_{1k} \\ b_{2k} \\ \vdots \\ b_{pk} \end{bmatrix}, \qquad k = 1, 2, ..., p \tag{10.7}$$

Since the covariance matrix R is symmetric, these p eigenvectors are perpendicular and not correlated with each other. Then we can obtain a matrix $B = \left[b_{jk}\right]_{p\times p}$ containing p eigenvectors as follows.

$$B = \left[b_{jk}\right]_{p\times p} = \left[\vec{b}_1, \vec{b}_2, \cdots, \vec{b}_p\right] = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{p1} & b_{p2} & \cdots & b_{pp} \end{bmatrix}, \quad j = 1, 2, ...p, \quad k = 1, 2, ..., p \tag{10.8}$$

Step 6 (determine the number of principal components to be considered). The number of the components of the dataset is equal to the number of the eigenvalues/the eigenvectors/the indicators (p). The eigenvalues can be the same (the multiple roots), and the eigenvectors obtained based on the multiple roots are also irrelevant since the covariance matrix R is a real symmetric matrix. We choose the top m components as the principal components based on the descending order of the eigenvalue that can cumulatively express more than 80% of data variance. In other words, more than 80% of the information of the dataset can be explained based on these m principal components.

$$\frac{\sum_{k=1}^{m} \lambda_k}{\sum_{k=1}^{p} \lambda_k} = \frac{\sum_{k=1}^{m} \lambda_k}{p} 0.8, \qquad k = 1, 2, ..., m \quad \text{and} \quad m \leq p \tag{10.9}$$

Step 7 (Construct the decision matrix $B^0 = \left[b^0_{jk}\right]_{p\times m}$). Unit vector can ensure that the importance level of indicators can be compared among different eigenvectors. Therefore, we transformed the vector b_k into a unit vector as follows.

$$\vec{b}_k^0 = \frac{\vec{b}_k}{\left|\vec{b}_k\right|} = \begin{bmatrix} b_{1k}^0 \\ b_{2k}^0 \\ \vdots \\ b_{pk}^0 \end{bmatrix}, \qquad k = 1, 2, ..., m \quad \text{and} \quad m \le p \tag{10.10}$$

where $\left|\vec{b}_k\right|$ is the magnitude (modulus) of the vector b_k. b_k^0 is the unit vector, indicating that the square sum of its components equals 1. The absolute value of the component in the vector b_k^0 reflects the importance level of the corresponding indicators. The decision matrix B^0 can be constructed based on the following equation.

$$B^0 = \left[b_{jk}^0\right]_{p \times m} = \left[\vec{b}_1^0, \vec{b}_2^0, \ldots, \vec{b}_m^0\right] = \begin{bmatrix} b_{11}^0 & b_{12}^0 & \cdots & b_{1m}^0 \\ b_{21}^0 & b_{22}^0 & \cdots & b_{2m}^0 \\ \vdots & \vdots & \ddots & \vdots \\ b_{p1}^0 & b_{p2}^0 & \cdots & b_{pm}^0 \end{bmatrix} \tag{10.11}$$

To be noticed, the results obtained using SPSS software are the 'component matrix' ($F = \left[\vec{f}_1, \vec{f}_2, \ldots, \vec{f}_m\right]_{p \times m}$) with the loadings as its elements instead of the decision matrix ($B^0 = \left[\vec{b}_1^0, \vec{b}_2^0, \ldots, \vec{b}_m^0\right]_{p \times m}$). The relationship between the 'component matrix' and the decision matrix is as follows.

$$\vec{b}_k = \frac{\vec{f}_k}{\sqrt{\lambda_k}}, \qquad k = 1, 2, ..., m \quad \text{and} \quad m \le p \tag{10.12}$$

Step 8 (Construct the primary component models). The principal component is a linear combination of all the indicators that go through the origin. The m principal components of DMU i can be formulated as follows.

$$\begin{cases} F_{i1} = b_{11}^0 z_{i1} + b_{21}^0 z_{i2} + \cdots + b_{p1}^0 z_{ip} \\ F_{i2} = b_{12}^0 z_{i1} + b_{22}^0 z_{i2} + \cdots + b_{p2}^0 z_{ip} \\ \vdots \\ F_{im} = b_{pm}^0 z_{i1} + b_{p2}^0 z_{i2} + \cdots + b_{pm}^0 z_{ip} \end{cases} \tag{10.13}$$

where $F_{i1},\ F_{i2}, \ldots, F_{im}$ are the m principal components of DMU i. $z_{i1}, z_{i2}, \ldots, z_{ip}$ indicates the value of indicators from 1 to p for DMU i. The rank of principal components ($F_{i1},\ F_{i2}, \ldots, F_{im}$) is based on the extent of variance included in the components measured by eigenvalue ($\lambda_1 \ge \lambda_1 \ge \cdots \ge \lambda_m$). In other words, F_{i1} includes the maximum variance of the dataset, while F_{im} has the minimum variance. These principal components are not correlated but perpendicular to each other, indicating that they contain the information of different 'statistical dimensions'.

