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The Impact of Green Innovation Capacity on Urban Economic Resilience: Evidence from China's Yangtze River Delta Region

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Abstract: Urban green innovation plays a crucial role in achieving sustainable urban economic development, and urban economic resilience is an important manifestation of urban economic development. This prese nt study aims to investigate how green innovation contributes to urban economies' resilience, which is essential for long-term urban agglomeration expansion and sustainable economic development. To decrease subjectivity and achieve comprehensive evaluation, this study first constructs an index system for evaluating green innovation capability on urban economic resilience, which contains 21 indicators in three areas, including innovation input, innovation output, and green innovation foundation, and the performs a scientific evaluation using the TOPSIS method. On this basis, using the Super-SBM model, the green innovation efficiency value of cities in the Yangtze River Delta (YRD) is calculated. Finally, ArcGIS 10.8 software is used to classify the economic resilience of the 26 cities in the YRD city cluster and analyze the spatial layout characteristics of urban economic resilience. The results show that: (1) the decision evaluation model used in this study is stable and effective, and it can effectively address the issues of subjective assessment processes and information redundancy; (2) green innovation capacity has a positive contribution to urban economic resilience, and its contribution is more significant for cities with strong economic strength; and (3) the green innovation capacity of the YRD city cluster is unevenly distributed, with Shanghai, Suzhou, Hangzhou, and Nanjing having high levels of green innovation capacity and strong urban economic resilience, thus forming the core area of cities radiating outward, showing a "core-edge" spatially. Finally, suggestions for improving the overall economic resilience of urban agglomerations are provided.

Keywords: green innovation; urban economic resilience; Yangtze River Delta (YRD)

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1. Introduction

Since the outbreak of the coronavirus disease (COVID-19) pandemic in 2020, global economic weakness and the trend of counter-urbanization have intensified, and the environment at home and abroad has become increasingly severe, which has greatly tested the anti-risk ability of the urban economy [1]. Within this context, "urban economic resilience" has emerged as a frontier in research. "Urban economic resilience" refers to the ability of an urban economy to withstand and recover from external shocks [2,3]. In the face of the complex situation of increasing internal and external environmental risks, improving urban economic resilience has become a key concern for the Chinese government. In October 2022, the Chinese government stressed that "to build livable, resilient and smart cities, this will help to use cities as an important engine of economic development and an important highland for scientific and technological innovation." [4]. As a subsystem of urban resilience, improving urban economic resilience has become an important measure for reducing urban economic risks and achieving sustainable development of the urban economy [5].

However, China's urban economic growth still finds it difficult to completely eliminate using the traditional extensive development model, thereby restricting the ability of urban economic resilience to resist risks [6]. In this context, China regards green development as an important path for transforming its mode of economic development and achieving high-quality development [7]. Green innovation can realize industrial transformation and upgrading, reduce resource consumption and environmental damage, and improve resource allocation efficiency, making it an effective way to achieve high-quality development of the urban economy [8,9]. Accordingly, it is important to enhance urban economic resilience and promote the sustainable development of the urban economy by studying the impact of green innovation on urban economic resilience.

For the following two reasons, the YRD region was chosen as the subject of this study: 1. In terms of economic development, the YRD city cluster is one of the most economically dynamic, open, and innovative agglomerations in China. The total economic output of the YRD region accounted for about 24.1% of the country's total economic output in 2021, occupying a key position in China's regional development pattern. However, with rapid economic development, the YRD region is facing ecological damage and environmental pollution, which restrict high-quality economic development [10]. Thus, in the context of a pattern of development that includes both opportunities and challenges, changing the rough economic development mode using green technology innovation, on the one hand, reduces environmental pollution and resource consumption internally, realizes sustainable economic development externally, improves the economic resilience of the urban agglomeration as a whole, and solidifies the leading position of green innovation in the nation [11]. On the other hand, it is highly significant for the economic transformation and upgrading of other urban agglomerations and is favorable to promoting the growth of the entire East China area and the Yangtze River Economic Belt. 2. In terms of collaborative innovation, although the YRD city cluster has reached more than one-fourth of the national share of R&D investment, the uneven development within the urban agglomeration has led to many difficulties and drawbacks in terms of collaborative innovation, including inefficient synergy, uneven distribution of innovation resources, and impeded flow of development resources, among others. These difficulties and drawbacks are faced by the integrated development strategy of urban agglomeration in terms of enhancing regional synergy [12]. Analyzing the characteristics of the current situation of green innovation in the cities of the YRD city cluster, discovering the existing problems, and proposing corresponding countermeasures and suggestions are of great significance to enhancing the overall green collaborative innovation capacity of the YRD city cluster and the economic resilience of the urban agglomeration.

Therefore, combining the above analysis and Appendix A, it is representative to select the YRD city cluster as the research object. This study explores whether green innovation capacity can effectively enhance urban economic resilience by constructing an evaluation index system for green innovation capacity to urban economic resilience. It investigates whether green innovation capacity can effectively improve the economic resilience of cities. Finally, this study empirically examines the current state of green innovation capacity in cities, which can improve the overall economic resilience of urban agglomerations. It also provides references to other urban agglomerations in terms of sustainable development, which helps improve the overall economic resilience of urban agglomerations and provides a reference for the sustainable development of other urban agglomerations.

In this paper, we focus on investigating a method that can impartially assess the contribution of green innovation to urban economic resilience. We first conduct a literature review on the definition of urban economic resilience and green innovation. The related research on urban economic resilience and green innovation is covered in Section 2. Section 3 presents the construction of an evaluation index system for green innovation capacity and urban economic resilience. Section 4 presents the empirical analysis of the evaluation results, and Section 5 summarizes the research conclusions and proposes policy recommendations. The specific evaluation process used in this paper to determine the impact of green innovation capacity on urban economic resilience is shown in Figure 1.

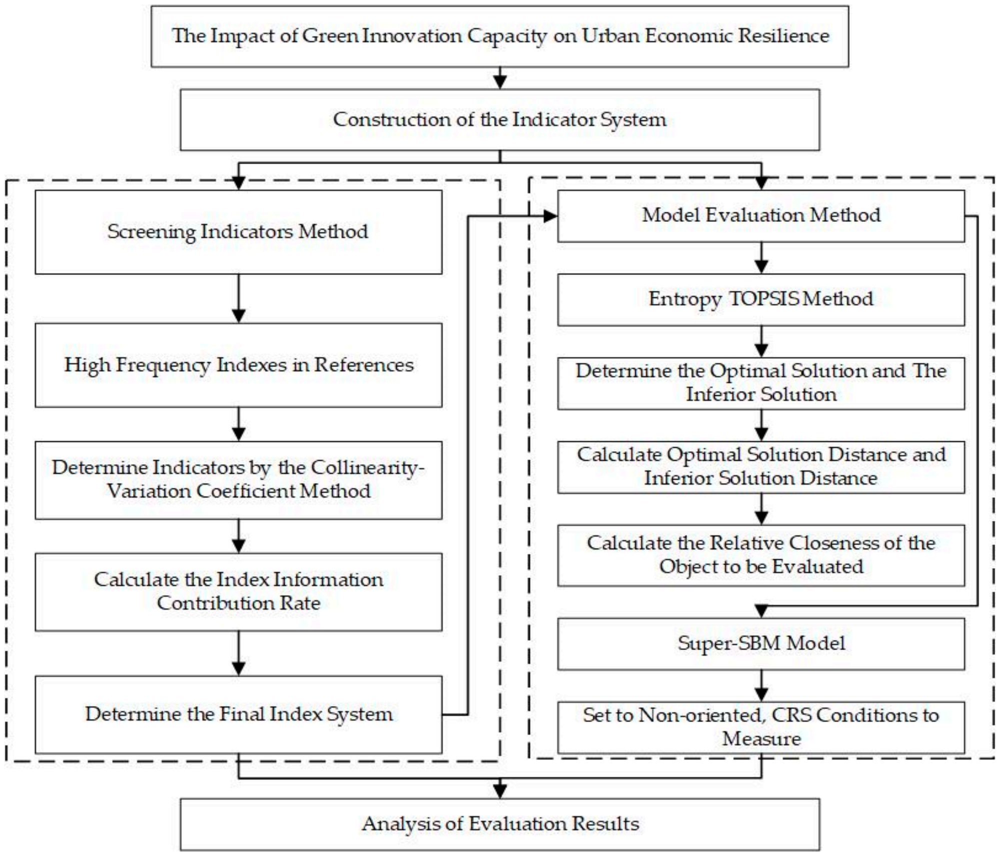

Figure 1. Flowchart of the process used to determine the impact of green innovation capacity on urban economic resilience. (Source: Organized by the authors).

2. Literature Review

2.1. The Definition of Urban Economic Resilience

"Resilience" is a multidisciplinary concept that was first derived from physics [13]. Holling was the first to propose the idea of "engineering resilience", which represents the ability of a system to recover to its initial state after being stressed by an impact. Since then, the use of resilience has gradually been extended to other social science fields including engineering and ecology [14]. In the development of the connotation of economic resilience, two definitions have emerged: "ecological resilience" and "adaptive resilience". "Ecological resilience" refers to a system's ability to absorb perturbations to the maximum extent possible without changing its structure, thus achieving a stable state [15]. Economic systems undergo structural changes over time and cannot always be in equilibrium. Therefore, this definition is not suitably applicable to economic systems. Therefore, an increasing number of scholars prefer the term "adaptive resilience" as the origin of economic resilience to view the development of an economic system from a dynamic perspective. Martin systematically studied economic resilience in four dimensions, viz. resistance, resilience, adaptability, and renewal, after systematically integrating the relevant literature [16].

Urban economic resilience refers to the ability of urban economies to withstand and recover from external shocks when they are encountered [17]. The urban economic system involves a process of dynamic change in multiple stages, specifically, the ability to resist before facing a shock, the ability to adapt and stabilize when facing a shock, and the ability to recover after the shock [18]. Summarizing the above literature, this study argues that urban economic resilience reflects the competitive strength of a city in several ways. If a city's economic system can maintain stable growth, adapt to changes in response to shocks, allocate factor resources effectively, and optimize industrial composition in the face of market, competitive, and environmental shocks, the city will have strong urban economic resilience.

