Pol. J. Environ. Stud. Vol. 34, No. 3 (2025), 2497-2511
DOI:*10.15244/pjoes/188231* ONLINE PUBLICATION DATE: 2024-10-28

Review

Research on the Relationship between Carbon Emissions and Resilience of Resource-based Cities: Taking Liaoning Province, China as an Example

Haiyan Lan[1]*, Rong Li[1], Lin Wang[1], Siqi Yang[2]

[1]College of Business, Hunan Women's University, Changsha, Hunan 410004, China
[2]School of Economics and Management, Liaoning University of Technology, Jinzhou, Liaoning 120001, China

Received: 28 February 2024
Accepted: 2 May 2024

Abstract

Achieving carbon peaking and carbon neutrality targets necessitates a holistic green transformation of both the economy and society, presenting a formidable challenge for resource-dependent cities with high energy needs. Liaoning Province, China was the first to pilot the economic transformation of resource-based cities, exploring the relationship between urban resilience and carbon emissions, which holds crucial implications for steering resource-based cities towards models of decarbonized development and innovative energy systems. This article establishes a comprehensive indicator system, encompassing five key dimensions: economy, society, resources, ecology, and technological innovation. It constructs an urban resilience evaluation model using combined weighting and improved TOPSIS and a resilience obstacle degree model. To evaluate the spatiotemporal resilience shifts in Liaoning's resource-based cities and their correlation with carbon emissions. The findings reveal: (1) A fundamental alignment between the resilience of resource-based cities and the dual carbon goals, particularly noticeable in sectors or cities with lower energy reliance. A negative correlation exists between carbon dioxide emissions and urban resilience. (2) In industries highly dependent on fossil fuels, carbon dioxide emissions, and urban resilience tend to increase together. However, a development strategy that compromises ecological resilience is unsustainable. The degree of energy dependence critically influences this trend. (3) Examining the spatiotemporal changes in urban resilience, the disparity among cities is diminishing, with notable resilience fluctuations aligning closely with carbon emission levels. Technological innovation and economic dimensions emerge as the primary hurdles to enhancing the resilience of Liaoning's resource-based cities.

Keywords: resilience of resource-based city, decarbonization development, energy dependence degree, technological innovation, carbon peaking and carbon neutrality

*e-mail: lanhaiyan0909@163.com

Introduction

On September 22, 2020, during the 75th United Nations General Assembly, the Chinese government pledged to strive to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060 (hereinafter referred to as the "dual carbon" targets), marking China's commitment to active participation in global climate governance as a major responsibility. As the largest energy producer and consumer worldwide, China recognizes that the transformation of its energy system is crucial for achieving the "dual carbon" goal. This means that the economic growth mode relying on fossil energy will be transformed step by step towards decarbonization and a new energy system in a planned way, and embark on the road of green and low-carbon development. This transition, while complex and challenging, underscores China's dedication to a sustainable future.

Resource-based cities are defined by their reliance on the extraction and processing of natural resources, such as minerals and petroleum, playing a crucial role in the sustained and healthy development of the national economy [1]. However, as mineral resources deplete, the production and industrial magnitude of these resource-based industries gradually shrink, and urgently seek a path of transformation. The pursuit of the "dual carbon" goal introduces a novel challenge for these cities amidst their transition [2]. Firstly, the core industries of resource-based cities, which are predominantly reliant on fossil fuels, are poised for significant overhaul, with the high costs associated with exiting these industries posing a significant barrier to advancing "dual carbon" initiatives [3–4]. Secondly, enterprises that are both resource-intensive and high in energy consumption and emissions stand at the forefront of the energy revolution, bearing the brunt of transformation and emission reduction pressures [5–6]. Urban resilience refers to the ability of cities to recover from external disturbances and maintain their original state after digestion and absorption [7]. In the context of achieving carbon peak and carbon neutrality, whether resource-based cities possess adequate resilience to cope with new requirements for emission reduction and decarbonization development, and to navigate towards green and sustainable urban development, emerges as a research topic of significance and practical importance.

The global landscape is experiencing multiple crises, underscoring the need for resilience to endure these challenges [8]. In 1973, Holling introduced the concept of resilience, which was originally rooted in physics, to the field of ecology to evaluate the resilience and stability of ecosystems [9]. Based on the coastal resource-dependent communities in Vietnam, Adger [10] explored the potential relationship between social resilience and ecological resilience. Since then, resilience has been used in social disciplines. However, it wasn't until the Southeast Asian financial crisis of 2008 that resilience was formally recognized within the urban sustainable development framework [11], garnering significant academic interest. Since then, research related to urban resilience has expanded, and it generally presents the following aspects.

Firstly, urban economic resilience is defined as the capacity of urban economic systems to withstand or mitigate potential losses in the face of external shocks and disturbances [12]. This adaptability allows urban economies to diverge from traditional development paradigms and identify new pathways for stable growth [13]. However, the operation of urban economic systems is intricately linked with government regulation and policy intervention, making the adjustment to economic resilience a multifaceted process [14]. When this adjustment process follows a path of restructuring-development-protection, it means that the city has achieved economic growth. Conversely, a path characterized by protection-release-restructuring represents either a decline or transformation of the economy.

Secondly, focusing on urban ecological resilience, this concept has emerged from growing concerns over environmental issues. Urbanization processes have compressed urban ecological space, adversely impacting ecological resilience [15]. Initial interdisciplinary studies on resilience primarily focused on ecosystems [9–10]. Ecological resilience is crucial for enabling ecosystems to self-repair and return to a stable state [16]. Later scholars had divergences on system stability. Dakos et al. [17] employed the theory of bistable systems to bridge these differences, giving the relationship between local and non-local stability and further proving the multi-stable properties of ecosystems. Factors such as resistance, adaptability, and restoring force are frequently utilized in constructing urban ecological resilience models [18]. Moreover, ecological resilience is often integrated and analyzed alongside other dimensions, including economic resilience and social resilience, to provide a comprehensive understanding of urban resilience [19].

Third, concerning urban social resilience. When the economy suffers from external shocks, such as COVID-19, political change, and other emergencies, social resilience is the ability of urban stability and transition [20–21]. It stems from the intricate web of social relationships within a given social structure [22]. Social resilience, however, has its strengths and vulnerabilities, which refer to the susceptibilities within social systems. Cinner and Barnes [23] measured this vulnerability using a social-ecological network consisting of six elements: assets, flexibility, social organization, learning, social cognitive structure, and agency. This approach provided both theories and methods for improving the resilience of vulnerable systems. Zebardast [24] used the F'ANP model to assess Tehran's social resilience from four aspects: social structure, social equity, social values, and social capital. It's important to note that public health crises [25] and environmental issues directly affect social resilience [26].

Fourth, with respect to the evaluation of urban comprehensive resilience, this concept encapsulates the resistance and recovery capabilities that ensure urban safety and sustainable development [27]. The evaluation dimensions are broad and the evaluation methods are varied. From the perspective of the dimensions, Gao L., et al. [28]

evaluated the comprehensive resilience of Hohhot City across four dimensions: society, ecological environment, disaster preparedness, and lifeline system. Beceiro et al. [29] provided a comprehensive resilience framework that includes environmental, social, and economic benefits. Chen X., et al. [30] constructed an urban resilience evaluation system that integrates ecology, economy, society, and engineering aspects. Economic, ecological, and social resilience are the dimensions most frequently considered by researchers. As for evaluation methods, they range from quantitative models and analytic hierarchy processes to the entropy method and the TOPSIS method, among others [31–32].