Step 9 (Evaluate the performance of DMUs). The study constructs the comprehensive component model of DMU i as follows (Zhu 1998).

$$F_i = \sum_{k=1}^{m} W_k \times F_{ik} = a_1 z_{i1} + a_2 z_{i2} + \cdots + a_p z_{ip}, \tag{10.14}$$
$$i = 1, 2, ..., n, \quad k = 1, 2, ..., m \quad \text{and} \quad m \leq p$$

$$W_k = \begin{cases} \lambda_k / \sum\limits_{k=1}^{m} \lambda_k, & if \quad \sum\limits_{j=1}^{p} b_{jk}^0 \geq 0 \\ -\lambda_k / \sum\limits_{k=1}^{m} \lambda_k, & if \quad \sum\limits_{j=1}^{p} b_{jk}^0 < 0 \end{cases} \tag{10.15}$$

The percentage of variance explained by each component represents its relative importance. Therefore, the study uses the $\lambda_k / \sum_{k=1}^{m} \lambda_k$ as the weight of the primary component k, which is denoted as W_k. The sign of W_k depends on the $\sum_{j=1}^{p} b_{jk}^0$, and a negative sign will be added to W_k once $\sum_{j=1}^{p} b_{jk}^0$ is negative. The sign change does not change the explanation of the principal component (Zhu 1998). a_j means the importance level of the indicator j. F_i indicates the performance scores of DMU i. The higher the F_i, the better the performance is. z_{ij} is the standardized value of the indicator j for DMU i based on step 3.

Step 10 (Standardize the performance of DMUs to make scores range from 0 to 100). The performance score of DMUs based on step 9 can be negative or positive, which makes it not straightforward to compare and demonstrate. Therefore, we further standardize the scores to make them range from 0 to 100. The higher the standardized scores of a DMU ($F_i^{'}$), the better the sustainability is. 0 indicates the worst performance, while 100 means the best performance. The standardization process is as follows.

$$F_i^{'} = 100 \times \frac{F_i - \min\limits_{1 \leq i \leq n}(F_i)}{\max\limits_{1 \leq i \leq n}(F_i) - \min\limits_{1 \leq i \leq n}(F_i)} \tag{10.16}$$

where $\min\limits_{1 \leq i \leq n}(F_i)$ and $\max\limits_{1 \leq i \leq n}(F_i)$ indicate the minimum and maximum value among all the F_i of DMU i.

10.2.2 Sample Cities and Data

Table 10.1 presents the indicators of three aspects, including economy, environment, and society. 14 indicators are included in this study. The data of these indicators are collected from the statistical yearbook of each city. The innovation capacity indicates

Table 10.1 List of indicators regarding economy, society, and environment

Aspect	No	Indicator	Unit	Dimension
Economy	1	GDP per capita	10,000 Yuan /person	Positive
	2	GDP growth rate	%	Positive
	3	Share of tertiary industry	%	Positive
Society	4	Share of the unemployed person	%	Negative
	5	Ratio of teacher to total population	%	Positive
	6	Share of foreign direct investments to GDP	%	Positive
	7	Innovation capacity	Unit/person	Positive
	8	Student–teacher ratio of regular higher education institutions	–	Positive
	9	Number of public transportation vehicles per 10,000 persons	Unit /10^4 persons	Positive
Environment	10	CO_2 emissions per capita	Tonnes /person	Negative
	11	CO_2 emissions intensity	Tonnes/10^4 ¥	Negative
	12	Volume of industry sulfur dioxide per capita	Tonne /person	Negative
	13	Ratio of industrial solid wastes comprehensively utilized	%	Positive
	14	Ratio of waste water centralized treated of sewage work	%	Positive

the patent per capita. The patent data are collected from the State Intellectual Property Office of China, which includes invention patents, utility model patents, and design patents. The GDP has been converted to the 2005 constant price based on the GDP index. CO_2 emissions are sourced from Chen et al. (2020).

According to 'The Plan for the Sustainable Development of Chinese Resource-based Cities (2013–2020)' issued by the State Council, there are 262 resource-based cities in China, among which 69 are resource-exhausted. In this study, owing to the data unavailability at the county level, we only take the prefectural level cities into consideration. A prefectural-level city doesn't indicate the usual meaning of the term (i.e., urban settlement), but means an administrative unit that with not only urban area but rural area. Daxinganling city is also not included because of insufficient data. Thus, a total of 24 prefectural level cities are studied and some descriptions of these 24 cities can be found in Table 10.2.

Table 10.2 List of resource-exhausted cities at the prefectural level of China

No	Province	City	Note	Establishment time
1	Inner Mongolia	Wuhai	Coal	2011
2	Liaoning	Fushun	Coal	2009
3	Liaoning	Fuxin	Coal	2008
4	Liaoning	Panjin	Crude oil	2008
5	Jilin	Liaoyuan	Coal	2008
6	Jilin	Baishan	Coal	2008
7	Heilongjiang	Hegang	Coal	2011
8	Heilongjiang	Shuangyashan	Coal	2011
9	Heilongjiang	Yichun	Forest	2008
10	Heilongjiang	Qitaihe	Coal	2009
11	Anhui	Huaibei	Coal	2009
12	Anhui	Tongling	Copper	2009
13	Jiangxi	Jingdezhen	Porcelain	2009
14	Jiangxi	Pingxiang	Coal	2008
15	Jiangxi	Xinyu	Iron	2011
16	Shandong	Zaozhuang	Coal	2009
17	Henan	Jiaozuo	Coal	2008
18	Henan	Puyang	Crude oil	2011
19	Hubei	Huangshi	Iron, copper, coal, and wollastonite	2009
20	Guangdong	Shaoguan	Coal and iron	2011
21	Sichuan	Luzhou	Natural gas	2011
22	Tibet	Tongchuan	Coal	2009
23	Gansu	Baiyin	Silver and copper	2008
24	Ningxia	Shizuishan	Coal	2008