2.2. The Research on Urban Economic Resilience

Academics have conducted in-depth research on the issue of urban economic resilience, which includes two aspects: measurement and influencing factors of urban economic resilience. First, methods for measuring economic resilience in academic circles are divided into two methods. The first is the core variable measurement method. For example, Martin's difference between the real and predicted gross domestic products (GDPs) of 85 cities in the UK showed four major recessions and recoveries of cities during the period of 1971–2015 and analyzed the significant changes in the four fluctuations and differences between northern and southern cities [19]. Based on the urbanization perspective, Sensier et al. selected real GDP and unemployment rates to study changes in economic shocks in EU countries and further analyzed the size of the shocks and the speed of recovery [20,21]. Faggian divided Italy into hundreds of regional economic systems, selected the unemployment rate index to measure economic resilience, and concluded that the population and industrial system will play a fundamental role in regional economic resilience [22]. In summary, most current scholars using the core variable method tend to use indicators such as real GDP or employment rates that are sensitive to economic shocks as core variables. Kitsos also highlighted that compared with other measurement methods, the core variable method is rarely subject to causal confusion and is more economical [23].

However, some scholars have proposed economic resilience as a composite concept that covers the adaptation, resistance, and adjustment periods. It is difficult for a single indicator to fully reflect the implications of overall economic resilience. Therefore, a multi-index system measurement method is required. For example, Briguglio et al. divided economic resilience into four parts—macro-environment, micro-market, government intervention, and social development—and performed a measurement analysis [24]. Cox constructed an evaluation index system of regional economic resilience from an investment and environmental perspective, and posited suggestions from various angles to reduce the gap with expectations [25]. Paolo selected indicators from the three dimensions of economic, social, and ecological environments to construct an evaluation system for evaluating the economic resilience of more than 200 regions in Europe [26].

In conclusion, although the multi-index vehicle measurement method can reflect the overall connotation of economic resilience, different scholars do not use a unified method for the selection and weight of relevant indicators of the index system. Therefore, the constructed index system is quite different. Although this study adopted a multi-index evaluation system, the collinearity–variation coefficient method was used to ensure the rationality of the index system, which differs from other studies.

Another aspect of the research on urban economic resilience is the study of influencing factors. Most scholars discuss the impact of urban economic resilience from the perspectives of industrial structure, disease disasters, and population aggregation. Brown and Greenbaum proposed that a region with a diversified industrial structure would show greater economic resilience in the face of a crisis because the gains of prosperous industries can offset the losses in declining industries, thus stabilizing the regional economy [27]. Zhang et al. selected monthly data from the Beijing–Tianjin–Hebei urban agglomeration from June 2019 to September 2020 to explore the impact of COVID-19 on the economic resilience of urban agglomerations. The research conclusions showed that the Beijing–Tianjin–Hebei urban agglomeration was impacted by the new coronavirus epidemic, and the economic resilience of urban agglomerations presented different development types over time [1]. From the perspective of population agglomeration, some scholars used 284 cities in China as samples to empirically analyze the impact of population agglomeration on urban economic resilience in the context of the 2008 financial crisis. The research conclusions showed that population agglomeration can enhance a city's resistance to economic crises. It was also conducive to economic recovery after the crisis and had a positive spatial spillover effect on surrounding cities [28].

However, few studies have focused on the importance of innovation in terms of urban economic resilience. Bristow and Healy found that regions identified as innovation leaders can recover from a crisis more quickly than other regions [29]. Moreover, no more studies examine the impact of green innovation capabilities on urban economic resilience. Green innovation focuses on sustainability and social responsibility, which are crucial to high-quality economic development. The only way to raise green productivity, resource conservation, environmental protection, and economic sustainability and further boost cities' resilience to economic hazards is through green innovation. Thus, it is of great significance to study the impact of green innovation on urban economic resilience.

2.3. The Research on Green Innovation

"Green innovation" is also known as "eco-innovation", "environmental innovation", and "sustainable innovation" [30,31]. Fussler et al. first described "eco-innovation", arguing that it provides business value to companies and consumers as well as reduces environmental impact [32]. The difference between "green innovation" and "innovation" is that "innovation" emphasizes the role of technology promotion and market pull in innovation activities and introduces new products, processes, or services that may ignore environmental considerations [33]. "Green innovation" is guided by environmental protection and sustainable development and reduces the external environmental costs of products by using technology and business models [34].

By organizing and summarizing the existing literature, we find that scholars' research on green innovation mainly focuses on research perspectives, evaluation methods, and influencing factors. On the one hand, in terms of research perspectives, the three research perspectives from micro to macro are the enterprise perspective, industry perspective, and regional perspective. 1. From an enterprise perspective, Wu, Xia, and Li studied whether green innovation could promote the improvement of green total factor productivity with the unstudied objects of A-share listed companies. Using an empirical analysis, they found that green innovation can improve the GTFP, but the impact on different enterprises is heterogeneous [35]. 2. From an industry perspective, Wang and Li used the SBM-undesirable model and Malmquist–Luenberger productivity index to evaluate the green innovation performance of China's pollution-intensive industries from 2014 to 2018 from the dual perspectives of transformation efficiency and productivity. They also studied the impact of innovation-driven green development on the transformation of pollution-intensive industries [36]. 3. From a regional perspective, Dai et al. explored the impact of the digital economy on promoting regional green innovation based on data from 30 provincial-level administrative regions (excluding Tibet) in China from 2011 to 2018. Their empirical results show that a digital economy can effectively improve regional economic resilience [37].

On the other hand, there are two types of evaluation methods for green innovation: objective empowerment evaluation method and subjective empowerment evaluation method. The objective empowerment evaluation method includes the entropy weight method (EWM), gray correlation analysis method, etc. The subjective empowerment evaluation method includes the analytic hierarchy process (AHP) method, fuzzy synthesis evaluation method, and so on.

1. Entropy weight method (EWM). Zou et al. constructed an evaluation index system for the energy green consumption revolution (EGCR) from four perspectives: economic, social, energy, and environmental, and used the entropy weight technique for order preference by similarity to ideal solution (TOPSIS) method to calculate and objectively evaluate China's EGCR from 2011 to 2019 [38].2. Gray correlation analysis method. Xu and Zhai studied the evaluation method for enterprise green innovation capacity combined with

the cloud model method, decision-making trails, and the evaluation laboratory method to determine the comprehensive weight of indicators. They also determined the similarity between each value and the ideal value using the cloud distance measurement and grey correlation analysis methods. Finally, the effectiveness of the method was verified using an empirical analysis [39]. 3. Analytic hierarchy process (AHP) method. Pan et al. proposed that most green innovation capacity evaluation methods are subjective and cannot solve the problem of index information duplication. Therefore, they combined the analytic hierarchy process (AHP) and osculating value process (OVP) to construct an AHP-OVP evaluation model to evaluate the green innovation capacity of enterprises and empirically analyze its effectiveness, which solved the problem of information repetition and subjective evaluation methods [40]. 4. Fuzzy synthesis evaluation method. In order to study the green competitiveness change trend in 30 provinces in China from 2004 to 2014, Cheng et al. developed a regional green competitiveness evaluation index system based on the connotation of regional green innovation competitiveness using the fuzzy comprehensive evaluation method and the entropy weight method and graded the output results [41].

Furthermore, in terms of decision analysis methods, the main methods included are the TOPSIS method, the ELimination Et Choix Traduisant la REalité (ELECTRE) method, the VIse Kriterijumski Optimizacioni Racun (VIKOR) method, etc. The TOPSIS method is widely used in social [42], industry [43], engineering [44], and other domains of judgment and assessment [45]. The ELECTRE method is a multi-criteria decision-making method that can quantify the decision-making process and resolve complex decision-making issues, but it has the drawback of requiring more factors that must be taken into account and contains non-data table factors, which can have erratic effects on decision-making and are unsuitable for long-term decision-making [46]. Compared with the TOPSIS method, the VIKOR method has an additional decision mechanism coefficient and requires the researcher to determine data such as weighting coefficients, which is difficult to realize in practical decision-making [47].

In this paper, the entropy weight approach and TOPSIS method are coupled to assess the variations in each city's level of green innovation. On the one hand, the entropy weight method is an objective empowerment evaluation method, whereas AHP [40], DEMATEL [48], and other evaluation methods rely on subjective empowerment by experts. The entropy weight method is an objective evaluation method that is not susceptible to the issue of imbalance in the weight ratio due to subjective reasons. The entropy weight method calculates weights using the entropy value information of the research data itself, ensuring the rationality of the indicator weights and improving the objectivity and fairness of the research findings [49]. On the other hand, the TOPSIS method can derive the positive and negative ideal solutions for urban green innovation using the indicator data of each city and provide a reference standard for the development level of green innovation among cities with the index data of each city [50]. However, the TOPSIS method's drawback is that it lacks the support of indicator weights [51]. Therefore, this paper uses a research method of combining the entropy weight and TOPSIS methods because this type of combined research method is more mature, the two advantages complement each other, it has been widely used in all types of evaluation-based research, and the research results are objective, reasonable, and highly credible [52].

Moreover, the factors influencing green innovation capability contain two categories: internal factors and external factors, of which most of the literature studies examine external indicators. 1. Internal factors. Using a survey of 262 manufacturing enterprises in China, Wang and Du found that an improvement in green absorptive capacity and green market orientation, two internal factors of green innovation, has a significant effect on the promotion of green innovation of enterprises [53]. 2 External factors. The existing research posits several key factors that can affect green innovation capacity, such as, regulation environment [54], digital economy [37], FDI [55], environmental investment [56], etc. Based on the above research, few studies have been conducted on green innovation involving urban economic resilience. Green innovation affects urban economic resilience by improving factor allocation [57], optimizing industrial structures [58], and utilizing human resource advantages [59]. This study fills this research gap by examining the impact of green innovation on urban economic resilience.