Fifth, in the context of the resilience of resource-based cities, the body of research literature, particularly over the past two years, exhibits distinct characteristics. Firstly, the research methodologies employed closely mirror those used in the evaluation of urban comprehensive resilience [33–34]. Secondly, the evaluation dimensions largely align with those of urban comprehensive resilience, emphasizing a blend of economic, ecological, social, infrastructure, and engineering resilience dimensions [35]. The distinction, however, lies in the more focused analysis of sample data, which is further refined by examining different types of resource-based cities [36]. Finally, there is a noticeable gap in research concerning the resilience of resource-based cities considering the "dual carbon" initiative. Liu et al. [3] concluded that the trend between the resilience of 30 resource-based cities and their carbon emissions is almost parallel, except that the growth rate of urban resilience surpasses that of carbon emissions. Feng et al. [37] applied the MinDS super-efficiency model to evaluate the resilience of 24 resource-exhausted cities under the constraints of carbon emission. In terms of indicator selection, this approach is akin to that used for evaluating the transformation of resource-based cities, grounded in the DPSIR framework. The findings suggest a correlation: cities with low carbon emissions demonstrate higher resilience efficiency.

Based on the analysis of existing literature, it's clear that research on urban resilience forms the foundation of this study. However, further examination reveals areas for improvement. Firstly, there's room to explore the relationship between carbon emissions and urban resilience more deeply. Secondly, the impact of technological innovation on urban resilience deserves more attention. Lastly, compared to general cities, resource-based cities face more pressing resilience challenges, especially in the context of achieving carbon peak and carbon neutrality goals. This article contributes in several ways: Firstly, it seeks a breakthrough perspective for resource-based cities to achieve their dual carbon goals. Secondly, it examines the seldom-explored relationship between the resilience of resource-based cities and carbon emissions. Establishing a barrier diagnosis model aims to enhance the resilience of these cities against the developmental risks posed by peak carbon and carbon neutrality. Thirdly, it broadens the research dimensions and adds evaluation indicators. Existing studies have predominantly focused on a resilience model encompassing economic, ecological, social, and infrastructure (engineering) dimensions [30, 33–34, 36], with a few incorporating innovative indicators within the engineering or infrastructure dimensions [3]. Rarely do they explore the resilience dimension of technological innovation independently. Drawing on the fifth dimension "R" (Response) of the DPSIR framework [36], this article transforms it into the resilience dimension of technological innovation, thereby creating a five-dimensional evaluation model that includes economy, society, resources, ecology, and technological innovation. In this study, we took Liaoning Province, China, as a case study, to evaluate systematically the resilience of resource-based cities. We aim to uncover the obstacles hindering urban resilience, examine the interplay between the "dual carbon" goal and urban resilience, and explore viable pathways for resource-based cities under the constraints of carbon emission reduction. To circumvent the issue of inverse ranking inherent in the traditional TOPSIS method [38], this article constructs a comprehensive evaluation model of urban resilience, leveraging an enhanced TOPSIS method [3, 32], which is still applicable for analyzing economic and environmental issues.

Material and Methods

Indicator Research Methods

Selection of Evaluation Indicators

Drawing on the insights from relevant research literature [3, 30, 33–34, 36], this article delves into the influence of technological innovation on the resilience of resource-based cities and constructs an evaluation framework encompassing five key dimensions: economic, social, resource, ecological, and technological innovation resilience. An initial sift resulted in 47 high-frequency indicators, a number significantly exceeding that found in comparable studies within the cited literature [3, 30, 33–34, 36]. To mitigate the issue of indicator correlation we employed R-type clustering and the coefficient of variation methods for a more refined indicator selection process. Consequently, we calculated the sum of the squares of deviations S_i, and the total sum of the squares of deviations S, as follows:

$$S_i = \sum_{j=1}^{n_i} (X_i^{(j)} - \overline{X}_i)(X_i^{(j)} - \overline{X}_i) \tag{1}$$

$$S = \sum_{i=1}^{k} \sum_{j=1}^{n_i} (X_i^{(j)} - X_i)(X_i^{(j)} - \bar{X}_i) \tag{2}$$

where S_i denotes the sum of the squares of deviations of class i and (i = 1, 2, …, m); n_i indicates the number of evaluation indicators in class i; $X_i^{(j)}$ denotes the vector of sample values for the jth evaluation indicator in class i after standardization $j = (1, 2, \ldots, n_i)$, $\overline{X}_j$ denotes the sample mean vector for the indicator of class i. The coefficient of variation was calculated as follows:

$$V_j = \frac{\sqrt{1/\mathrm{m}\sum_{i=1}^{m}(x_{ij}-\bar{x}_j)^2}}{\bar{x}_j} \quad (3)$$

$$\bar{x}_j = 1/\mathrm{m}\sum_{i=1}^{m} x_{ij} \quad (4)$$

where V_j represents the coefficient of variation for the jth indicator and $\bar{x}_j$ denotes the overall mean value of the jth evaluation indicator.

Standardization of Indicator Data

The indicators chosen for this study were categorized into three categories, i.e., positive, negative, and moderate, according to their effects on the research objectives. Moreover, the method for the standardization of the original indicator data was proposed. Considering m evaluation objects and n evaluation indicators, x_{ij} denotes the original data for the jth evaluation indicator in the ith object and y_{ij} denotes the standardized data for the jth evaluation indicator of the ith object. Here, ρ is the threshold value designated for moderate indicators. The formula for index standardization was as follows:

(I) Nondimensionalization of positive-type indicators:

$$y_{ij} = \frac{x_{ij} - \min\, x_{ij}}{\max\, x_{ij} - \min\, x_{ij}} (1 \le i \le m, 1 \le j \le n) \quad (5)$$

(II) Nondimensionalization of negative-type indicators:

$$y_{ij} = \frac{\max\, x_{ij} - x_{ij}}{\max\, x_{ij} - \min\, x_{ij}} (1 \le i \le m, 1 \le j \le n) \quad (6)$$

(III) Nondimensionalization of moderate indicator:

$$y_{ij} = 1 - \frac{|\rho - x_{ij}|}{\max(|\rho - \min_{1<=i<=m} x_{ij}|, |\max_{1<=i<=m} x_{ij} - \rho|)} \quad (7)$$

Indicator Screening

Utilizing standardized data on the resilience of six resource-based cities in Liaoning Province in 2022, variable clustering was performed on five dimensions of scheme-level indicators using SPSS software. This process identified groups of similar indicators, which were subsequently described and subjected to statistical analysis. From these groups, the indicator with the highest coefficient of variation was selected for inclusion in the indicator system. This secondary screening process retained the original numbering of the indicator system, effectively reducing the initial set of 47 indicators down to 33. The refined resilience evaluation index system for resource-based cities in Liaoning Province is detailed in Table 1.

Weight Determination Method

To enhance the reliability of the resilience evaluation of resource-based cities, this article adopts a composite weighting approach to ascertain the significance of each indicator. Based on the entropy weight method [33–34], we further refine the weighting through the analytic hierarchy process, and the qualitative and quantitative weighting process incorporates both qualitative and quantitative elements into the weighting procedure. The process unfolds as follows.

Step 1: Construct the contribution matrix P_{ij}, where y_{ij} ($i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$) denotes the standardized data of the i the indicator of the jth evaluation object.

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}, i = 1,2\ldots, m; j = 1,2\ldots, n \quad (8)$$

Step 2: Calculate the information entropy value E_j of the j index.