10.3 Structure Detection of Dataset

Table 10.3 shows the results of Bartlett's test and Kaiser–Meyer–Olkin measure, which are tested using the SPSS software. The Kaiser–Meyer–Olkin measure is a

Table 10.3 Results of the Kaiser–Meyer–Olkin measure

KMO and Bartlett's Test		
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.630
Bartlett's Test of Sphericity	Approx. Chi-Square	1620.822
	df	91
	Sig	0.000

Table 10.4 Interpretation of the results using Kaiser–Meyer–Olkin measure (Dziuban and Shirkey 1974)

KMO measure	Meaning
KMO $\geq$ 0.9	Marvellous
0.8 $\leq$ KMO < 0.9	Meritorious
0.7 $\leq$ KMO < 0.8	Middling
0.6 $\leq$ KMO < 0.7	Mediocre
0.5 $\leq$ KMO < 0.6	Miserable
KMO < 0.5	Unacceptable

test that shows the share of variance in the indicators which could be caused by underlying factors (Dziuban and Shirkey 1974). The result of the Kaiser–Meyer–Olkin measure ranges from 0 to 1 (Dziuban and Shirkey 1974). It is generally more convincing to conduct PCA analysis if the value of the result becomes higher. If the value is larger than 0.6, indicating the sample complies with the requirement of data structure and can use the PCA (Dziuban and Shirkey 1974). For Bartlett's test of sphericity, the null hypothesis is that the correlation matrix of the dataset is an identity matrix. If it cannot reject the null hypothesis, it means that your indicators are not related and thus it is not appropriate for structure detection. Small values (less than 0.05) of the significance level indicate that factor analysis may be useful with this dataset.

The results in Table 10.3 show that it is suitable for the dataset to conduct structure detection since the value of the Kaiser–Meyer–Olkin measure is 0.630 and the null hypothesis is rejected at a 1% significant level.

Table 10.4 can be a reference to show the meaning of value based on the Kaiser–Meyer–Olkin measure.

Table 10.5 shows the correlation matrix of 14 indicators. The order of the variables shown in Table 10.5 is the same as in Table 10.1. The bottom left triangle indicates the Pearson correlation, while the top right triangle means the Spearman correlation. The eigenvalue and eigenvector are based on the correlation matrix measured by the Pearson correlation and this matrix is symmetric. The symbols *, **, and *** indicates the value is significant at 10%, 5%, and 1% levels, respectively. The value in the matrix shows that many indicators are significantly correlated with each other, and the PCA can be used to reduce the correlation and simplify the dimensions.

10.4 The Weights and Sustainability Performance Based on the Principal Component Analysis

Table 10.6 shows the communalities of 14 indicators. Extraction commonalities can be used to evaluate the variance of each indicator that can be extracted by the factors in the PCA. If the extraction is low, this indicator is not fit well with the factor solution and can be discarded in further analysis. The results in Table 10.6 show that the initial

Table 10.5 Correlation matrix of the 14 variables

	var1	var2	var3	var4	var5	var6	var7	var8	var9	var10	var11	var12	var13	var14
var1	1	−0.499 ***	0.05	−0.249 ***	−0.195 ***	0.196 ***	0.538 ***	−0.137 **	0.483 ***	−0.559 ***	0.182 ***	−0.003	0.135 **	0.579 ***
var2	−0.370 ***	1	−0.278 ***	0.058	0.239 ***	0.027	−0.456 ***	0.034	−0.118 **	0.295 ***	−0.059	−0.217 ***	−0.237 ***	-0.428 ***
var3	0.104 *	−0.276 ***	1	−0.368 ***	−0.103 *	−0.094	0.057	−0.017	0.115 *	−0.098 *	−0.078	0.008	−0.028	−0.008
var4	-0.249 ***	0.076	−0.271 ***	1	0.094	−0.126 **	0.094	−0.079	−0.463 ***	0.462 ***	0.369 ***	0.215 ***	0.242 ***	−0.022
var5	−0.110 *	0.202 ***	0.015	0.033	1	−0.149 **	−0.222 ***	0.253 ***	−0.211 ***	0.08	−0.330 ***	−0.284 ***	−0.218 ***	−0.009
var6	0.188 ***	0.063	−0.133 **	−0.051	−0.105 *	1	0.247 ***	−0.126 **	0.049	0.185 ***	0.397 ***	0.053	0.201 ***	0.183 ***
var7	0.408 ***	−0.300 ***	0.145 **	0.082	−0.093	0.129 **	1	−0.348 ***	−0.119 **	−0.117 **	0.385 ***	0.297 ***	0.298 ***	0.438 ***
var8	−0.102 *	0.046	0.006	−0.056	0.185 ***	−0.104 *	−0.244 ***	1	−0.018	−0.186 ***	−0.345 ***	0.088	−0.075	−0.099 *
var9	0.577 ***	−0.133 **	0.123 **	−0.453 ***	−0.138 **	−0.024	−0.039	−0.033	1	−0.440 ***	−0.140 **	−0.290 ***	−0.009	0.143 **
var10	−0.711 ***	0.281 ***	−0.100 *	0.382 ***	−0.051	0.088	0.01	−0.053	−0.626 ***	1	0.674 ***	0.185 ***	0.198 ***	−0.302 ***
var11	0.055	0.038	−0.077	0.317 ***	−0.300 ***	0.311 ***	0.308 ***	−0.297 ***	−0.216 ***	0.539 ***	1	0.282 ***	0.382 ***	0.101 *