2.4. Theoretical Analysis

Green innovation capacity can enhance the economic resilience of cities, as demonstrated by:

1. Green innovation capacity enhances the economic resilience of cities by optimizing the allocation of factors. Yao et al. argue that green innovation capacity is the key to achieving this goal. Cities may encourage specialization in the division of labor and boost production efficiency in terms of factor consumption and output by fully using the potential of inventive factor allocation. This might lessen a city's reliance on outside funding and improve its capacity to resist and recover from external risks [57]. What is more, by boosting innovation inputs and enhancing innovation outputs, green innovation may support the growth of the green economy. One way to boost the effectiveness of green innovation is to increase investment in it. This may be completed by allocating innovation resources as efficiently as possible. The lack of funding for the development of green technologies can be filled by FDI investment and domestic R&D money. Innovation in green technology can improve economic gains while lowering pollution-related expenses and environmental damage [60,61].
2. Green innovation can enhance the economic resilience of cities by optimizing the industrial structure. Increasing green innovation will support the growth of new industries, alter existing industries, eliminate outdated industries, and advance the diversity and progress of the industrial structure [62]. The "three highs" of high-pollution, high-energy-consumption, and high-water-consumption enterprises can be gradually eliminated in favor of high-technology, high-growth, and high-value industries, according to Cheng and Jin, who believe that green innovation capability can act as a major driving force for industrial restructuring [63].
3. Green innovation capacity further enhances the economic resilience of cities through human resource strengths. First, talent advantages and labor capital are examples of human resource benefits. A high-tech, high-quality, and high-knowledge personnel team is a must for innovation. The sustainable growth of a city depends on having a sufficient talent pool, which is also a necessary condition for speeding the development of green innovation and accomplishing the transition of scientific and technical advancements [64]. Second, by improving the workforce's quality and capabilities, science, technology, and innovation may better match the degree to which sectors are changed and improved. This will increase cities' economic resilience [65].

In summary, it is not difficult to find that the existing research has the following shortcomings. First, the research on the impact of the existing literature on urban economic resilience mainly focuses on industrial structure, disease disasters, population aggregation, and other perspectives, but there are few green innovation studies closely related to high-quality economic development. Second, although the multi-index measurement method in the existing literature has a strong comprehensiveness and comprehensive measurement range, information redundancy can easily occur in the same index layer, and the index screening lacks rationality analysis. Regarding the indicator system, the majority of researchers in the literature at hand did not examine the objectivity in choosing the indicators, and while the component of the indicator system that assesses innovation capacity has significant relevance, there are not many indicators that take the environment and sustainability into account.

Therefore, this study considers green innovation capacity from a research perspective. Based on the high-frequency indicators that have appeared in the literature, the collinearity–variation coefficient method was used to screen the indicators, solve the problem of information redundancy, and establish an evaluation index system of green innovation capacity for urban economic resilience to make the evaluation index system more scientific and reasonable. Then, the entropy weight TOPSIS method was used to analyze the urban economic resilience of 26 cities in the YRD city cluster from a green innovation perspective. On this basis, the Super-Slack Based Measure (Super-SBM) model is used to measure the current situation of green innovation efficiency in the YRD cities, and the spatial distribution differences in urban green innovation capacity are analyzed. This study attempts to make academic contributions from the following three aspects:

1. When compared with previous studies, this paper's main contribution is the construction of an evaluation model for evaluating regional green innovation capacity. This model screens the indicators covering all aspects of the evaluation system using a comprehensive set of the indicator screening process, and it studies a city's green innovation capacity with an objective and reasonable evaluation and decision-making method, which achieves the best decision-making results for regional green innovation capacity. The method not only corrects the flaws of earlier evaluation methods for green innovation capacity, such as the non-objective evaluation method and redundant information of indicators, but also passes the sensitivity test, demonstrating the viability of the method.
2. There is a dearth of academics conducting research on green innovation and urban economic resilience. This paper attempts to fill that gap by presenting quantitative analysis techniques and research ideas. It also offers a practical and scientific method for evaluation, which aids in the growth of this research field.
3. Despite city clusters being more economically interconnected in terms of the research region, there are not many studies on green innovation that focus on them in the present literature. As a result, this study uses the YRD region as its research object in order to both explore the effects of green innovation on urban economic resilience at the micro-city level and provides research ideas and methods for other regions.

3. Materials and Methods

3.1. The Structure of the Index System

At present, the indicator systems established by academics conducting research on green innovation are diverse and do not constitute an indicator system that is widely accepted [66]. This article holds the opinion that the index system should be built using the connotation of green innovation capabilities based on an analysis of a variety of studies in the literature. For instance, Hua thinks that green innovation capacity can be understood as "green + innovation + capacity". "Green" means "sustainable development", balanced economic development, and intergenerational equity, and "innovation" emphasizes the introduction of new products, services, and processes. "Capability" is a skill or potential, which focuses on innovation inputs and innovation outputs [67]. Ge et al. define regional green innovation capacity as a region's capability to generate new value while using fewer resources from the environment. This capacity must adhere to the principles of innovation, resource efficiency, and capacity building [68]. According to Cao et al., the definition of "green innovation capacity" is the "regional comprehensive development ability of a region to transform innovation inputs into innovation outputs within a certain period of time under the guarantee of sustainable development of economy, society, and environment". This definition embodies the concepts of "innovativeness", "capability", and "sustainable development" of green innovation capacity. Because of this, it is clear from the literature mentioned above that green innovation capability differs from general innovation capability, which embodies three principles: "green" stands for the principle of sustainable development; "innovation" stands for the principle of innovativeness; and "capability" stands for the principle of strong ability. "Capability" also stands for the idea of powerful capacity [69].

Based on the above analysis of the connotation of green innovation capacity to urban economic resilience, and according to the principles of strong capacity, innovation, and sustainable development, this paper, which supports the sustainable and steady growth of urban green innovation, evaluates the level of green innovation of cities from economic, social, and environmental perspectives based on the concept of green innovation. To achieve this, a set of accurate and effective index assessment systems should be constructed on the basis of adhering to relevant theories of green innovation.

The choice of the guideline level cannot be made without the relevant theoretical support. The theoretical basis for the guideline level selection in the research of this article is "Green Economy Theory", "Green Innovation Theory", and "Sustainable Development Theory".

The "Green Economy Theory", which emphasizes the economic development mode of increasing human capital input and reducing resource consumption, is represented as green innovation input. The "Green Economy Theory" encourages investing capital in resource-saving and environmentally friendly fields in order to realize economic benefits. In this paper, the various components of the green economy are represented by human input, material input, and capital input.

The "Green Innovation Theory", which stresses a reduction in environmental costs with the output and application of technical innovation, is represented as green innovation output. Application innovation and technological innovation are represented in this study by innovation industry output and innovation technology output.

The "Sustainable Development Theory", which encompasses the critical elements of sustainable development in economic, social, and environmental aspects, serves as the foundation for green innovation. Thus, the three elements of the theory of sustainable development are represented by economic development, social foundations, and environmental foundations in the study.

What is more, with reference to [70–72], we establish a framework of evaluation indicators of green innovation capacity to urban economic resilience using three broad criteria: innovation input, innovation output, and green innovation foundation, as shown in Table 1.

Table 1. Framework for evaluating green innovation capacity on urban economic resilience indicators.

	Tier 1 Guideline Level	Tier 2 Guideline Level
Green innovation capability	X_1 Innovation input	X_1-$_1$ Manpower input
		X_1-$_2$ Material input
		X_1-$_3$ Financial input
	X_2 Innovation output	X_2-$_1$ Innovative industrial output
		X_2-$_2$ Innovative technological output
	X_3 Green innovation foundations	X_3-$_1$ Economic development
		X_3-$_2$ Social foundations
		X_3-$_3$ Environmental foundations

Source: Based on the above literature, the authors organized this framework by themselves.

1. Innovation Input. In general, the urban innovation environment, which is primarily influenced by the gathering of inventive people resources and resource inputs, is directly connected to the amount of green innovation potential. The flow of innovation factors will be accelerated further, leading to a rise in innovation outputs and a further expansion of innovation inputs as there are more people and resource inputs. In accordance with Guo et al.'s methodology, this article chooses human, material, and capital inputs as the secondary indicators of innovation inputs [73–75].
2. Innovation output. Innovation output reflects the level of green innovation transformation in a city and is usually represented by indicators such as the number of patent applications [76], the turnover in the technology market [77], the income from sales of new products [78], etc. In this paper, the output of the innovation industry is selected to reflect the ability of current urban green innovation technology to transform economic benefits, and the output of innovation technology reflects the ability of future urban green innovation technology reserves.
3. Green innovation foundations. By conducting a review of the literature, this paper found that the foundation of green innovation frequently contains three main categories: the social environment, the economic environment, and the ecological

environment. The green innovation foundation is an important component of the urban green innovation system. A good green innovation foundation can promote the flow of various types of innovation factors in a city, which is conducive to the development of green innovation activities [68,69]. Therefore, a subset of indicators indicating green innovation foundations are constructed in this work using economic development, social foundations, and environmental foundations. Economic development is a reflection of a city's economic strength; the more resources a city has to invest in innovation, the more it can advance the degree of green innovation inside the city [79]. The social basis contributes to ensuring the framework for green innovation; the stronger a city's social base, the more green aspects it will be able to draw in [80]. The environmental base reflects the level of urban pollution emissions and environmental governance, and it is closely linked to the development of an urban green economy [81]. The indicator system developed in this study thus far satisfies the criteria for completeness, hierarchy, and comparability.

The full set of index possibilities for comprehensive evaluation was initially built in order to screen the indexes for systematicity and representativeness and to ensure that there was no repetitive information for the screening of the indexes conducted later in this article. This was performed in accordance with the principles of systematicity, scientificity, and representativeness of the evaluation index system, as well as the high-frequency indexes appearing in the results of previous research.

3.2. Data Sources and Index Calculation Method

3.2.1. Data Sources

For data completeness, the data in this study were obtained from the China Statistical Yearbook 2022, China Science and Technology Statistical Yearbook 2022, Zhejiang Statistical Yearbook 2022, Anhui Statistical Yearbook 2022, Jiangsu Statistical Yearbook 2022, Shanghai Statistical Yearbook 2022, 2021 National Economic and Social Development Bulletin of 26 cities in the YRD city cluster, and the official websites of various local governments. Some missing data were supplemented by interpolation.

3.2.2. Evaluation Indicator Selection Process

Step 1: Construct a sample matrix with m indicators and n cities as follows:

$$X = \{x_{ij}\}_{m\times n}(1 \leq i \leq m, 1 \leq j \leq n) \tag{1}$$

where x_{ij} is the original value of indicator i for city j.

Step 2: Standardize the indicators:

$$\text{Data normalization formula for positive indicators}: \ Z_{ij} = \frac{x_{ij} - \min\limits_{1\leq j\leq n}(x_{ij})}{\max\limits_{1\leq j\leq n}(x_{ij}) - \min\limits_{1\leq j\leq n}(x_{ij})} \tag{2}$$

$$\text{Data normalization formula for inverse indicators}: \ Z_{ij} = \frac{\max\limits_{1\leq j\leq n}(X_{ij}) - X_{ij}}{\max\limits_{1\leq j\leq n}(X_{ij}) - \min\limits_{1\leq j\leq n}(X_{ij})} \tag{3}$$

where Z_{ij} is the standardized value of indicator i in city j; x_{ij} is the original value of indicator i in city j; $\min\limits_{1\leq j\leq n}(x_{ij})$ is the minimum value of indicator i in all cities; $\max\limits_{1\leq j\leq n}(x_{ij})$ is the maximum value of indicator i in all cities; and n is the number of cities.