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij} \ln p_{ij}, j = 1,2\ldots, n \quad (9)$$

Step 3: Calculate the weights of each index.

$$W_j = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} = \frac{1-E_j}{n-\sum_{j=1}^{n} E_j}, j = 1,2,\ldots n \quad (10)$$

Step 4: Establish the hierarchical structure model.

Step 5: Construct the judgment matrix. The 1–9 scale method was used for indicators of the same hierarchy.

Step 6: Perform a consistency test using the following test formulas:

$$CI = \frac{\lambda_{\max} - n}{n-1} \quad (11)$$

$$CR = \frac{CI}{RI} \quad (12)$$

The judgment matrix was completely consistent when $CI = 0$. The CI must be compared with the random consistency index RI, when the matrix order was greater than 2. The judgment matrix had satisfactory consistency when CR was smaller than 0.1; otherwise, it was necessary

Table 1. Resilience evaluation index system for resource-based cities in Liaoning Province.

Criterion layer	Intermediate layer	Program layer	Nature of indicators	Combination weights
Economic resilience	Economic growth	GDP per capita	Positive	0.0882
		GDP growth rate	Positive	0.0564
		Fixed asset investment as a proportion of GDP	Negative	0.0314
		Total output value of industrial enterprises above designated size	Positive	0.0254
		Amount of actual utilized foreign capital per capita	Positive	0.0148
	Industrial Structure	Share of secondary industries in GDP	Negative	0.0194
		Proportion of value added of high-tech industry in GDP	Positive	0.0334
		Proportion of employees in tertiary industry	Positive	0.0311
Social Resilience	Living standards	Per capita disposable income of urban residents	Positive	0.0037
		Urbanization rate	Positive	0.0236
		Urban registered unemployment rate	Negative	0.0766
		Natural growth rate	Moderate	0.0197
	Public services	Basic social security coverage rate	Positive	0.0111
		Urban bus ownership per 10,000 people	Positive	0.0047
		Number of hospital and health center beds per 10,000 people	Positive	0.0043
		Share of social security and employment expenditure in public budget expenditure	Positive	0.018
Resources Resilience	Resource utilization	Electricity consumption of the whole society	Negative	0.0201
		Water consumption per unit of GDP	Negative	0.0393
		Per capita daily domestic water consumption	Negative	0.021
	Resource carrying capacity	Per capita water resources ownership	Positive	0.0201
		Greening coverage rate of built-up areas	Positive	0.0059
		Per capita park green area	Positive	0.0023
Ecology Resilience	Environmental pollution	Industrial wastewater emissions	Negative	0.0353
		Emission of sulfur dioxide per unit area	Negative	0.0297
		Industrial smoke and dust emissions	Negative	0.0072
	Environmental governance	Comprehensive utilization rate of general industrial solid waste	Positive	0.0037
		Centralized treatment rate of sewage treatment plants	Positive	0.0023
		Energy saving and environmental protection as a proportion of public finance expenditure	Positive	0.0063
		Ratio of good days of urban air quality	Positive	0.0011
Technology Innovation Resilience	Science and technology inputs and outputs	Number of patent applications granted	Positive	0.0408
		Number of college students per 10,000 people	Positive	0.1221
		Number of scientific research and technical personnel	Positive	0.0213
		Share of education expenditure in public finance expenditure	Positive	0.1597

Table 2. Average random consistency index.

Matrix order	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

to return to the fifth step to re-evaluate the importance of the relevant index. Table 2 presents the random consistency index.

Step 7: Obtain the weight of each indicator based on the analytic hierarchy process U_j.

Step 8: The formula for calculating the combined weight θ_j as follow,

$$\theta_j = \frac{U_j W_j}{\sum_{j=1}^{n} UW}, j = 1, 2, ..., n \tag{13}$$

Comprehensive Evaluation Model Based on Improved TOPSIS

The TOPSIS method is a multi-criteria decision-making method that ranks and evaluates by measuring the relative proximity of each evaluation indicator to an ideal positive and negative solution set. This method is particularly well-suited for the evaluation of urban resilience, which often involves multiple objectives and indicators [3, 32]. However, a notable limitation arises when the number of evaluation objects changes, potentially altering the ranking outcomes. Therefore, this article makes two improvements to the traditional TOPSIS method: (1) refinement of the ideal positive and negative solution set. Instead of simply defining the ideal positive and negative solution sets based on the maximum and minimum values of the indicators for the current evaluation subjects, this modification takes into account the actual development trends of the indicators. By employing a standard deviation normalization technique to preprocess the indicator data, the values assigned to the ideal solution sets are standardized to either 1 or 0. This adjustment ensures that the ideal solution values remain constant, irrespective of the number of evaluation subjects, thereby minimizing the risk of rank reversal. (2) improving the calculation of the closeness. The traditional TOPSIS method may encounter difficulties when the distances to the ideal positive and negative solution sets are nearly identical for an evaluation subject. To overcome this challenge, the revised method considers both the positive and negative distances and computes a comprehensive closeness measure. This enhancement aims to make the evaluation of urban resilience more precise and dependable. The specific modeling process unfolds as follows.

Step 1: Construct the original matrix A, i.e, $A = (x_{ij})_{m \times n}$. Here, x_{ij} denotes the original value of the j evaluation index in the i evaluation object.

Step 2: Use Eqs. (5)–(7) to standardize the original index data and derive the standardization matrix Y_{ij}.

Step 3: Determine the indicator weights θ_j, using the combined weighting method.

Step 4: Construct the weighting matrix $z = \theta_j \times Y_{ij}$.

Step 5: Construct positive and negative ideal solution sets.

$$Z_j^+ = \max(Z_{1j}, Z_{2j}, \dots, Z_{ij}) \tag{14}$$

$$Z_j^- = \min(Z_{1j}, Z_{2j}, \dots, Z_{ij}) \tag{15}$$

Step 6: Calculate distances d_j^+ and d_j^- in each sample indicator value from the positive and negative ideal solution sets:

$$d_j^+ = \sqrt{\sum_{j=1}^{m} (Z_{ij} - Z_j^+)^2} \tag{16}$$

$$d_j^- = \sqrt{\sum_{j=1}^{m} (Z_{ij} - Z_j^-)^2} \tag{17}$$

Step 7: The improved comprehensive closeness degree value of the evaluation object,

$$C = \sqrt{[d_i^+ - \min(d_i^+)]^2 + [d_i^- - \max(d_i^-)]^2} \tag{18}$$

Step 8: Calculate the green transformation performance index of resource-based cities,

$$R_i = 1 - C_i \tag{19}$$

where R_i takes values between 0 and 1. The closer R_i is to 1, indicating that the higher the level of urban resilience.

Fig. 1. Schematic diagram of the research area.

The Model of Barrier Degree

This article presents a model designed to assess the degree of barriers to urban resilience, which can provide directional guidance for policy formulation. The model is predicated on two key metrics: the factor contribution degree and the indicator deviation degree. The factor contribution degree T_i is the importance of the ith indicator to the overall target, represented by the indicator weights. The indicator deviation degree S_i denotes the gap between the ith indicator and the ideal transformation effects of resource-based cities, i.e., $S_i = 1 - y_{ij}$. The barrier degree evaluation model is derived as follows.

$$P_{ij} = \frac{S_i T_i}{\sum_{i=1}^{33} S_i T_i} * 100\% \tag{20}$$

$$F_{ij} = \sum P_{ij} \tag{21}$$

where the barrier degree P_{ij} denotes the degree of influence of the jth evaluation index of the ith evaluation object on the resilience of resource-based cities, and F_{ij} is the barrier degree of each criterion level index.