(continued)

Table 10.5 (continued)

	var1	var2	var3	var4	var5	var6	var7	var8	var9	var10	var11	var12	var13	var14
var12	−0.269 ***	−0.074	0.042	0.342 ***	−0.227 ***	0.159 ***	0.217 ***	−0.046	−0.487 ***	0.589 ***	0.515 ***	1	0.322 ***	0.03
var13	0.043	-0.204 ***	−0.039	0.191 ***	−0.302 ***	0.120 **	0.123 **	−0.328 ***	−0.095	0.192 ***	0.362 ***	0.339 ***	1	0.326 ***
var14	0.496 ***	−0.316 ***	0.007	−0.056	−0.04	0.180 ***	0.346 ***	−0.105 *	0.116 **	−0.249 ***	0.119 **	−0.041	0.254 ***	1

Table 10.6 Communalities of 14 indicators

No	Indicator	Initial	Extraction
1	GDP per capita	1	0.887
2	GDP growth rate	1	0.736
3	Share of tertiary industry	1	0.842
4	Share of unemployed person	1	0.760
5	Ratio of teacher to total population	1	0.854
6	Share of foreign direct investments to GDP	1	0.830
7	Innovation capacity	1	0.817
8	Student–teacher ratio of regular higher education institutions	1	0.896
9	Number of public transportation vehicles per 10,000 persons	1	0.767
10	CO_2 emissions per capita	1	0.867
11	CO_2 emissions intensity	1	0.764
12	Volume of industry sulfur dioxide per capita	1	0.766
13	Ratio of industrial solid wastes comprehensively utilized	1	0.822
14	Ratio of wastewater centralized treated of sewage work	1	0.750

variance included in the dataset is 1 for all indicators. The extraction commonalities in the PCA are fit well, with the lowest level at 0.736 for the indicator 'GDP growth rate'.

Table 10.7 shows the total variance explained for each component. The leftmost section of Table 10.7 demonstrates the variance explained by the 14 components. There are 14 components in total, among which five components have eigenvalues larger than 1. The share of variance is equal to the share of the corresponding eigenvalue in the total eigenvalues considered. The total value of the eigenvalues is 14, and thus the share of variance for the first component is 24.226%, which means that 24.226% of the variance in the dataset can be explained by this component. For the second component, 19.541% of the variance can be explained using this component. The share of cumulative variance explained by the first and the second components is 43.767%.

The second section of Table 10.7 shows the variance that can be explained by the extracted components before conducting rotation. The cumulative variability explained by the top seven components in the extracted solution is about 81.131%, which is the same as the initial solution. Thus, there is no loss in the variation explained by the initial solution. In the case there is a difference between the values in the first section and the second section, it can be interpreted that the latent components are unique to the original variables and variability that simply cannot be explained by the component model. This study considers the top seven components as the principal component, which take up 81.131% of the variability of the dataset. The rightmost section of this table shows the variance explained by the extracted factors after rotation. The rotated factor model makes some small adjustments for all these 7 components.

Table 10.7 Total variance explained

	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
Comp.	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.392	24.226	24.226	3.392	24.226	24.226	3.122	22.298	22.298
2	2.736	19.541	43.767	2.736	19.541	43.767	1.586	11.329	33.626
3	1.326	9.471	53.238	1.326	9.471	53.238	1.491	10.65	44.276
4	1.182	8.439	61.677	1.182	8.439	61.677	1.36	9.712	53.988
5	1.032	7.375	69.052	1.032	7.375	69.052	1.294	9.246	63.234
6	0.918	6.558	75.609	0.918	6.558	75.609	1.26	9.002	72.237
7	0.773	5.522	81.131	0.773	5.522	81.131	1.245	8.895	81.131
8	0.587	4.19	85.322						
9	0.552	3.943	89.265						
10	0.438	3.128	92.393						
11	0.401	2.865	95.258						
12	0.338	2.411	97.669						
13	0.269	1.921	99.59						
14	0.057	0.41	100						

The results of the decision matrix can be found in Table 10.8. There are seven principal components considered, each of which has an eigenvalue and an eigenvector (Table 10.8). Table 10.9 shows the component matrix obtained using SPSS software instead of the MATLAB code shown in Sect. 10.6. The results obtained using SPSS software are the 'component matrix' ($F = \left[f_1, f_2, \ldots f_m\right]_{p\times m}$) instead of the decision matrix ($B^0 = \left[b_1^0, b_2^0, \ldots b_p^0\right]_{p\times m}$). The 'component matrix' can be transferred to the decision matrix based on $\vec{b}_k = \frac{\vec{f}_k}{\sqrt{\lambda_k}}$, as shown in step 7 in Sect. 10.2.1. Based on Table 10.8, the first principal component (PC1) is mainly explained by Var 10 (0.490), followed by Var 9 (–0.410), and Var 12 (0.394). Var 10, Var 9, and Var 12 indicate 'CO_2 emissions per capita', Number of public transportation vehicles per 10,000 persons', and 'Volume of industry sulfur per capita', respectively. For the second principal component (PC2), it is primarily composed of Var 7 (–0.394), Var 14 (–0.369), and Var 1 (–0.369). Var 7, Var 14, and Var 1 means 'Innovation capacity', 'Ratio of wastewater centralized treated of sewage work', and ' GDP per capita', respectively. The top three compositions of each principal component have been highlighted in bold as shown in Table 10.8.