Step 3: Introduce the variance expansion factor (VIF) to determine the presence of multicollinearity and eliminate the presence of multicollinearity indicators using a cointegration test to avoid the duplication of information reflected by the indicators.

$$R_i^2 = \frac{\sum_{j=1}^{n} (\hat{x_{ij}} - \overline{x_i})}{\sum_{j=1}^{n} (x_{ij} - \overline{x_i})} \tag{4}$$

$$VIF_i = \frac{1}{1 - R_i^2} \tag{5}$$

where R_i^2 is the decidability factor of indicator i; $\hat{x_{ij}}$ is the ordinary least-squares (OLS) estimate of indicator i in region j; and $\overline{x_i}$ is the mean value of x_i. The larger the R_i^2, the more severe the multicollinearity between the other indicators and the i indicator and the larger the VIF_i. It is generally believed that when $VIF_i > 10$, there is severe multicollinearity between the i indicator and the other indicators, and the i indicator should be deleted. The calculation formulae refer to [66,68,69].

Step 4: Select of the most informative indicators using the coefficient of variation method

$$v_i = \frac{\sqrt{\frac{1}{n}\sum_{j=1}^{n} (x_{ij} - \overline{x_i})^2}}{\overline{x_i}}; \overline{x_i} = \frac{1}{n}\sum_{j=1}^{n} x_{ij} \tag{6}$$

where v_i is the coefficient of variation of the i indicator; n is the evaluated city; $\overline{x_i}$ is the mean value of each city for the i indicator; and x_{ij} is the value of the i indicator for city j. The calculation formula refers to [66,68,69].

Step 5: Determine of the reasonableness of the indicator system.

The evaluation indicators screened by the covariance–variance coefficient are expressed in terms of information contribution In :

$$In = \frac{trs_s}{trs_h} \tag{7}$$

where In denotes the information contribution of the screened indicators to the selected indicators; S denotes the covariance matrix of the data; trS denotes the trace of the covariance matrix; s denotes the number of screened indicators; and h denotes the number of selected indicators. The calculation formula refers to [66,68,69].

Step 6: Define the evaluation indicator system.

Step 7: Weight the standardized indicators using the entropy weighting method.

$$P_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{n} Z_{ij}} \tag{8}$$

where P_{ij} is the weight of indicator i in city j; Z_{ij} is the dimensionless value of indicator i in city j; and $\sum_{i=1}^{n} Z_{ij}$ is the sum of the dimensionless data of indicator i in city j.

Step 8: Calculate the entropy value of each indicator.

$$E_{ij} = -k\sum_{j=1}^{m} P_{ij} InP_{ij};\ k = \frac{1}{Inm} \tag{9}$$

When $P_{ij} = 0$, $P_{ij}InP_{ij} = 0; E_{ij} \in [0, 1]$.

Step 9: Calculate the redundancy of the entropy value of each indicator.

$$D_{ij} = 1 - E_{ij};\ D_{ij} \in [0,1] \tag{10}$$

Step 10: Calculate entropy weights.

$$W_{ij} = \frac{D_{ij}}{\sum_{j=1}^{m} D_{ij}};\ W_{ij} \in [0,1],\ \sum_{j=1}^{m} W_{ij} = 1 \tag{11}$$

Step 11: Calculate the economic resilience of individual cities.

$$F_{ij} = W_{ij} \times Z_{ij} \tag{12}$$

The basic formulas for TOPSIS and Super-SBM are in Appendix B.

4. Results and Discussion

4.1. Indicator Screening Results

4.1.1. Initial Screening of Indicators and Standardization of Data

In this study, based on the constructed evaluation framework and the principles of scientificity and representativeness of data selection, an initial set of 72 indicators for the evaluation of green innovation capacity on urban economic resilience was established. Among the 72 indicators initially selected, X_{1-1} is the ratio of employees in scientific and technological activities to the total employed population (%), the number of university students per 10,000 people, and the number of scientific and technological activities in higher education institutions (person) in human input; X_{1-2} is the number of higher education institutions per 10,000 people in physical input; X_{2-1} is the industry in innovation industry output diversification index (%), and the index of advanced industrial structure (%); X_{2-2} is 28 unobservable indicators such as the number of scientific and technological papers published (articles) and the number of scientific and technological achievements registered (items) in innovation output. A total of 44 indicators were retained, of which 36 were positive indicators, including full-time equivalent of R&D personnel (man-year) and internal expenditure on R&D funds of industrial enterprises above the scale (CNY 1 billion), and patent authorizations (pieces), and eight were negative indicators, including foreign trade dependence (%), mortality rate (‰), and urban industrial wastewater emissions (billion tons). The data were standardized using Equations (2) and (3). The data were standardized to reduce the urban household waste disposal rate (%) using X_{3-2} environmental base indicators.

4.1.2. Screening the Indicators Using Coefficient Tests

The indicators under each of the nine secondary criteria layers were tested for covariance. Taking the secondary criteria layer X_{1-3} financial input as an example, the data in the six columns under X_{1-3} financial input were substituted into Formula (5) to calculate the VIF value. Only two indicators, i.e., local expenditure on science and technology (CNY 1 billion) and total R&D expenditure, had variance inflation factors greater than 10. Therefore, these two indicators were excluded, while the other indicators were retained. The covariance test was applied to screen the remaining indicators; finally, 4 indicators were excluded, and 39 indicators were retained.

4.1.3. Selection of Indicators Using the Coefficient of Variation Method

The coefficient of variation method was applied to screen the 39 indicators. The coefficient of variation of each indicator within the secondary criterion layer was calculated, and indicators with a coefficient of variation v_i greater than the mean value of the coefficient of variation were retained. Taking X_{1-3} capital investment as an example, the coefficient of variation values of each indicator were calculated using Equation (6) to obtain the total actual foreign investment spent (USD billion), the proportion of expenditure on science and technology to general public budget expenditure (%), the proportion of expenditure on education to general public budget expenditure (%), and the proportion of R&D expenditure to local GDP (%): 1.56, 0.42, 0.26, and 0.25, respectively. For X_{1-3}, the mean value of the coefficient of variation under the capital input indicator is 0.84. Indicators with a coefficient of variation v_i greater than the mean value of the coefficient of variation were retained; thus, the total actual foreign investment used in the indicator (USD 1 billion) was retained. After screening each indicator layer individually, 18 indicators were deleted, including the full-time equivalent of R&D personnel (man-year), road area per capita (m2), expenditure on science and technology as a proportion of general public budget expenditure (%), education expenditure as a proportion of general public budget expenditure (%), and R&D expenditure as a proportion of local GDP (%). The remaining 21 indicators were retained, including 19 positive and 2 negative indicators.

4.1.4. Reasonableness of the Judging Indicator System

Based on the above method for screening the retained indicators, the sum of variances of the retained indicator trS_s and the sum of variances of the selected indicators trS_h were calculated from the original collected data and substituted into Equation (7) to obtain the information contribution rate as follows:

$$In = trS_s/trS_h = 0.926 \times 10^{10}/0.928 \times 10^{10} \approx 99.80\%$$

Of the 72 indicators, 21 indicators ($21/72 \approx 29.17\%$) were selected to reflect 99.80% of the original information, indicating that the constructed indicator system is reasonable and representative.

4.1.5. Determining a System of Indicators for Evaluating the Economic Resilience of Cities in Terms of Green Innovation Capacity

In this study, we used the entropy weighting method to calculate the weights of each indicator, and after the dimensionless processing of the data, in order to make the data processing meaningful, it was necessary to eliminate zero and negative values. Therefore, for the overall translation of the processed data, $Xij = Xij + \alpha$, the value of α must be very small in order not to destroy the original data; in this study α = 0.00001. The weights of each index were calculated using Equations (8)–(11), and the final evaluation system was determined, as shown in Table 2.

Table 2. Green innovation capacity to urban economic resilience evaluation system.

(1) Tier 1 Guideline Level	(2) Tier 2 Guideline Level	(3) Indicators Layer	(4) Weights	(5) Nature
X_1 Innovation input	$X_{1\text{-}1}$ Manpower input (0.121)	Full-time equivalent of R&D personnel (man-year)	0.067	+
		R&D personnel of industrial enterprises above the scale (10,000 person)	0.053	+
	$X_{1\text{-}2}$ Material input (0.207)	Total public library collections (10,000 copies)	0.078	+
		Number of internet users (10,000 households)	0.074	+
		Internal expenditure on R&D expenses of industrial enterprises (CNY 100 Million)	0.055	+
	$X_{1\text{-}3}$ Financial input (0.095)	Total actual utilization of foreign capital (USD 100 million)	0.095	+

Table 2. *Cont.*

(1) Tier 1 Guideline Level	(2) Tier 2 Guideline Level	(3) Indicators Layer	(4) Weights	(5) Nature
X_2 Innovation output	$X_{2\text{-}1}$ Innovative industrial output (0.107)	Share of tertiary sector in GDP (%)	0.045	+
		Value added of industries above the scale (CNY 100 million)	0.062	+
	$X_{2\text{-}2}$ Innovative technological output (0.182)	Number of approved trademark registrations (10,000 pieces)	0.095	+
		Technology contract turnover (CNY 100 million)	0.087	+
X_3 Green innovation foundations	$X_{3\text{-}1}$ Economic development (0.053)	GDP per capita (CNY/person)	0.026	+
		Disposable income per capita (CNY 10,000)	0.027	+
	$X_{3\text{-}2}$ Social foundations (0.156)	Number of beds in medical institutions per 10,000 people (pcs)	0.028	+
		Birth rate (‰)	0.025	-
		Mortality rate (‰)	0.037	+
		Urbanization rate (%)	0.021	+
		Share of social insurance and employment expenditure in general public budget expenditure (%)	0.021	+
		Total retail sales of consumer goods as a share of GDP (%)	0.024	+
	$X_{3\text{-}3}$ Environmental foundations (0.079)	Total particulate emissions (10,000 tons)	0.020	-
		Greening coverage of built-up areas (%)	0.021	+
		Forest coverage (%)	0.038	+

Source: Organized by the authors; "+"represents positive indicator,"-" represents reverse indicator.