Data Sources

The geographical focus of this article is depicted in Fig. 1. Situated in the southern reaches of Northeast China, Liaoning Province stretches between 118°53' and 125°46' east longitude and 38°43' and 43°26' north latitude. This region is endowed with abundant oil and mineral reserves, earning its reputation as the birthplace of China's industry sector and a quintessential resource-based province. Notably, Liaoning leads the nation with 15 districts, counties, and cities recognized on the national roster of resource-based cities, underscoring its pivotal role in the strategic initiative to rejuvenate the Northeast. For this study, six prefecture-level cities within Liaoning Province, i.e., Anshan, Fushun, Benxi, Fuxin, Panjin, and Huludao, were selected as the research objects to evaluate the city resilience spanning from 2010 to 2022. The data utilized in this analysis were derived from publicly accessible records, including the Liaoning Statistical Yearbook, China Urban Statistical Yearbook, China Energy Database, and data published on the official websites of the respective cities. Any instances of missing data were addressed by extrapolating from the trends observed in data from preceding years.

Results and Discussion

Evaluating the Spatial and Temporal Dynamics of Resilience in Resource-Based Cities

Upon determining the indicator weights through a composite weighting method, the improved TOPSIS method was used to evaluate the resilience of six resource-based cities in Liaoning Province over the period from

Table 3. Comprehensive score of resource-based resilience in Liaoning Province.

Year	Anshan	Fushun	Benxi	Fuxin	Panjin	Huludao
2010	0.9082	0.9431	0.8611	0.9530	0.9178	0.9331
2011	0.8711	0.8769	0.9240	0.9040	0.9008	0.9364
2012	0.8944	0.8632	0.9244	0.8966	0.8514	0.8754
2013	0.8815	0.8831	0.8599	0.8720	0.8612	0.8571
2014	0.9155	0.9050	0.9102	0.8843	0.9062	0.9137
2015	0.9346	0.8801	0.9227	0.8854	0.8971	0.8816
2016	0.9046	0.9104	0.8940	0.9020	0.9232	0.8874
2017	0.8973	0.9096	0.8979	0.9080	0.9066	0.8937
2018	0.8914	0.9138	0.9064	0.9040	0.9222	0.9163
2019	0.9014	0.9149	0.8995	0.8907	0.9135	0.9054
2020	0.9010	0.9141	0.9003	0.8989	0.9187	0.9068
2021	0.9017	0.9153	0.9107	0.9075	0.9211	0.9136
2022	0.9062	0.9288	0.9178	0.9143	0.9232	0.9209

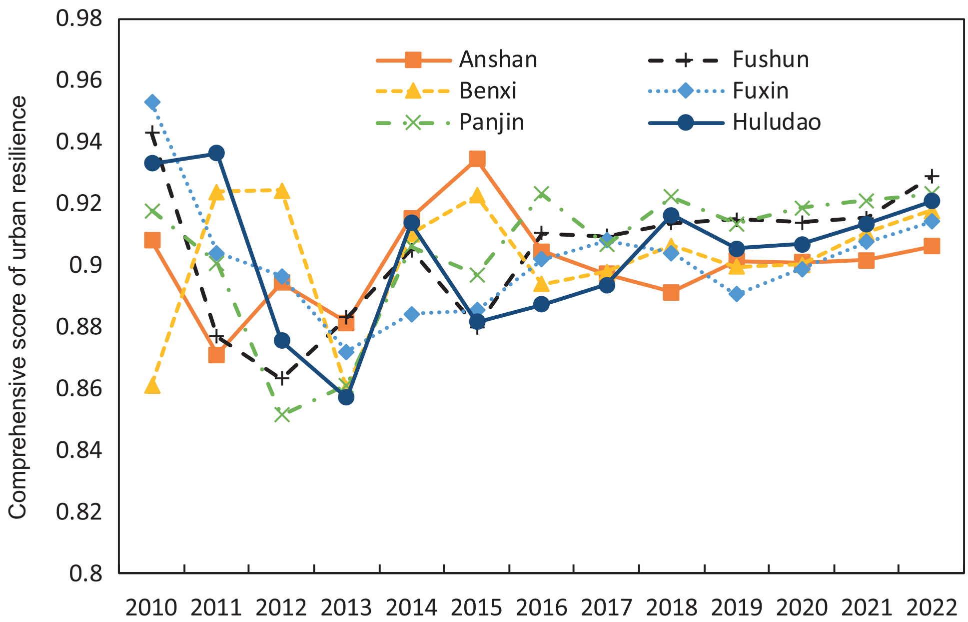

Fig. 2. Trend of resilience in resource-based cities of Liaoning Province.

2010 to 2022. The empirical process was completed using both Python and SPSS. The aggregated weights for each indicator are detailed in Table 1, and the comprehensive scores of resilience for each resource-based city are shown in Table 3. To visually depict the resilience development trends across these cities, a trend chart has been prepared, as illustrated in Fig. 2. This graphical representation aids in understanding the evolving resilience characteristics of each city over the specified timeframe.

Fig. 2 illustrates that the comprehensive resilience scores of resource-based cities in Liaoning Province have experienced notable fluctuations, yet the disparity among cities has gradually diminished. The progression of changes can be categorized into four distinct phases. Before 2013, there was a pronounced decline in the resilience scores across the cities. This downturn can be attributed to the period post-2008 when Liaoning Province was navigating a phase of economic and social transformation.

Table 4. Analysis of Resilience Barriers Degree in Resource-based Cities of Liaoning Province.

Year	Economic resilience	Social resilience	Resource resilience	Ecological resilience	Technological innovation resilience
2010	29.27%	15.24%	7.23%	6.49%	41.77%
2011	27.30%	13.46%	8.60%	10.88%	39.76%
2012	27.17%	16.79%	9.44%	11.86%	34.73%
2013	27.38%	16.17%	9.17%	14.86%	32.42%
2014	25.50%	11.45%	8.43%	11.42%	43.20%
2015	30.44%	15.97%	8.92%	8.61%	36.07%
2016	38.71%	12.07%	10.76%	5.02%	33.43%
2017	31.88%	13.99%	11.55%	2.78%	39.80%
2018	28.20%	15.83%	11.33%	2.43%	42.20%
2019	25.95%	18.01%	11.83%	2.24%	41.98%
2020	24.94%	18.73%	12.05%	2.26%	42.02%
2021	23.58%	19.66%	12.17%	2.31%	42.28%
2022	24.11%	21.02%	13.07%	2.18%	39.62%

During this early stage of transformation, cities were in the process of identifying new industrial alternatives, even though the traditional industrial and mining sectors continued to predominate. From 2013 to 2015, except for Anshan, which saw a significant improvement in its resilience score due to a robust steel market bolstering its economic vitality, the resilience scores of other cities continued to exhibit variability. This period marked a phase of fluctuation in the broader industrial transformation, where alternative industries in various cities were still in the nascent stages of development. The year 2015 marked a turning point when China witnessed its first decline in steel output, signaling a downturn in market demand. This resulted in consecutive losses for the Anshan Iron and Steel Group. However, by the end of 2018, the steel industry had achieved its five-year target for reducing excess capacity ahead of schedule, and the profitability of Anshan Iron and Steel Group began to rebound, a turnaround that was mirrored in Anshan's resilience score. Concurrently, the resilience scores of other cities gradually improved as they each sought transformation pathways aligned with their unique urban development trajectories, leading to a steady enhancement in economic and social development. Post-2019, the gap in resilience scores among the cities had significantly narrowed, manifesting a collective and stable upward trajectory. This phase reflects a period where the cities, leveraging their distinct characteristics, have embarked on compatible transformation models, contributing to an overall improvement in resilience.