Table 10.10 shows the transformation matrix of the seven principal components. This matrix can be used to demonstrate the rotation level of the component matrix compared with the unrotated component matrix. If the values of off-diagonal elements are small, it indicates there are smaller rotations between these two matrices. By contrast, the large values in the off-diagonal elements mean larger rotations.

Table 10.11 shows the sustainability performance of 24 resource-exhausted cities from 2005 to 2016, while Table 10.12 shows the sustainability performance after

Table 10.8 Decision matrix of the seven principal components

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Eigenvalue	3.392	2.736	1.326	1.182	1.032	0.918	0.773
Var1	−0.355	**−0.369**	0.127	−0.160	0.040	0.028	0.210
Var2	0.149	0.313	**0.463**	0.023	0.191	−0.276	0.034
Var3	−0.122	−0.075	**−0.618**	0.176	**0.383**	−0.246	−0.183
Var4	0.327	−0.022	0.020	−0.324	**−0.437**	0.023	0.308
Var5	−0.061	0.276	−0.044	**−0.599**	0.066	**−0.337**	−0.356
Var6	0.072	−0.218	**0.453**	−0.086	**0.555**	0.190	−0.258
Var7	0.014	**−0.394**	−0.178	**−0.346**	0.154	**−0.292**	**0.368**
Var8	−0.070	0.276	−0.175	−0.244	0.220	**0.733**	0.147
Var9	**−0.410**	−0.095	0.179	0.296	0.016	−0.024	0.182
Var10	**0.491**	0.057	−0.060	0.055	0.166	−0.060	−0.048
Var11	0.322	−0.330	0.155	0.055	0.188	−0.082	0.218
Var12	**0.394**	−0.184	−0.234	0.026	0.174	0.211	0.041
Var13	0.177	−0.337	0.015	0.225	−0.367	0.102	**−0.504**
Var14	−0.133	**−0.369**	0.058	**−0.384**	−0.107	0.155	**−0.370**

Table 10.9 Component Matrix

	Component						
Variable	1	2	3	4	5	6	7
GDP per capita	−0.653	0.61	0.147	0.174	0.041	0.027	−0.185
GDP growth rate	0.274	−0.518	0.533	−0.025	0.194	−0.265	−0.03
Share of tertiary industry	−0.225	0.124	−0.712	−0.191	0.389	−0.235	0.161
Share of unemployed person	0.603	0.036	0.023	0.352	−0.444	0.022	−0.271
Ratio of teacher to total population	−0.113	−0.457	−0.051	0.651	0.067	−0.323	0.313
Share of foreign direct investments to GDP	0.132	0.36	0.521	0.093	0.564	0.182	0.227
Innovation capacity	0.025	0.652	−0.205	0.377	0.156	−0.28	−0.324
Student–teacher ratio of regular higher education institutions	−0.129	−0.456	−0.201	0.266	0.223	0.702	−0.129
Number of public transportation vehicles per 10,000 persons	−0.755	0.158	0.206	−0.322	0.016	−0.023	−0.16
CO_2 emissions per capita	0.904	−0.094	−0.069	−0.06	0.169	−0.058	0.042
CO_2 emissions intensity	0.592	0.546	0.178	−0.06	0.191	−0.079	−0.192
Volume of industry sulfur dioxide per capita	0.726	0.304	−0.27	−0.029	0.176	0.202	−0.036
Ratio of industrial solid wastes comprehensively utilized	0.326	0.557	0.017	−0.245	−0.373	0.098	0.443
Ratio of waste water centralized treated of sewage work	−0.244	0.61	0.067	0.417	−0.108	0.148	0.325

standardization. The average sustainability of these cities is 53.783 in 2015, while the level increases to 64.297 in 2016 (see Table 10.12). However, there is still much room for improvement. Among the 24 cities, Shuangyashan, Fushun, Fuxin, Shizuishan, and Wuhai see the most significant risk in sustainability, at a mere 52.242, 52.447, 47.371, 34.062, and 4.113 in 2016 (see Table 10.12).