4.2. City Economic Resilience Composite Score

Figure 2 shows that the three lines of innovation input score, innovation output score, and overall score are basically the same. The stronger the economy of the city, the greater the innovation input. Innovation input and output remain positively proportional; therefore, the stronger the green innovation capacity, the higher the overall score, that is, the city's economic resilience. Examples include Shanghai, Suzhou, Hangzhou, and Hefei. The green innovation foundations, where green is the most extensive level of scale, consist of three secondary levels: economic development, social foundations, and environmental foundations. Therefore, the green innovation foundation score did not fluctuate significantly from city to city (Figure 2); rather, the schemes followed the same format.

The weighted scores were used to calculate the scores of each indicator, and the comprehensive score of green innovation capability and the score of the first-level criterion layer were considered to rank the 26 cities in the YRD city cluster. Table 3 shows that the mean value of the comprehensive score of green innovation capability is 0.26, the maximum value of the comprehensive score is 0.783, and the minimum value is 0.129, with a difference of 6.07 times. This indicates an uneven distribution of green innovation capacity in the YRD city cluster. The strongest green innovation capability is in Shanghai (0.783), which ranks first, and Anqing (0.129) has the lowest score, ranking 26th. The top five cities in terms of overall green innovation capacity are Shanghai, Hangzhou, Suzhou, Nanjing, and Wuxi, and the bottom five cities are Tongling, Zhoushan, Chizhou, Yancheng, and Anqing. Only seven cities have higher-than-average scores for green innovation capacity.

This indicates that the overall level of green in cities in the YRD is low. This is due to the fact that Shanghai, the city with the strongest comprehensive economic power in China, has advanced infrastructure, abundant human resources, strong scientific and technological strength, more policy support, and international exchange opportunities to learn from foreign cutting-edge green and low-carbon knowledge and innovative technologies. This provides a good demonstration of the role and radiation of the YRD city cluster.

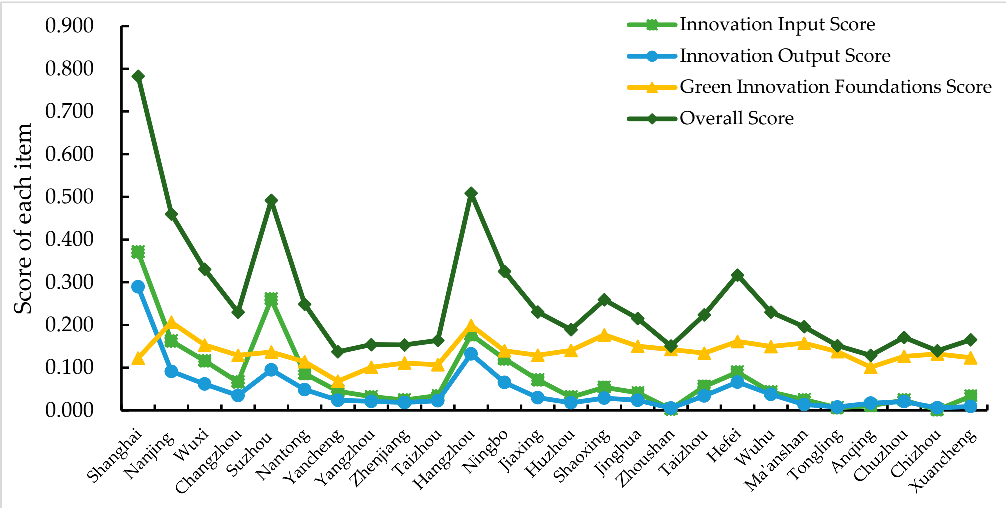

Figure 2. Green innovation capacity tier 1 guideline tier score (Source: Organized by the authors).

Table 3. Ranking of the YRD city cluster green innovation capacity tier 1 guideline tier.

City	Overall Score	Overall Score Rank	Innovation Input Rank	Innovation Output Rank	Green Innovation Foundation Rank
Shanghai	0.783	1	1	1	20
Nanjing	0.460	4	4	4	1
Wuxi	0.331	5	6	7	6
Changzhou	0.230	12	10	10	17
Suzhou	0.492	3	2	3	13
Nantong	0.249	9	8	8	21
Yancheng	0.136	25	13	15	26
Yangzhou	0.154	20	18	17	25
Zhenjiang	0.153	21	21	19	22
Taizhou	0.164	19	16	16	23
Hangzhou	0.509	2	3	2	2
Ningbo	0.326	6	5	6	11
Jiaxing	0.230	10	9	12	16
Huzhou	0.189	16	19	20	10
Shaoxing	0.259	8	12	13	3
Jinghua	0.215	14	15	14	7
Zhoushan	0.151	23	25	26	9
Taizhou	0.224	13	11	11	14
Hefei	0.317	7	7	5	4
Wuhu	0.230	11	14	9	8
Ma'anshan	0.196	15	20	22	5
Tongling	0.151	22	24	24	12
Anqing	0.129	26	23	21	24
Chuzhou	0.171	17	22	18	18
Chizhou	0.139	24	26	25	15
Xuancheng	0.165	18	17	23	19

Source: Organized by the authors.

As shown in Table 3, in the ranking of the three first-level criterion layers of innovation input, innovation output, and green innovation foundation, the cities ranked in the top 10 for innovation input and innovation output are also ranked in the top 10 in their overall ranking, except for Changzhou, which has a lower ranking for green innovation foundation and is therefore not in the top 10 in the overall ranking. Cities in the bottom three of three green innovation base rankings were in the bottom 20. In the innovation input and output rankings, only the top eight scores were above average, and the two rankings remained largely consistent. In the green innovation base ranking, only the top 13 scored above the average.

Figure 3 shows the precise composition of the scores for each city in the YRD city cluster for the tier 2 guideline level of green innovation capacity. Figure 3a shows that each city has a higher percentage of the material input score as compared with the other cities, and this score proportion is essentially consistent with the trend in the folded innovation input score. In Figure 3b, Specific analysis of the indicator layer reveals that material input contains indicators including total public library collections (10,000 Copies), the number of Internet users (10,000 households), and internal expenditure on R&D expenses of industrial enterprises (CNY 100 million). Internal expenditure on R&D expenses of industrial enterprises (CNY 100 million) is one of them, and it directly affects green innovation; the more money a company invests in R&D, the more probable it is to produce green innovation [82]. The first two indicators can indirectly create a supportive atmosphere for green innovation, which can have an influence on green innovation even though they do not directly affect it in cities [83,84]. In Figure 3c innovation output scores, innovative technological output and innovative industrial output account for a balanced ratio, demonstrating that the covariance–coefficient of variation method can successfully screen out the indicator information with the greatest information content in accordance with the evaluation requirements, ensuring that the information at the guideline level is representative. In Figure 3d green innovation foundations, we discovered that a city's environmental foundations score decreases as its economic strength increases, as in the cases of Shanghai, Suzhou, and Hefei. On the one hand, a city's industrialization process increases with its economic might, destroying some of its environmental roots in the long-term process of economic growth. On the other hand, as environmental protection awareness increases, the pursuit of economic quality and sustainable development replaces the pursuit of economic growth in urban development. Companies will continue to be forced to implement green technological innovation and green investment and reduce resource consumption and pollutant emissions, and environmental foundations will continue to be improved [85,86].

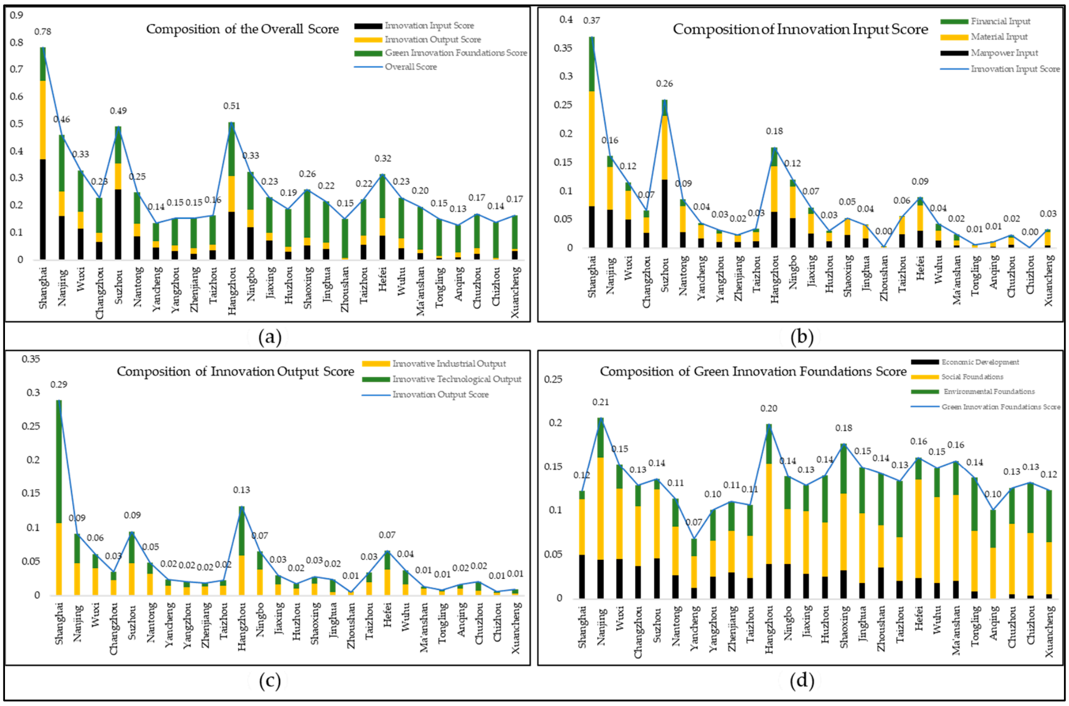

Figure 3. Green innovation capacity tier 2 guideline tier score (Source: Organized by the authors).

4.3. Empirical Analysis of the Impact of Green Innovation Capacity on Urban Economic Resilience Using Entropy-Weighted TOPSIS

The greater the closeness of the Green Innovation Index, the greater is the level of green innovation capability of the city. Table 4 shows that the top three cities in the Green Innovation Index are Shanghai, Suzhou, and Hangzhou, whereas the bottom three cities were Yangzhou, Anqing, and Yancheng. The maximum value of combined closeness was 0.753 and the minimum value was 0.136, with a difference of 5.54 times. Once again, this shows that cities in the YRD cluster have significant differences in green innovation capability.