Analysis of Resilience Barriers Degree

To systematically delineate the pathway for enhancing the resilience of resource-based cities in Liaoning Province, this article conducts an analysis of the barriers to resilience across five dimensions. The findings from the comprehensive analysis of obstacle factors are shown in Table 4, while the cumulative degree of these obstacles is visually depicted in Fig. 3.

As delineated in Table 4, the hierarchy of barriers impeding the enhancement of comprehensive resilience in Liaoning's resource-based cities from 2010 to 2022 has largely remained stable, that is, technological innovation resilience > economic resilience > social resilience > resource resilience > ecological resilience. The cumulative barrier diagram presented in Fig. 3 highlights that the dimensions of technological innovation resilience and economic resilience constitute the most significant obstacles, collectively accounting for over 60% of the total barrier value across the years. This underscores their critical importance as focal areas for bolstering the resilience of Liaoning's resource-based cities. The average obstacle value for social resilience over the 13-year period stands at 16.03%, marking it as another significant barrier. Meanwhile, the obstacle value for resource resilience has seen fluctuations between 7.23% and 13.07%, suggesting that resource-based cities need to enhance both resource utilization efficiency and carrying capacity. The ecological resilience barrier, on the other hand, has been relatively minor, with its value demonstrating a consistent decline

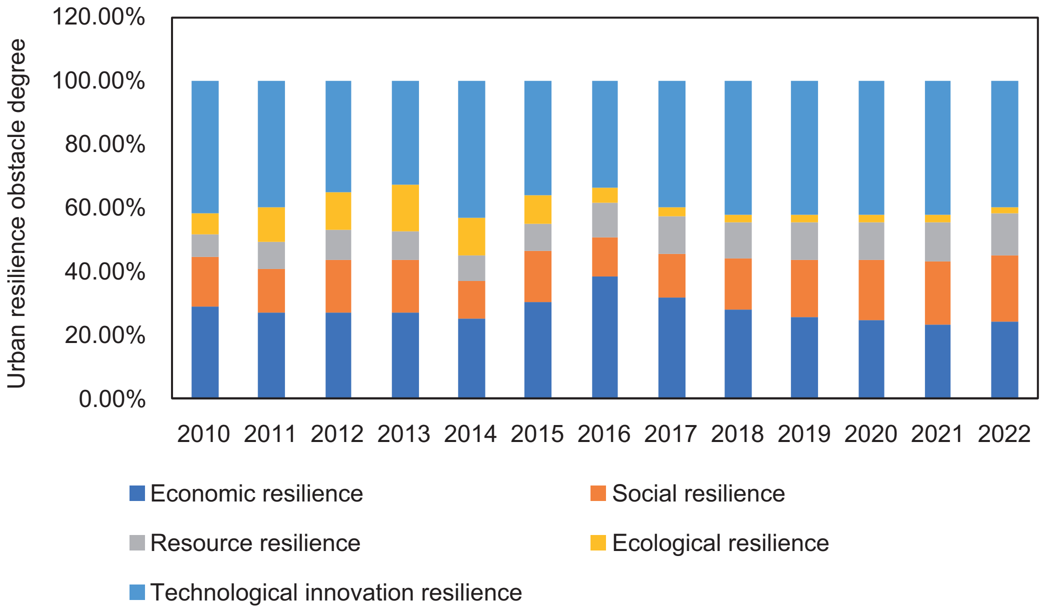

Fig. 3. Cumulative diagram of resilience barriers degree in Liaoning's resource-based cities.

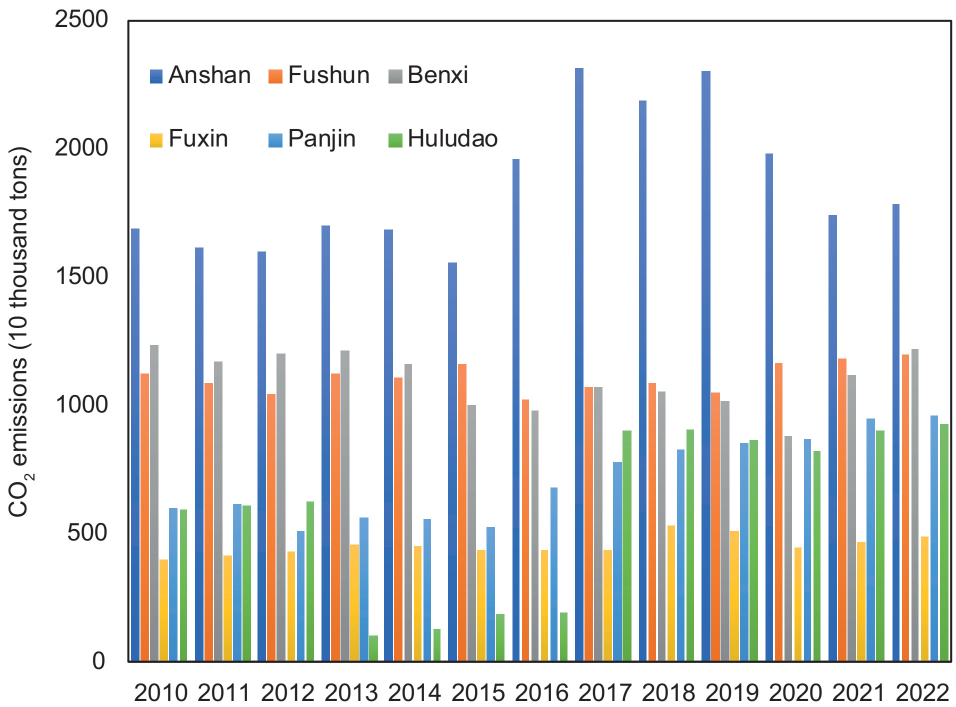

Fig. 4. Trend of carbon dioxide emissions in Liaoning's resource-based cities.

since 2014. This trend indicates a notable improvement in Liaoning's ecological environment, contributing positively to the overall resilience landscape.

The Relationship Between Carbon Dioxide Emissions and City Resilience

According to the IPCC framework's established carbon dioxide conversion coefficient, this study's analysis of carbon emissions identifies four key sources: liquefied gas, natural gas, electricity, and coal. Carbon dioxide emissions data for six cities over the past 13 years are shown in Fig. 4. The data depicted in the figure consistently places Anshan, Benxi, and Fushun as the top three emitters, with Anshan's emissions markedly surpassing those of the other cities. In 2017, emissions in Anshan reached a peak of 23.1596 million tons, contrasted with a significant dip in 2015, where emissions fell to 15.5664 million tons. In addition, the trend