Figure 10.1 compares the sustainability level of the 24 resource-exhausted cities in 2005 with that in 2016. Most of the resource-exhausted cities see an increase in sustainability from 2005 to 2016, except Panjin, Shuangyashan, and Yichun-HLJ (see Fig. 10.1). This indicates that Panjin, Shuangyashan, and Yichun-HLJ face significant sustainability risks and prompt actions should be taken to reverse this deterioration. Panjin, Shuangyashan, and Yichun-HLJ are located in Liaoning province, Heilongjiang province, and Heilongjiang province, respectively. These two provinces belong to Northeast China and are used to be the old industrial base of China. Because

Table 10.10 Component transformation matrix

Component	1	2	3	4	5	6	7
1	0.935	−0.122	−0.006	0.136	0.241	0.087	0.164
2	−0.047	0.583	0.549	0.397	−0.065	0.28	0.341
3	−0.297	−0.217	−0.173	0.009	0.657	0.586	0.242
4	0.105	0.244	0.466	−0.71	0.32	0.066	−0.319
5	0.082	−0.374	0.197	−0.045	−0.536	0.673	−0.269
6	0.054	0.373	−0.275	0.396	0.197	0.166	−0.748
7	0.121	0.51	−0.581	−0.401	−0.279	0.291	0.255
Extraction Method: Principal Component Analysis							
Rotation Method: Varimax with Kaiser Normalization							

of the decline of its once-powerful resource-related sectors, the Northeast region is named the Rust Belt of China (Campbell 2005; Xiao et al. 2019a), whose development path is different from the Yangtze River Delta region (Xiao et al. 2019b). Many cities in Northeast China used to be abundant in natural resources. However, after decades of the exploitation of natural resources, many cities are facing resource depletion problems and Panjin, Shuangyashan, and Yichun-HLJ are the typical cases. The sustainability risks of these cities threaten the long-term development and integrated measures should be taken to improve sustainability and reduce the risk of deterioration.

10.5 Conclusions and Policies for Mitigating Sustainability Risks

Considering the significant sustainability risks faced by the resource-exhausted cities, the study constructs an evaluation framework covering economic, social, and environmental dimensions to evaluate the sustainability of resource-exhausted cities and identify potential risks. The PCA is used to evaluate the sustainability risks of 24 resource-exhausted cities in China from 2005 to 2016. The main findings are as follows:

The sustainability of resource-exhausted cities sees an increasing trend. The average sustainability of these cities is 53.783 in 2015, while the level increases to 64.297 in 2016. However, there is still much room for improvement. Among the 24 cities, Shuangyashan, Fushun, Fuxin, Shizuishan, and Wuhai see the most significant risk in sustainability, at a mere 52.242, 52.447, 47.371, 34.062, and 4.113 in 2016.

Panjin, Shuangyashan, and Yichun-HLJ are the only three cities whose sustainability sees a decreasing trend from 2005 to 2016. This indicates that Panjin, Shuangyashan, and Yichun-HLJ face relatively significant sustainability risks and prompt actions should be taken to reverse this deterioration. These three cities are

Table 10.11 The sustainability scores of 24 resource-exhausted cities from 2005 to 2016

No	City	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1	Wuhai	−2.799	−2.168	−2.054	−1.879	−1.707	−1.361	−1.632	−1.604	−1.906	−2.335	−2.860	−2.673
2	Fushun	−0.833	−0.646	−0.234	−0.465	−0.124	0.020	−0.336	−0.510	−0.034	−0.092	−0.344	−0.525
3	Fuxin	−0.744	−0.521	−0.469	−0.280	−0.183	0.108	0.034	−0.129	−0.196	0.027	−0.411	−0.710
4	Panjin	0.005	−0.082	0.031	−0.011	0.294	0.858	1.678	1.163	0.899	0.253	−0.088	−0.279
5	Liaoyuan	−0.613	−0.576	−0.263	−0.220	0.277	0.620	0.352	0.360	0.486	0.348	0.342	0.518
6	Baishan	−0.775	−0.610	−0.290	−0.408	−0.417	−0.307	−0.075	−0.351	−0.099	−0.138	−0.030	0.260
7	Hegang	−1.058	−1.050	−0.895	−0.856	−0.352	−0.168	−0.415	−0.367	−0.512	−0.498	−0.381	−0.478
8	Shuangyashan	−0.188	−0.172	0.051	−0.046	−0.024	−0.024	0.089	0.047	−0.073	−0.412	−0.354	−0.489
9	Yichun-HLJ	−0.428	−0.396	−0.245	−0.189	0.073	0.276	0.258	0.078	−0.065	−0.324	−0.459	−0.445
10	Qitaihe	−0.309	−0.320	−0.342	−0.276	−0.202	−0.109	0.157	0.100	−0.332	−0.419	−0.469	−0.191
11	Huaibei	−0.296	−0.318	−0.073	0.122	0.259	0.475	0.653	0.776	0.890	0.916	0.982	1.188
12	Tongling	0.272	0.543	0.315	0.715	0.890	0.870	0.687	0.831	0.898	0.764	0.862	0.982
13	Jingdezhen	0.309	−0.120	0.251	0.052	0.521	0.655	0.499	0.479	0.455	0.439	0.453	0.577
14	Pingxiang	0.039	−0.006	0.423	0.656	0.671	0.722	0.595	0.606	0.584	0.590	0.599	0.797
15	Xinyu	0.031	0.187	0.495	0.937	0.725	0.928	0.890	0.736	0.341	0.409	0.393	0.444
16	Zaozhuang	−0.032	0.381	0.258	0.594	0.679	0.692	0.566	0.556	0.490	0.475	0.419	0.399
17	Jiaozuo	0.075	0.123	0.367	0.165	0.482	0.642	0.754	0.778	0.745	0.699	0.826	1.010
18	Puyang	0.457	0.497	0.096	0.497	0.552	0.734	0.815	0.995	1.035	0.985	1.047	1.061
19	Huangshi	−0.192	0.008	−0.020	0.099	0.227	0.176	0.395	0.553	0.695	0.732	0.268	0.355