Table 4. City green innovation capability proximity score and ranking.

City	City Green Innovation		Innovation Input		Innovation Output		Green Innovation Foundation	
	Closeness	Rank	Closeness	Rank	Closeness	Rank	Closeness	Rank
Shanghai	0.753	1	0.807	1	1.000	1	0.426	20
Nanjing	0.397	4	0.381	4	0.299	4	0.650	2
Wuxi	0.296	6	0.273	6	0.215	7	0.501	10
Changzhou	0.209	14	0.165	10	0.119	11	0.439	18
Suzhou	0.467	2	0.543	2	0.323	3	0.471	15
Nantong	0.232	9	0.204	8	0.181	8	0.386	22
Yancheng	0.136	26	0.107	14	0.083	16	0.270	26
Yangzhou	0.149	24	0.078	18	0.074	18	0.354	25
Zhenjiang	0.156	23	0.061	21	0.070	19	0.390	21
Taizhou	0.160	22	0.086	17	0.078	17	0.370	24
Hangzhou	0.466	3	0.410	3	0.441	2	0.672	1
Ningbo	0.302	5	0.281	5	0.227	5	0.506	8
Jiaxing	0.213	13	0.166	9	0.111	13	0.469	16
Huzhou	0.183	18	0.074	19	0.059	21	0.501	11
Shaoxing	0.234	8	0.131	12	0.098	14	0.603	3
Jinghua	0.223	10	0.113	13	0.111	12	0.544	5
Zhoushan	0.176	20	0.012	25	0.028	26	0.503	9
Taizhou	0.219	11	0.139	11	0.121	10	0.495	12
Hefei	0.289	7	0.213	7	0.223	6	0.545	4
Wuhu	0.214	12	0.107	15	0.126	9	0.510	7
Ma'anshan	0.193	15	0.072	20	0.055	22	0.537	6
Tongling	0.189	16	0.018	24	0.038	23	0.489	13
Anqing	0.149	25	0.035	23	0.061	20	0.374	23
Chuzhou	0.169	21	0.058	22	0.083	15	0.434	19
Chizhou	0.177	19	0.005	26	0.031	25	0.482	14
Xuancheng	0.184	17	0.107	16	0.035	24	0.446	17

Source: Organized by the authors.

The cities in the first tier rank in the top five in terms of proximity to innovation inputs and outputs, indicating that the stronger the economy, the greater the investment in innovation. However, Suzhou and Shanghai are ranked in the middle to lower tiers of the green innovation base proximity ranking, which, when combined with the proximity rankings of the second-tier criteria in Table 4, can be attributed to their low environmental base proximity ranking.

Most cities in the YRD city cluster are within this range. The low innovation base of cities lowers the level of innovation output and hinders them from fully exploiting their own characteristics and advantages. Figure 4a–c show that Zhoushan, Ma'anshan, Tongling, Chuzhou, and Chizhou are the five cities with low levels of innovation investment, which should focus on strengthening human, material, and financial investment. Figure 4g shows that Nantong, Zhenjiang, Taizhou, Zhoushan, and Taizhou should focus on improving their social infrastructure. Figure 4h shows that Wuxi, Changzhou, Nantong, and Hefei should focus on optimizing their environmental infrastructure.

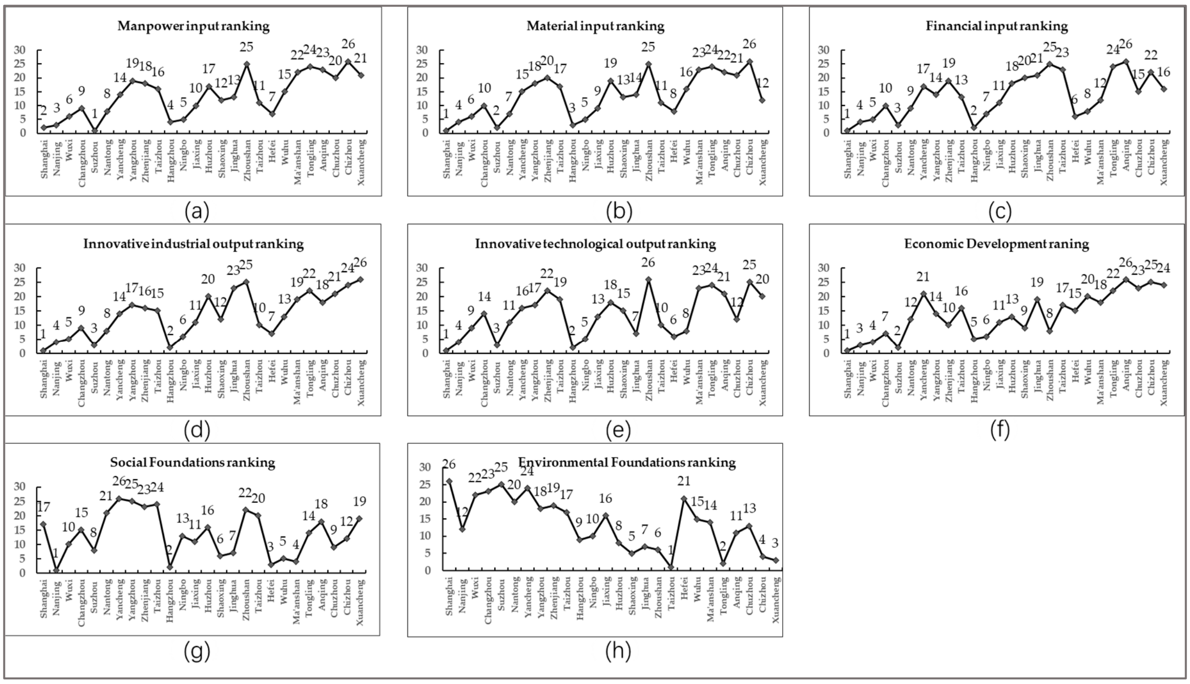

Figure 4. Ranking of the closeness of each tier 2 guideline level (Source: Organized by the authors).

The cities in the third tier, whose Green Innovation Index closeness is between 0.1 and 0.15, are ranked low. Yangzhou and Anqing lag behind in terms of the innovation investment index and should focus on investment in research and innovation, optimize infrastructure, focus on the training and introduction of highly skilled personnel, and attract foreign investment. At the same time, the three cities lagged in terms of the proximity of their green innovation bases. Figure 4f–h show that Yancheng should further improve its social infrastructure and economic development, and Yangzhou should further optimize its social and environmental bases. Figure 4a–e show that Anqing, which ranks 26th in terms of economic development indicators, should focus more on green innovation investment and the transformation of scientific research results to lay the foundation for sustainable development in the future.

4.4. Analysis of Calculation Results Using the Super-SBM Model

According to Figure 5, the YRD city cluster has a very diverse distribution of green innovation efficiency. Shanghai has the highest green innovation efficiency (1.957), placing it first, while Anqing has the lowest efficiency (0.423), placing it in 26th place. Shanghai, Jiangsu, Zhejiang, and Anhui have average green innovation efficiency ratings of 1.957, 0.979, 0.974, and 0.664, respectively. Accordingly, the YRD city cluster's overall capacity for green innovation is still not very high, with the exception of Shanghai, where the average efficiency value of green innovation has reached the efficiency frontier, whereas the other provinces' average efficiency values have not. Among these is Anhui Province's average value for green innovation efficiency. Anhui Province's average green innovation efficiency score is the lowest among them, and the province's overall green innovation efficiency rating is essentially poorer. The lowest efficiency ratings are seen in Tongling, Anqing, Chuzhou, Chizhou, and Xuancheng. This is because Anhui Province has a poor level of innovation and development, insufficient investment in innovation, inadequate environmental protection, and a low degree of green innovation efficiency. Combined with Figure 6, we can observe that the provinces of Jiangsu and Zhejiang have the highest concentration of effective DMUs, and the cities with the highest green innovation efficiency values are Shanghai, Nanjing, Wuxi, Suzhou, Hangzhou, Ningbo, Shaoxing, and Hefei. Shanghai, Nanjing, Hangzhou, and Hefei are the capital cities of the province, which is a municipality directly under the central government. They have a strong innovation base, abundant innovation resources, and the agglomeration effect of radiating the region. The four cities of Wuxi, Suzhou, Ningbo, and Shaoxing have strong economies, a wealth of innovative accomplishments, and a focus on green innovation and development. The radar map also reveals a polarization effect in the YRD cities' green innovation efficiency, with Shanghai, Suzhou, Hangzhou, and Hefei serving as the key hubs.

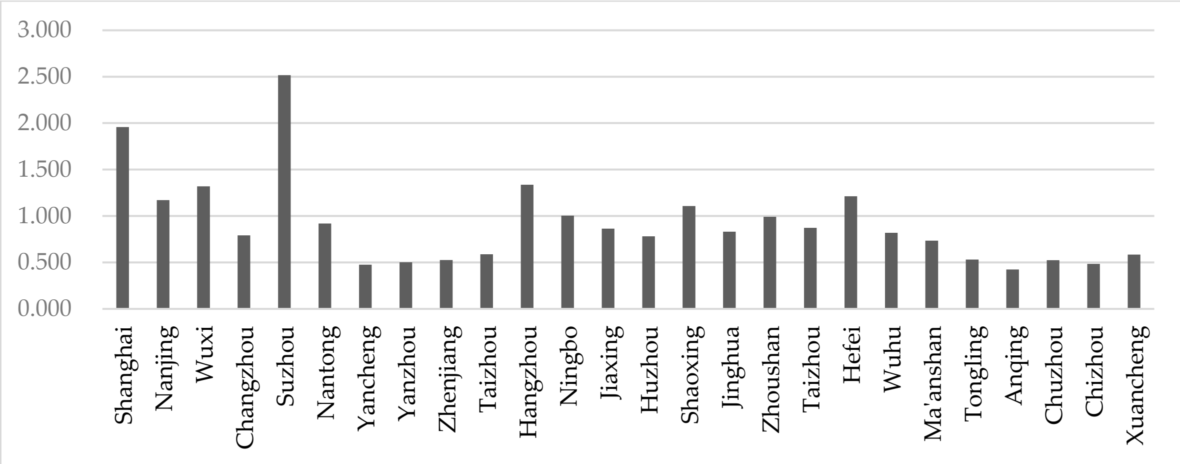

Figure 5. The YRD cities' green innovation efficiency values (Source: Organized by the authors).