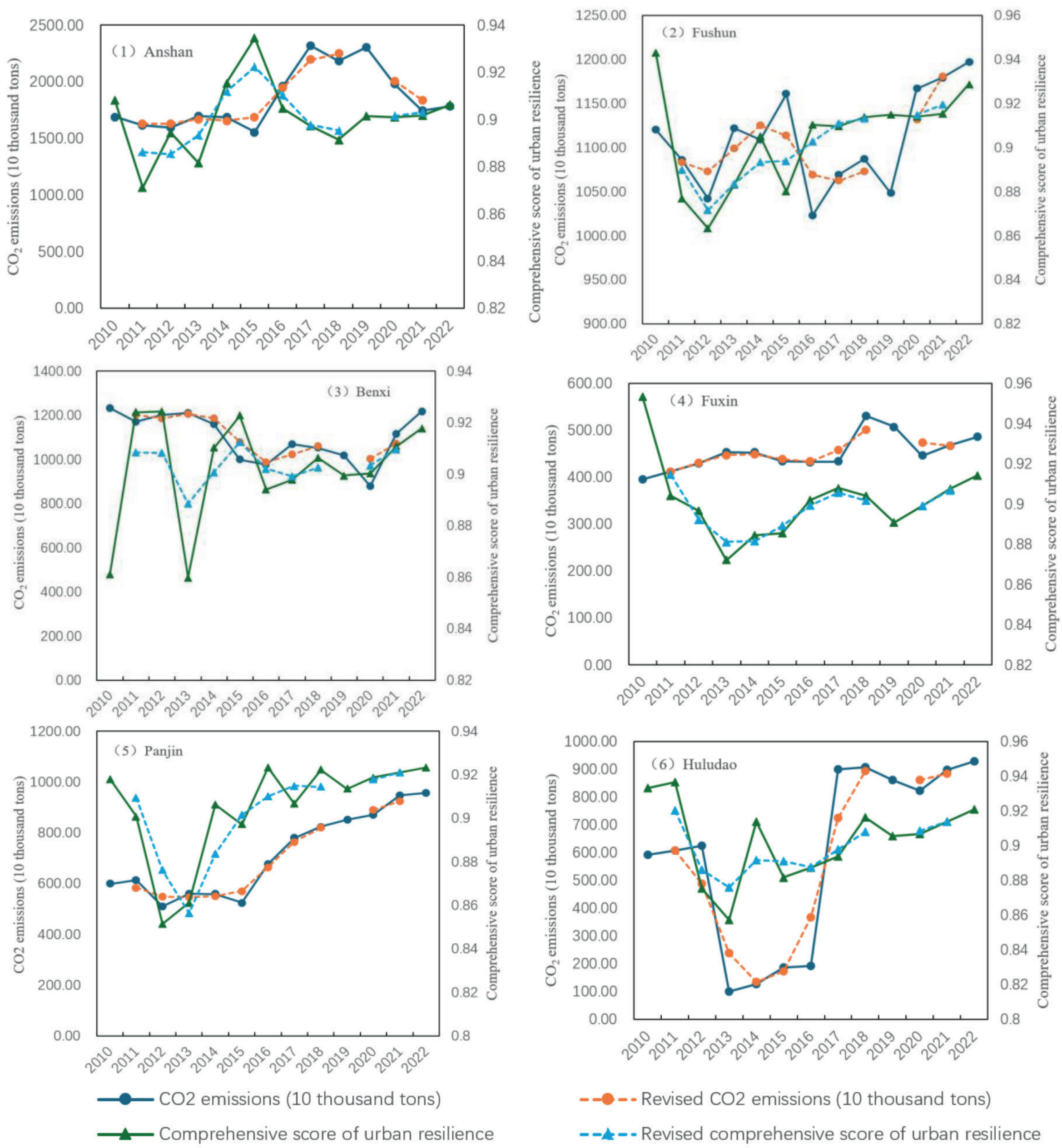

Fig. 5. Comparison of the relationship between carbon emissions and urban resilience in resource-based cities in Liaoning Province.

of carbon dioxide emissions in Huludao City is worth paying attention to due to their substantial reduction from 2013 to 2016, plummeting to just 999,300 tons in 2013. This downward trend is closely associated with the city's industrial structure and governmental policies. Key urban industries such as the Anshan Iron and Steel Group, Benxi Iron and Steel Group, and Fushun Petroleum Group, which rely heavily on natural resources, significantly contribute to the high levels of carbon dioxide emissions. Additionally, in 2015, China's response to steel production overcapacity and the enforcement of stricter carbon emission reduction targets facilitated a decrease in carbon emissions during this period.

The comparative relationship between the resilience of six cities and their carbon dioxide emissions is shown in Fig. 5. Given the substantial variability when directly comparing the resilience composite scores of each city with their carbon emissions, this study has statistically adjusted the indicator data. The revised trend curve offers insights that diverge from conventional findings in the literature. Specifically, it reveals that the relationship between carbon emissions and economic resilience is not merely linear, either positive [3] or negative [36], but rather a complex interplay of both. In particular, Fig. 5 indicates that Fuxin City exhibits a negative correlation between carbon dioxide emissions and urban resilience, suggesting that as resilience improves, emissions tend to decrease. Conversely, Panjin City's relationship curve, despite its fluctuations, generally indicates a positive correlation, where increased resilience is associated with higher emissions. The remaining four cities present a mixed pattern of relationships, with 2013 and 2015 serving as pivotal years. Post-2015, Anshan and Fushun display a negative trend, indicating a shift towards improved resilience with reduced emissions. On the other hand, Benxi and Huludao exhibit a negative correlation between 2013 and 2015, with the subsequent years showing varying trends of increase or decrease, highlighting the nuanced and dynamic nature of the relationship between urban resilience and carbon emissions.

Further examination of regional development reveals that Fuxin was the earliest pilot city for economic transformation in Liaoning Province. With over two decades of relentless efforts, it has successfully nurtured four burgeoning alternative industries: new energy, green food, high-end equipment, and fine chemicals. This diversification has significantly altered its previously coal-dominated industrial landscape. Anshan City, with steel as its cornerstone industry, faced a downturn in the steel market in 2015. In response, Anshan Iron and Steel Group Anshan Iron and Steel Group initiated technological advancements and restructuring, leveraging the steel sector to expand the industrial chain. By focusing on intensive processing and embracing green, environmentally friendly practices, Anshan broadened its industrial scope, yielding substantial outcomes. Post-2017, Huludao City witnessed a staggering increase in total carbon dioxide emissions by over 300%, a trend closely tied to its industrial composition. The city's economy leans heavily on four mainstays: the petrochemical industry, non-ferrous metallurgy, machinery shipbuilding, and energy and power, all of which predominantly depend on fossil energy. This high-carbon economic growth model serves as a double-edged sword. While an increase in carbon emissions may enhance the city's overall resilience score, it concurrently weakens urban ecological resilience. This finding aligns with the challenges Huludao faces in bolstering urban resilience. Therefore, this paper concludes that improving the resilience of resource-based cities aligns with achieving the targets of "dual carbon". Transitioning away from an energy-dependent development model necessitates an ongoing evolution and refinement of the industrial structure. Although this intricate process may temporarily impede the enhancement of urban resilience, adopting a low-carbon, green development strategy that decouples economic growth from energy consumption represents a sustainable path forward.

Discussion

Existing research on urban resilience typically encompasses four key dimensions: economy, ecology, society, and infrastructure (or engineering) [22, 23, 27]. These studies often incorporate technological innovation within the broader categories of engineering or infrastructure, usually through a limited set of innovation indicators [4]. However, resource-based cities, characterized by their relatively homogeneous industrial structure, high reliance on energy and resource endowments, and comparatively modest technological innovation capabilities, present a unique challenge. Recognizing this, our article introduces a distinct dimension of technological innovation into the analysis. This new dimension is measured using four specific indicators: the rate of patent application authorization, the number of college students per 10000 people, the count of scientific research and technical personnel, and the proportion of education expenditure to public finance expenditure. These indicators aim to measure the impact of science and technology investment and output on the resilience of resource-based cities in Liaoning Province. The findings of our research indicate that, since 2010, the dimension of technological innovation has consistently been the most important factor in inhibiting the resilience improvement of resource-based cities in Liaoning Province. Therefore, to bolster their capacity for independent innovation and increase investment in scientific and technological advancements, particularly in sectors with low energy dependence, it is necessary to refine the incentive mechanism for scientific and technological innovation. This entails developing strategies for talent attraction and support, as well as leveraging intellectual resources to facilitate the diversification of the industrial structure.