(continued)

Table 10.11 (continued)

No	City	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
20	Shaoguan	0.091	0.298	0.436	0.426	0.233	0.364	0.464	0.182	0.238	0.316	0.204	0.153
21	Luzhou	0.444	0.442	0.601	0.181	0.161	0.373	0.449	0.516	0.586	0.642	0.731	0.833
22	Tongchuan	−0.617	−0.399	−0.552	−0.489	−0.101	0.084	0.222	0.306	0.232	0.114	0.045	0.065
23	Baiyin	−1.246	−1.081	−0.856	−0.834	−0.810	−0.613	−0.513	−0.432	−0.202	−0.267	−0.278	−0.144
24	Shizuishan	−1.650	−1.635	−1.248	−1.168	−1.630	−1.335	−0.879	−0.812	−0.607	−0.682	−1.142	−1.314
	Average	−0.419	−0.318	−0.176	−0.112	0.021	0.195	0.238	0.202	0.189	0.106	0.015	0.058

Table 10.12 The standardized scores of sustainability of 24 resource-exhausted cities from 2005 to 2016

No	City	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
1	Wuhai	1.339	15.235	17.753	21.608	25.391	33.033	27.059	27.676	21.005	11.557	0.000	4.113
2	Fushun	44.666	48.789	57.861	52.760	60.283	63.469	55.623	51.775	62.273	60.999	55.446	51.448
3	Fuxin	46.629	51.528	52.687	56.855	58.981	65.390	63.758	60.180	58.693	63.621	53.962	47.371
4	Panjin	63.128	61.200	63.699	62.769	69.489	81.935	100.000	88.643	82.830	68.599	61.086	56.862
5	Liaoyuan	49.512	50.335	57.225	58.166	69.122	76.672	70.777	70.961	73.730	70.676	70.551	74.432
6	Baishan	45.941	49.581	56.617	54.037	53.823	56.258	61.357	55.284	60.827	59.977	62.351	68.742
7	Hegang	39.712	39.888	43.296	44.157	55.258	59.305	53.864	54.929	51.734	52.051	54.614	52.483
8	Shuangyashan	58.876	59.221	64.135	62.008	62.491	62.493	64.986	64.048	61.409	53.933	55.223	52.242
9	Yichun-HLJ	53.587	54.289	57.622	58.851	64.636	69.110	68.702	64.731	61.584	55.868	52.907	53.221
10	Qitaihe	56.198	55.963	55.491	56.934	58.567	60.610	66.468	65.219	55.702	53.791	52.675	58.813
11	Huaibei	56.502	56.012	61.418	65.702	68.731	73.485	77.417	80.117	82.627	83.207	84.663	89.200
12	Tongling	69.011	74.993	69.955	78.771	82.630	82.190	78.156	81.326	82.804	79.860	82.008	84.654
13	Jingdezhen	69.827	60.362	68.554	64.156	74.503	77.453	74.004	73.583	73.054	72.681	73.000	75.723
14	Pingxiang	63.877	62.875	72.331	77.476	77.793	78.917	76.135	76.376	75.877	76.018	76.209	80.572
15	Xinyu	63.691	67.149	73.934	83.661	79.000	83.459	82.630	79.234	70.529	72.035	71.670	72.801
16	Zaozhuang	62.305	71.418	68.703	76.100	77.989	78.268	75.501	75.260	73.816	73.483	72.247	71.806
17	Jiaozuo	64.665	65.721	71.107	66.652	73.634	77.156	79.638	80.161	79.433	78.422	81.224	85.284
18	Puyang	73.085	73.964	65.135	73.965	75.178	79.189	80.984	84.941	85.834	84.722	86.090	86.400
19	Huangshi	58.782	63.204	62.575	65.190	68.015	66.890	71.721	75.197	78.329	79.148	68.913	70.844
20	Shaoguan	65.024	69.589	72.635	72.411	68.155	71.044	73.239	67.023	68.261	69.975	67.519	66.383
21	Luzhou	72.801	72.752	76.260	66.999	66.567	71.238	72.908	74.397	75.941	77.167	79.126	81.383

(continued)

Table 10.12 (continued)

No	City	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
22	Tongchuan	49.426	54.221	50.863	52.237	60.797	64.876	67.909	69.750	68.132	65.520	63.998	64.442
23	Baiyin	35.560	39.196	44.163	44.637	45.159	49.514	51.702	53.489	58.558	57.126	56.897	59.852
24	Shizuishan	26.656	26.990	35.515	37.269	27.102	33.601	43.654	45.116	49.650	47.992	37.841	34.063
	Average	53.783	56.020	59.147	60.557	63.471	67.315	68.258	67.476	67.193	65.351	63.343	64.297