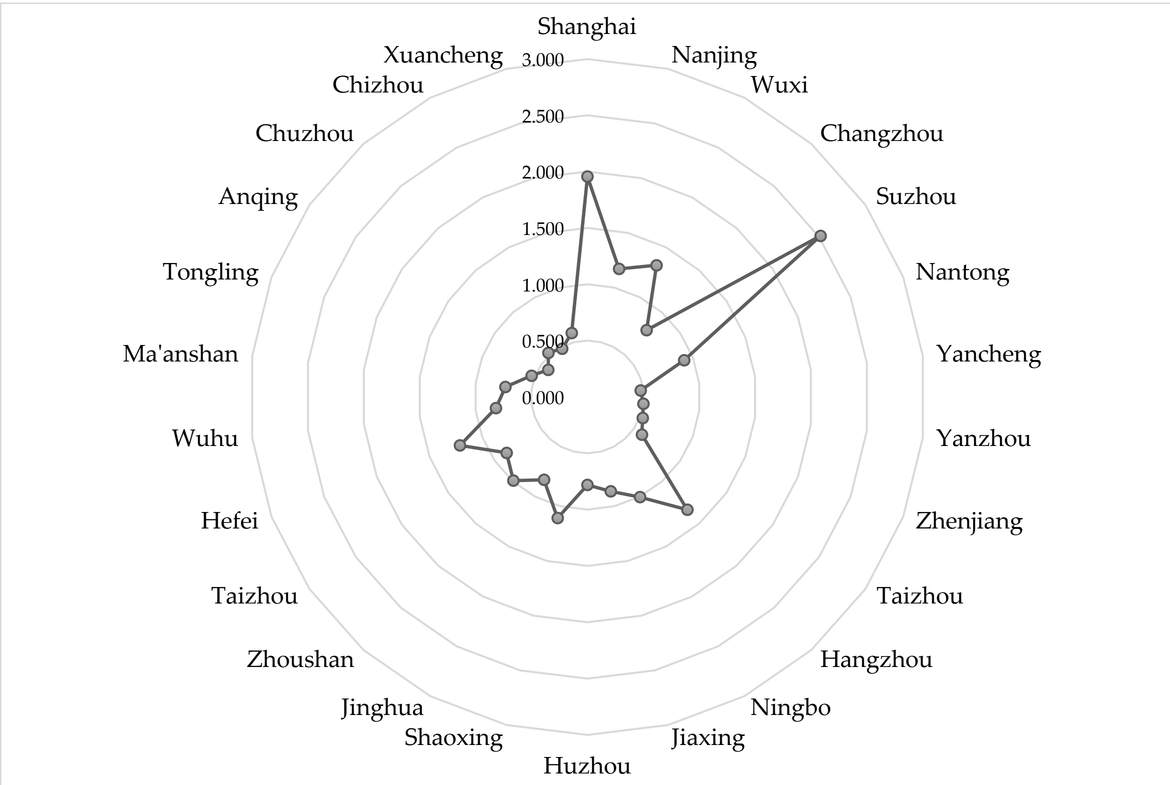

Figure 6. Radar distribution map of green innovation efficiency (Source: Organized by the authors).

4.5. Spatial Characterisation of Urban Economic Resilience

Using ArcGIS 10.8 software, the economic resilience of the 26 cities was classified according to 50%, 100%, and 150% economic resilience scores using the World Bank's regional economic criteria classification method, and the economic resilience intensity of 26 cities in the YRD in 2021 was visualized [87].

As shown in Figure 7, the economic resilience scores of cities can be classified into four levels: very low, low, medium and high. From the classification results, very-low-resilience cities included one city: Anqing; low-resilience cities included 18 cities: Changzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou, Wuhu, Ma'anshan, Tongling, Chuzhou, Chizhou, and Xuancheng; medium-high-resilience cities included three cities: Wuxi, Ningbo, and Hefei; and high-resilience cities included four cities: Shanghai, Hangzhou, Suzhou, and Nanjing.

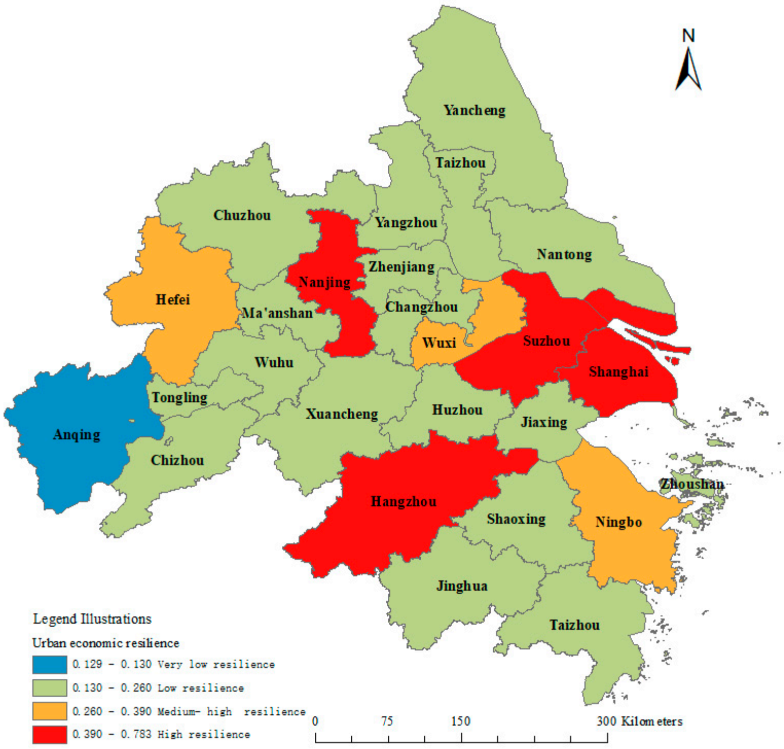

Figure 7. Geographical distribution of economic resilience in the YRD city cluster's 26 cities (Source: Organized by the authors).

From an academic perspective, the spatial pattern of economic resilience in the YRD city cluster indicates a general trend of high and low resilience in the east and west, respectively. The city cluster's overall economic resilience level was low, with only a small number of highly resilient cities and a large number of low-resilience cities. Furthermore, the unevenness of a city's level of economic resilience is more pronounced. Specifically, the economic resilience of the YRD city cluster followed a radiative distribution from the core area to the periphery, referred to as the spatial pattern of the core edge. The core area comprised four highly resilient cities: Shanghai, Hangzhou, Suzhou, and Nanjing. These cities have an edge in politics, economy, transportation, and culture with abundant development resources, robust economic strength, and a higher capacity for green innovation. The economic resilience of the cities in the core area shows a "ladder" distribution in terms of spatial radiation, with Nantong, Wuxi, Changzhou, Wuhu, Hefei, Jiaxing, Shaoxing, and Ningbo being within the radiation range of the cities in the core area. These cities have close economic exchanges with the cities in the core area, advanced manufacturing and modern service industries, and more complete infrastructure. They also have advanced manufacturing and modern service industries, a well-developed infrastructure and social foundation, and better conditions for green innovation, so their urban economic resilience level is higher than that of the cities on the edge of radiation. Cities on the periphery of the core cities, such as Anqing, have a lower level of economic resilience as they move farther from the core cities. These cities tend to have weak industrial bases, inadequate infrastructure, low levels of urban economic development, and low investment in green innovation capacity. Therefore, from the perspective of green innovation capacity, these cities have poor urban economic resilience.

5. Conclusions, Recommendations, and Research Limitations

5.1. Conclusions

Green innovation capability is an important indicator for assessing the comprehensive strength of a city and is a key factor in promoting sustainable urban economic development. This study uses the integrated index method to construct an index system for evaluating the green innovation capability of the economic resilience of cities and uses the covariance coefficient method to solve the problem of redundancy of index information, reflecting 99.8% of the original index information with 29.17% of the index. The green innovation capacity of 26 cities within the YRD cluster was assessed using the entropy-weighted TOPSIS method, and the effectiveness of each city's green innovation was examined using the Super-SBM model. Finally, ArcGIS 10.8 software was used to divide the economic resilience of the 26 cities in the YRD city cluster using the natural breakpoint method and to analyze the spatial layout characteristics of urban economic resilience. The main conclusions are as follows.

1. The existing evaluation techniques for green innovation capacity are more arbitrary and unable to address the issue of information duplication. This paper combines the entropy weight method and the TOPSIS method in order to address these drawbacks. An entropy weight TOPSIS evaluation model is created, which not only solves the issue of unbalanced weight ratios caused by the subjective empowerment evaluation method but also addresses the TOPSIS method's lack of indicator weight guidance that causes one-sidedness in the research findings. The weights are determined using the entropy value of the data itself, which also ensures the objectivity and fairness of the research findings. The covariance coefficient of variation method is then used to filter out the indicator data with the highest information content and remove the redundant indicators in order to further improve the completeness and representativeness of the indicator system. The findings demonstrate that the assessment model developed in this study is capable of accurately determining the extent of urban green innovation and may serve as a methodological foundation for determining the potential for regional green innovation. And the method have passed the sensitivity test in Appendix C, demonstrating the viability of the method.
2. Green innovation capability has a positive impact on the economic resilience of cities, and the level of green innovation capability of cities is often closely related to the economic level of the cities themselves. The stronger the economic strength of cities, the stronger their green innovation capability, which further feeds into the economic resilience of cities, forming a cycle of positive development and realizing the sustainable development of cities' economies. Cities with weaker economies, on the other hand, tend to have limited investment in green innovation. Green innovation is a long-cycle research activity that consumes large amounts of human, material, and financial resources and has limited output in the short term, making it difficult for cities with weaker economies to achieve a positive cycle of development.
3. The distribution of green innovation capacity in the YRD city cluster is uneven, with Shanghai, Suzhou, Hangzhou, and Nanjing having high levels of green innovation capacity and strong economic resilience, thus forming a core area where cities radiate outward, showing a "core-edge" distribution feature in space.

5.2. Recommendations

Based on the above findings, this study proposes policy recommendations for enhancing green innovation capacity and improving the economic resilience of cities.