Is there a contradictory relationship between reducing carbon emissions and enhancing the resilience of resource-based cities? The trends depicted in Fig. 5, showcasing carbon emissions and the overall resilience scores of six cities, affirm that there is no inherent contradiction between reducing carbon emissions and enhancing urban resilience, with Fuxin City serving as a prime example. Having adopted a new development model that significantly reduces coal dependence, Fuxin City has undergone a notably successful green transformation. In other cities observed, a pattern emerges where the overall resilience score tends to rise as carbon emissions fall. Although Liaoning Province's experience with development practice spans a relatively brief 13 years, its early start in transforming resource-based cities provides valuable insights. This assertion is further supported by examining the relationship between ecological resilience and urban development, where ecological resilience not only fosters urbanization [15, 18] but also enhances social resilience [16] and plays a crucial role in boosting overall urban resilience [30, 33–34, 36]. Consequently, focusing on improving urban resilience can be a strategic approach to achieving the objectives of reaching a carbon peak and realizing carbon neutrality. The tension between the heavy reliance of industries on energy and the aspirations for a carbon peak and carbon neutrality can be resolved through the lens of urban resilience. The persistent skewness in the industrial structure, heavily dependent on natural resources, lies at the heart of the economic resilience shortfall in resource-based cities. There is a pressing need for the proactive transformation and upgrading of traditional sectors, alongside the integration of strategic, emerging technological sectors such as new energy and digital information technology. This strategic shift aims at gradually steering resource-dominant industries towards becoming dominated by mid to high-end technologies. The government plays a pivotal role in this transition and must leverage its regulatory powers to oversee resource-intensive enterprises notorious for high energy consumption and pollution. It should guide these enterprises towards adopting green environmental protection technologies, ensuring that high-tech solutions support green production practices throughout the entire mineral resource development lifecycle. Such measures are essential not only for reducing environmental pollution but also for enhancing the ecological resilience of resource-based cities, paving the way towards a more sustainable and resilient future.

Conclusion

This study focuses on the relationship between the resilience of resource-based cities in Liaoning Province and carbon emissions. We establish a comprehensive evaluation framework for assessing the resilience of resource-based cities, grounded in five critical dimensions: economic resilience, social resilience, resource resilience, ecological resilience, and technological innovation resilience. This framework incorporates 33 high-frequency indicators, offering a robust basis for analysis. The analytic hierarchy process and entropy weight method are used to combine subjective and objective weighting, and an improved TOPSIS evaluation model and resilience barrier degree model are established. Drawing on empirical data from six resource-based cities in Liaoning Province, we derive several insightful conclusions. This methodological approach not only underscores the multifaceted nature of urban resilience but also provides a nuanced understanding of how resource-based cities can navigate towards achieving the “dual carbon” objectives.

(1) Enhancing the resilience of resource-based cities and achieving the “dual carbon” goal are inherently aligned. The pursuit of carbon peak and carbon neutrality is an important challenge in the transformation and development of resource-based cities. Liaoning, a province rich in resources located in Northeast China, plays a leading role in the revitalization of the region. From the perspective of its transformation and development practice, it becomes clear that there is no inherent conflict between enhancing the resilience of resource-based cities and the ambition to reduce carbon dioxide emissions. This alignment is particularly pronounced in Fuxin City, which was the earliest pilot city for economic transformation in the region. The experiences of Fuxin City underscore the potential for harmonizing urban resilience with the objectives of carbon reduction, showcasing a path forward for similar cities.

(2) The energy dependence degree of the industry crucially influences the interplay between carbon dioxide emissions and urban resilience. In scenarios where the industrial framework is heavily reliant on fossil fuels, a positive correlation emerges between the volume of carbon dioxide emissions and urban resilience. Conversely, in contexts characterized by low energy dependence, this relationship shifts to a negative correlation. Instances such as Anshan and Fushun before 2015, and Huludao post-2015, exemplify industrial structures with substantial energy dependence. Although elevated carbon emissions may temporarily bolster urban resilience, this mode of development, which compromises ecological resilience, is ultimately unsustainable.

(3) Examining the temporal and spatial dynamics of urban resilience reveals a direct correlation with the levels of carbon emissions. From 2010 to 2022, the resilience of six resource-based cities in Liaoning Province experienced significant fluctuations, with the disparities among these cities gradually diminishing. This trend is mirrored in the considerable variances observed in the comprehensive urban resilience scores across different cities within the same year, as well as the notable fluctuations in the resilience of a single city across various years. Importantly, these changing patterns align closely with the fluctuations in carbon emissions levels, indicating a strong linkage between urban resilience and carbon footprint.

(4) The analysis of resilience barrier degrees reveals that technological innovation resilience and economic resilience pose the most significant challenges to the resilience of Liaoning’s resource-based cities, with these two dimensions accounting for over 60% of the obstacles combined. While the specific barriers impacting each city’s resilience vary, certain high-frequency obstacle indicators emerge as common challenges across the board. These include the number of college students per 10,000 people, the proportion of education expenditure within public financial expenditure, per capita GDP, the urban registered unemployment rate, and water consumption per unit of GDP, all of which are critical factors in the cities’ resilience enhancement efforts. Notably, Fuxin City, which has successfully diversified beyond its single energy dependency structure, exhibits the lowest resilience in technological innovation, highlighting a specific area for focused improvement.

There are certain limitations in this article. First, regarding the sample size, the findings are derived from 13 years of empirical data from resource-based cities in Liaoning Province, rendering the sample size relatively small. This limitation may affect the precision of the research outcomes. An expansion of the sample size could potentially yield more accurate conclusions and facilitate comparisons with other resource-based cities across China. Despite its modest sample size, Liaoning Province, as a pioneering industrial base in Northeast China with the earliest practices of economic transformation in the country, offers valuable insights and a model for regional economic development. Secondly, concerning the calculation of indicator weights, this study incorporates subjective weighting to complement the objective weighting method, aiming for more realistic weight outcomes. However, the weights derived from the Analytic Hierarchy Process (AHP) depend on expert assessments, which could introduce certain biases. Future research could employ more varied methods to determine expert weights and strive to minimize subjective influences. Moreover, while this paper has reviewed extensive literature, it has not exhaustively examined the relationship between the resilience of resource-based cities and carbon emissions. Future studies should aim to broaden the research data and delve deeper into the quantitative link between carbon emissions and the resilience of resource-based cities, to enhance understanding and inform more effective strategies for sustainable development.

Acknowledgments

This work was financially supported by the National Social Science Foundation Project (No. 22BGL202); the Scientific Research Fund of Hunan Provincial Education Department (No. 21A0598, 22A0678); grant number, and the Hunan Provincial Social Science Achievement Review Committee (No. XSP24YBZ078).

Conflict of Interest

The authors declare no conflict of interest.