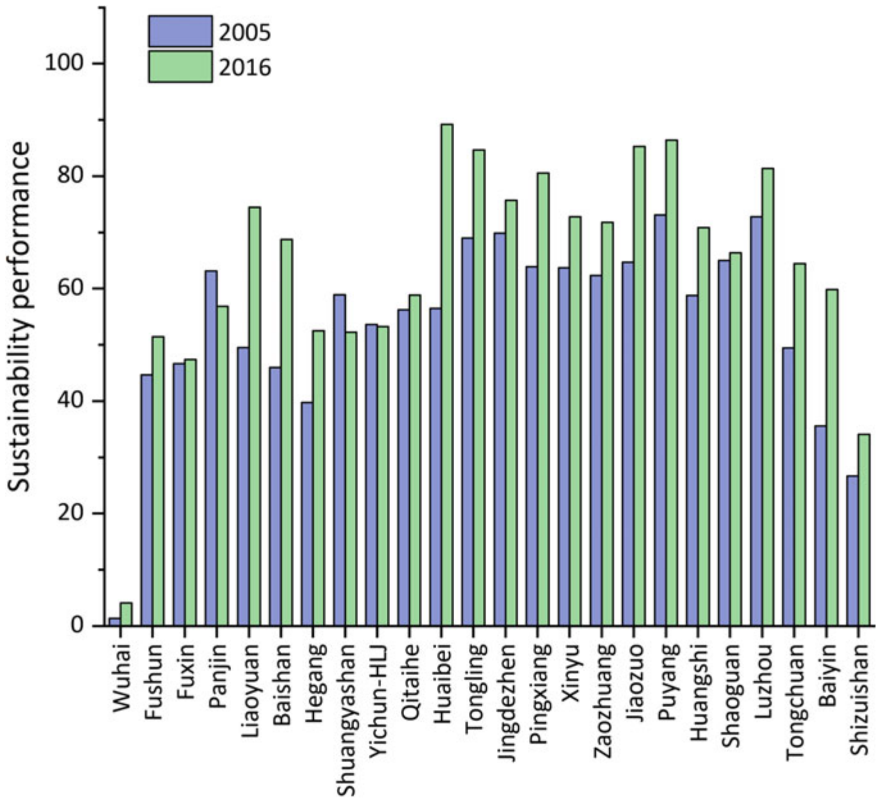

Fig. 10.1 The sustainability scores of 24 resource-exhausted cities in 2005 and 2016. The value in the figure is based on Table 10.12

located in the Northeast region, the Rust Belt of China. Many cities in Northeast China used to be abundant in natural resources. However, after decades of the exploitation of natural resources, many cities are facing resource depletion problems, and Panjin, Shuangyashan, and Yichun-HLJ are the typical cases. The sustainability risks of these cities could threaten the long-term development and integrated measures needed to be taken to improve sustainability and reduce the risk of deterioration.

Some policies are proposed to mitigate the sustainability risks of resource-exhausted cities. First, policy-makers should keep a close eye on the economic, social, and environmental development of resource-exhausted cities. The evaluation framework used in this study can be a reference to take stock of where resource-exhausted cities stand in terms of sustainability, identify the potential risks, and further promote sustainable development. Second, for the laggard cities in sustainability, relevant policies should be implemented to mitigate the sustainability risks and then reverse the deterioration process. For the other cities, they should plan in advance to avoid getting into similar situations.

10.6 Code Availability

The MATLAB code used to evaluate the performance of the DUMs using principal component analysis (PCA) is published for transparency, as follows.

```
% Evaluating and ranking the performance of DMU using the Principal Component Analysis
% Step 1: Import data and construct the origin matrix Y
% Note (1): Please put the 'Table.xlsx' file in the same path as the code file.
% Note (2): Please make sure all the indicators are in positive dimensions
% Note (3): The format of excel file: the first row is variable names.
clear
Y=xlsread('Table.xlsx','Sheet1');

% Step 2: Standardize the matrix Y and obtain matrix Z
Z=zscore(Y)

% Step 3: Construct the covariance matrix R
R = cov(Z);

% Step 4: Calculate the eigenvalue (lamda) and eigenvector (B)
% Note (1): The eigenvector has been automatically transformed to unit vector
% Note (2): The code 'svd' and 'eig' return results in different order (one sorted large to small, the other in
reverse):
[B,lamda_matrix] = svd(R);
lamda = diag(lamda_matrix);

% Step 5: Determine the number of principal components to be considered
fprintf('Cumulative variance: %6.3f \n', cumsum(lamda)/sum(lamda));
k = find((cumsum(lamda)/sum(lamda)) > 0.8, 1, 'first');

% Step 6: Construct the decision matrix b
b = B(:, 1:k);

% Step 7: Construct the comprehensive component models
W = zeros(k, 1);
Sum_b = sum(b);
for i=1:k
    if Sum_b(i)>0
        W(i)=lamda(i) / sum(lamda(1:k));
    else
        W(i)=-lamda(i) / sum(lamda(1:k));
    end
end
a = zeros(size(Y,2), 1);
for i=1:size(Y,2)
    a(i) = a(i) + b(i,:)*W;
end
```

```
% Step 8: Evaluate the performance score of the DMU
score = Z * a
% Step 9: Standardize the performance of DMUs to make scores range from 0 to 100
for i=1:size(Y,1)
      score2(i) = 100*(score(i)-min(score))/(max(score)-min(score));
end
fprintf('Scores is: %6.3f \n', score2);
```

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