1. Increase financial investment to attract talent inflows. Rich innovation resources are important for improving green innovation. Cities should actively respond to the country's innovation-driven development strategy, increase investment in innovation

funds, attract foreign investment, and give full play to the guiding and incentivizing roles of fiscal policies in green innovation activities. Second, to adhere to green development, governments should consider the importance of talent in innovation and development. It is necessary to further optimize talent introduction policies, reduce the threshold for talent introduction, encourage talent inflow, promote the transformation of scientific and technological achievements, and provide a steady stream of power for green innovation.

2. Promote urban cooperation and strengthen coordinated development. To improve the overall level of green innovation and coordinated development of the YRD city cluster, cities should actively explore the establishment of a regional linkage development mechanism and promote regional integration. First, we should give full play to the "growth pole" advantages of Shanghai, Hangzhou, Suzhou, and Nanjing in urban green innovation and promote the development of high-tech and modern service industries in central cities. Second, to strengthen exchanges and cooperation between cities in the core area and radiation cities to promote the free flow of green elements, radiation-edge cities should comprehensively consider green innovation and economic development, cultivate urban characteristic industries, and promote coordinated economic development within urban agglomerations.
3. Implement local conditions and enhance economic resilience. A city's comprehensive strength is the key to determining its economic resilience. From the perspective of green innovation, the difference in urban economic resilience is mainly due to differences in innovation investment and foundations. Although Hefei and Nanjing are not affected by the spillover effect of green innovation space in the eastern part of the YRD, the two cities rely on the quantitative advantages of universities and research institutions to achieve the integrated development of the "industry-university-research-application", making urban economic resilience reach the levels of medium-high-resilience and high-resilience cities, respectively. Other cities can combine their factor endowments, clarify their positioning, and accurately implement policies according to local conditions to continuously improve the overall economic resilience of urban agglomerations.

5.3. Research Limitations

There are some limitations in this paper that need to be addressed in future research. This study focused on the evaluation and analysis of urban agglomerations in the YRD. The lack of comparisons between different urban agglomerations is one avenue of exploration for future research. Further research conclusions should be drawn in future studies based on a comparison of different urban agglomerations. This study only collected data from 26 cities in the YRD in 2021, which does not intuitively reflect the development level of green innovation capacity and urban economic resilience over time. In future studies, we will focus on multiyear panel data econometric regressions to make the research results more intuitive and convincing.

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Appendix A. Utilization of Expert Knowledge

Expert knowledge is subjective and based on the individual experiences of an expert. The reliability of expert knowledge depends on how well-versed the expert is in his or her area, and the opinions of experts on a given subject may vary based on their backgrounds and levels of experience [88]. Participants brainstormed the issue of this study, focused on the center of the problem and provided various points of view, widening the scope of the research in this paper. For instance, Lv thinks that resources are crucial to urban green innovation because "green innovation"—in contrast to "innovation"—places a greater emphasis on social responsibility and environmental friendliness. As a result, more resources are needed to give businesses the energy they need to research and develop green technology, lower the cost of pollution and environmental pressure, and increase the share of the green economy in a city's economy. The capacity for green innovation is closely correlated with a city's economic strength. The more economically developed cities are better able to take advantage of the resource clustering effect, which is also reflected in this paper's concluding remarks. Liu noted that the YRD integrated development plan's general outline was presented by China in 2019. In the study, it is crucial to focus on both the green innovation growth of individual cities within the urban agglomeration and the green synergistic innovation of the YRD city cluster as a whole, which is of great significance for the development of the regional economy in other areas. According to the study findings presented in this paper, the YRD city cluster has an unequal distribution of green innovation capability, with a stepwise dispersion outward from the core green innovation cities. The rational division of labor among cities can help to further enhance the synergistic development of the urban agglomeration economy. This paper makes policy recommendations to strengthen the overall synergistic development of the urban agglomeration based on the research findings of the existing problems.

Appendix B. TOPSIS Method and Super-SBM Mode Introduction

Appendix B.1. TOPSIS Method Introduction

The TOPSIS method is a ranking method, first proposed by Hwang and Yoon, which ranks a limited number of evaluation objects according to their proximity to an idealized target; that is, the ranking of evaluation objects is determined according to their proximity to optimal and inferior solutions [89]. The calculation formulae refer to [38,90].

Determine the Optimal Solution F^+ and The Inferior Solution F^-

$$F_{ij} = W_{ij} \times Z_{ij}; (i = 1, 2, 3, \ldots n; j = 1, 2, 3, \ldots m)$$

$$F_i^+ = maxF_{ij} \; ; \; F^+ = (F_1^+, F_2^+, F_3^+, \ldots\ldots, F_m^+)$$

$$F_i^- = minF_{ij} \; ; \; F^- = (F_1^-, F_2^-, F_3^-, \ldots\ldots, F_n^-)$$

Determine the Optimal Solution Distance and Inferior Solution Distance

$$\text{Optimal solution distance}: \; D_i^+ = \sqrt{\sum_{j=1}^{m} (F_{ij} - F_i^+)^2}; (i = 1, 2, 3, \ldots\ldots n; j = 1, 2, 3 \ldots m)$$

$$\text{Inferior solution distance}: \; D_i^- = \sqrt{\sum_{j=1}^{m} (F_{ij} - F_i^-)^2} \; ; (i = 1, 2, 3, \ldots\ldots n; j = 1, 2, 3 \ldots m)$$

Calculate the Closeness of the Evaluation Object to the Ideal Solution C_i Value

$$C_i = \frac{D_i^-}{D_i^- + D_i^+}; (i = 1, 2, 3, \ldots\ldots n); C_i \in [0, 1]$$

In the equation, C_i indicates the closeness of green innovation capacity to the optimal and inferior solutions of each indicator of the evaluation object in a city's economic resilience evaluation index system. The smaller the value of C_i, the weaker the green innovation capability of the city and the lower the performance. By ranking the evaluation objects in descending order of relative closeness, we can obtain a ranking of the green innovation capabilities.

Appendix B.2. Super-SBM Model Introduction

Currently, data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are the two approaches most frequently used in academic settings to assess the efficacy of green innovation. One benefit of SFA over DEA is its capacity to take into account the effects of numerous random mistakes in the calculation outputs, enhancing measurement accuracy. Green innovation often requires several inputs and outputs, whereas SFA is only relevant to situations with a single outcome. For this reason, the DEA technique is used by the majority of academics when evaluating the effectiveness of green innovation. However, because of problems with relaxation, the conventional DEA model has a restriction in terms of measurement precision. To address the relaxation issue with the conventional DEA model, Tone (2001) introduced the SBM model. However, it also appears that numerous decision-making units are effective using the SBM model [91]. Based on this, Tone (2002) proposed the Super-SBM model, which can compare and sort many effective decision-making units as well as address the relaxation problem [92].

Based on the aforementioned analyses and the current state of research, this paper selects the Super-SBM model with non-oriented and constant returns to scale (CRS) to measure the green innovation capacity of 26 cities in the YRD city cluster in 2021.

Appendix B.3. Model Expression

The mathematical expression of the model is as follows:

$$\min\rho_{SE} = min\frac{1+\frac{1}{m}\sum\limits_{j=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{q_{1+q_2}}\left(\sum\limits_{r=1}^{q1}\frac{s_i^+}{Y_{rk}}+\sum\limits_{r=1}^{q1}\frac{s_t^{b-}}{b_{tk}}\right)}$$

$$s.t.\begin{cases}\sum\limits_{j=1,j\neq k}^{n}\lambda_j x_{ij}-s_i^-\leq x_{ik}\\ \sum\limits_{j=1,j\neq k}^{n}\lambda_j y_{ij}+s_r^+\geq x_{rk}\\ \sum\limits_{j=1,j\neq k}^{n}\lambda_j x_{tj}-s_t^{b-}\leq x_{tk}\\ \sum\limits_{j=1,j\neq k}^{n}\lambda_j=1\\ \mathrm{i}=1,2,\ldots,\mathrm{m};\mathrm{r}=1,2,\ldots,\mathrm{q}_1;\mathrm{t}=1,2,\ldots,\mathrm{q}_2;\mathrm{j}=1,2,\ldots,\mathrm{n}(\mathrm{j}\neq\mathrm{k})\end{cases}$$

Among them, ρ_{SE} is the efficiency value, $\min\rho_{SE}\geq 0$, and the higher the ρ_{SE} value, the more productive the decision-making unit is. If $\rho_{SE}>1$, the decision-making unit exhibits an effective growth trend. Each input is represented by x_i, each expected output is represented by y_j, each undesirable output is represented by b_t, each slack variable of input is represented by s_i^-, and each slack variable of expected output is represented by s_r^+. s_t^{b-} represents the slack variable of undesirable output, m represents the number of input indicators, q_1 represents the number of expected output indicators, q_2 represents the number of undesirable output indicators, λ is the weight vector, and j is the number of DMUs. The calculation formulae refer to [93,94].

Appendix C. Model Sensitivity Analysis

We conducted a sensitivity analysis to examine the degree of change in the decision results. This was accomplished by changing the assumptions and statistical methods and conducting the statistical analysis again to determine the robustness of the assessment method. In this paper, the rank and ratio comprehensive (RSR) method and VIKOR method are used to make decisions based on the data again, and the decision results obtained from different decision methods are compared with the results of this paper, as shown in Table A1 below.

Table A1. Evaluation results of comparison methods.

City	TOPSIS Method Ranking	RSR Method Ranking	VIKORE Method Ranking
Shanghai	1	1	1
Nanjing	4	4	4
Wuxi	6	5	7
Changzhou	14	9	11
Suzhou	2	2	3
Nantong	9	8	9
Yancheng	26	26	26
Yangzhou	24	23	18
Zhenjiang	23	25	24
Taizhou	22	21	15
Hangzhou	3	3	2
Ningbo	5	6	5
Jiaxing	13	12	10
Huzhou	18	18	14
Shaoxing	8	11	12
Jinghua	10	14	17
Zhoushan	20	16	13
Taizhou	11	13	16
Hefei	7	7	6
Wuhu	12	10	8
Ma'anshan	15	15	20
Tongling	16	19	22
Anqing	25	24	25
Chuzhou	21	20	21
Chizhou	19	22	23
Xuancheng	17	17	19

Source: Organized by the authors.

According to the Table A1, we can see that no matter how the method is changed, Shanghai, Suzhou, Hangzhou, and Nanjing are cities that maintain their top rankings. This not only serves to confirm this study's findings that the four urban core area cities are Shanghai, Suzhou, Hangzhou, and Hefei, but it also demonstrates the efficacy and stability of the methodology proposed in this paper.

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