References

1. LI B., DEWAN H. Efficiency differences among China's resource-based cities and their determinants. Resources Policy, **51**, 31, **2017**.
2. WANG Y., CHEN H., LONG R., SUN Q., JIANG S., LIU B. Has the Sustainable Development Planning Policy Promoted the Green Transformation in China's Resource based Cities? Resources, Conservation and Recycling, **180**, 106181, **2022**.
3. LIU L.N., LEI Y.L., ZHANG W.Y. Research on the Resilient Development of Resource-based Cities under the "Double Carbon" Goal. Geological Bulletin, **2024**. *in press* (In Chinese)
4. WANG Z., DENG X., WONG C., LI Z., CHEN J. Learning urban resilience from a social-economic-ecological system perspective: A case study of Beijing from 1978 to 2015. Journal of Cleaner Production, **183**, 343, **2018**.
5. CLOERN J.E., ABREU P.C., CARSTENSEN J., CHAUVAUD L., ELMGREN R., GRALL J., YIN K. Human activities and climate variability drive fast-paced change across the world's estuarine–coastal ecosystems. Global Change Biology, **22**(2), **2016**.
6. MCGLADE C., EKINS P. The geographical distribution of fossil fuels unused when limiting global warming to 2°C. Nature, **517**, 187, **2015**.
7. LI G., KOU C., WANG Y., YANG H. System dynamics modelling for improving urban resilience in Beijing, China. Resources Conservation and Recycling, **161**, 104954, **2020**.
8. RASHIDFAROKHI A., DANIVSKA V. Managing crises 'together': how can the built environment contribute to social resilience? Building Research & Information, **1**, **2023**.
9. HOLLING C.S. Resilience and Stability of Ecological Systems. Annual Review of Ecology and Systematics, **4**, 1, **1973**.
10. ADGER W.N. Social and ecological resilience: are they related? Progress in Human Geography, **24**, 347, **2000**.
11. MILMAN A., SHORT A. Incorporating resilience into sustainability indicators: An example for the urban water sector. Global Environmental Change, **18**, 758, **2008**.
12. ROSE A., LIM D. Business interruption losses from natural hazards: conceptual and methodological issues in the case of the Northridge earthquake. Global Environmental Change Part B: Environmental Hazards, **4**,1, **2002**.
13. FENG Y., NIE C.F., ZHANG D. Measurement and analysis of economic resilience of urban agglomerations in China: based on the shift-share decomposition of economic resilience. Shanghai Economic Research, **5**, 60, **2020**. (In Chinese)
14. ZENG B., ZHANG Y. Commentary on the Connotation of Regional Economic Resilience and Its Research Progress. Exploration of Economic Issues, **1**, 176, **2018**.
15. WANG S.J., CUI Z.T., LIN J.J. Research on the Coupling and Coordination of Urbanization and Ecological Resilience in the Pearl River Delta Region. Acta Geographica Sinica, **76**, 973, **2021**. (In Chinese)
16. FOLKE C. Resilience: The emergence of a perspective for social–ecological systems analyses. Global Environment Change, **16**, 253, **2006**.
17. DAKOS V., KÉFI S. Ecological resilience: What to measure and how. Environmental Research Letters, **17**, 043003, **2022**.
18. LV T.G., HU H., FU S.F. Spatial and temporal differentiation characteristics and influencing factors of urban ecological resilience in the Yangtze River Delta region. Regional Research and Development, **42**, 54, **2023**. (In Chinese)
19. SHI C., ZHU X., WU H., LI Z. Urbanization Impact on Regional Sustainable Development: Through the Lens of Urban-Rural Resilience. International Journal of Environmental Research and Public Health, **19** (22),15407, **2022**.
20. KOLOPAKING L.M., WAHYONO E., IRMAYANI N.R., HABIBULLAH H., ERWINSYAH R.G. Re-Adaptation of COVID-19 Impact for Sustainable Improvement of Indonesian Villages' Social Resilience in the Digital Era. International Journal of Sustainable Development & Planning, **17** (7), **2022**.
21. CIESIÓŁKA P., MAĆKIEWICZ B. In Search of Social Resilience? Regeneration Strategies for Polish Cities. Sustainability, **14**, 11969, **2022**.
22. BOUWER R., PASQUINI L., BAUDOIN M.A. Breaking down the silos: Building resilience through cohesive and collaborative social networks. Environmental Development, **39**, 100646, **2021**.
23. CINNER J.E., BARNES M.L. Social dimensions of resilience in social-ecological systems. One Earth, **1**, 51, **2019**.
24. ZEBARDAST E. The Hybrid Factor Analysis and Analytic Network Process (F'ANP) model modified: Assessing community social resilience in Tehran metropolis. Sustainable Cities and Society, **86**, 104127, **2022**.
25. BUSIC A., SCHUBERT R. Social resilience indicators for pandemic crises. Available at SSRN, 3938198, **2022**.
26. COPELAND S., COMES T., BACH S., NAGENBORG M., SCHULTE Y., DOORN N. Measuring social resilience: Trade-offs, challenges and opportunities for indicator

models in transforming societies. International journal of disaster risk reduction, **51**, 101799, **2020**.
27. KONG L., MU X., HU G., ZHANG Z. The application of resilience theory in urban development: A literature review. Environmental Science and Pollution Research, **29** (33), 49651, **2022**.
28. GAO L., NA R., GUO E.L., WANG Y.F., DONG J.Y., JIA S.C. Research on Urban Resilience Evaluation Based on Green and Safety Concepts: Taking the Streets of Hohhot as an Example. Disaster Science, **39** (01), 216, **2024**. (In Chinese)
29. BECEIRO P., GALVÃO A., BRITO R.S. Resilience assessment framework for nature based solutions in stormwater management and control: Application to cities with different resilience maturity. Sustainability, **12**, 10040, **2020**.
30. CHEN X.H., LOU J.N., WANG Y. Research on the Spatial-temporal Pattern Evolution and Dynamic Simulation of Urban Resilience in the Harbin-Changchun Urban Agglomeration. Geographical Sciences, **40**, 2000, **2020**. (In Chinese)
31. OSMAN T. A framework for cities and environmental resilience assessment of local governments. Cities, **118**, 103372, **2021**.
32. ZHANG Z., ZHANG Y.C., ZHANG J.Q. Assessment of urban resilience based on entropy weight method and TOPSIS model: a case study of Changchun City. Journal of Hazards, **38**, 213, **2023**. (In Chinese)
33. WANG Z., FU H., ZHOU L. Multiple urban resilience evaluation of resource-based cities' sustainable transformation effect. Resources, Conservation and Recycling, **191**, 106912, **2023**.
34. TANG Y., SONG Y.Y., XUE D.Q. Spatial and temporal evolution of economic resilience and obstacles in resource based cities: a case study of Shanxi Province. Arid Land Resources and Environment, **36**, 53, **2022**. (In Chinese)
35. HUANG M.H., ZHANG W.G. Comparison of resilience levels and development strategies of four types of resource-based cities in China. Economic Geography, **43**, 34, **2023**. (In Chinese)
36. FENG D.M., GAO T. Evaluation of resilience efficiency of resource-exhausted cities under carbon emission constraints: based on the MinDS super-efficiency model and GML index. Environmental Protection, **51**, 35, **2023**. (In Chinese)
37. DENG Y., JIANG W., WANG Z. Economic resilience assessment and policy interaction of coal resource oriented cities for the low carbon economy based on AI. Resources Policy, **82**,103522, **2023**.
38. SIDHU J., SINGH S. Improved topsis method based trust evaluation framework for determining trustworthiness of cloud service providers. Journal of Grid Computing, **15**, 81, **2017**.