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Research on the Measurement of Low-Carbon Competitiveness of Regional Cold Chain Logistics Capacity Based on Triangular Fuzzy Evaluation Rating–Gray Correlation Analysis

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Abstract: Cold chain logistics is an industry that generates high levels of carbon emissions. In the context of a low-carbon economy, it is crucial to recognize the low-carbon competitiveness of regional cold chain logistics and to implement effective measures to guide the development and improvement of their low-carbon competitiveness. This is essential for transitioning the economic development model and promoting low-carbon economic growth. This article proposes a low-carbon competitiveness evaluation model known as the Triangular Fuzzy–Gray Correlation Evaluation Model. This model is based on the Triangular Fuzzy Theory and Gray System Theory. According to the calculated logistics low-carbon competitiveness index, a scatter plot is used to rank and classify the evaluation objects. This method utilizes triangular fuzzy numbers as evaluation levels and further expands upon them by introducing the concept of gray correlation in group decision making. By constructing relative closeness based on curve similarity, the improved method possesses a strong ability to capture information and objectivity compared to traditional models. The selected critical indicators cover four significant aspects: low-carbon environment, low-carbon flow service capability, energy consumption in cold chain logistics, and low-carbon energy transition. Empirical research is being conducted using relevant data from Henan in 2022. The measured results are divided into four levels of competition. Using the diamond model, this study analyzes the development of low-carbon cold chain logistics at different levels in each city and provides corresponding recommendations.

Keywords: triangular fuzzy number; improved gray relational analysis; competitiveness evaluation; cold chain logistics; low carbon

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1. Introduction

With the rapid development of the global economy and the continuous growth of the world's population, the detrimental effects of greenhouse gas emissions on the ecological environment and sustainable development have garnered close attention from countries worldwide [1]. To address global climate change, the Chinese government has implemented a series of policies and regulatory frameworks to promote the transition to green and low-carbon practices in various industries. The goal is to achieve "peak carbon" by 2030 and "carbon neutrality" (or the "dual carbon" strategic objectives) by 2060 [2]. The cold chain logistics industry is a sector that has relatively high carbon emissions. According to a report from the China Federation of Logistics & Purchasing (CFLP), the post-harvest cold chain for fresh agricultural products in China consumes approximately CNY 80 billion of electricity annually for low-temperature refrigeration. Despite the late start of the cold-chain logistics industry in China, it has experienced rapid growth in recent years. This can be attributed to the improvement of national consumption patterns and the rapid growth of online commerce. Not only has the cold chain infrastructure continuously expanded, but the supply chain system has also become more robust [3].

However, the continuous increase in total carbon emissions accompanies the rapid development of the cold chain logistics industry. Therefore, against the "dual carbon" goals, the Chinese cold chain logistics industry faces a sharp contradiction between scale expansion and carbon emission control. It must accelerate steps to reduce emissions and energy consumption and undergo a low-carbon transformation. Cold chain logistics' green and low-carbon transformation will be a crucial milestone in achieving China's "dual carbon" goals and a significant focus for promoting the high-quality, sustainable, and healthy development of the cold chain logistics industry. Under these circumstances, it is necessary to objectively evaluate the low-carbon competitiveness of regional cold-chain logistics, understand the level of low-carbon development in regional cold chain logistics, and take appropriate measures to guide the development and enhance the low-carbon competitiveness of regional cold chain logistics. This is essential for transforming the economic development mode and promoting the development of a low-carbon economy.

Domestic and international research on low-carbon logistics capacity mainly focuses on three aspects: enterprises, supply chains, and regions. Scholars in reference [4] have previously studied logistics capacity from the perspective of enterprise resources. They argue that logistics capacity is a strategic approach to effectively enhance resource utilization. Scholars in reference [5] have explored the relationship between logistics capability and the operational efficiency of enterprises in the international business environment. They have pointed out that the utilization of information technology can greatly enhance logistics capabilities, thereby improving the operational efficiency of the enterprise. Yumin Li et al. constructed a regional logistics low-carbon competitiveness evaluation index system from three aspects: logistics competitive environment, service capability, and development level. They used the projection tracking algorithm to conduct empirical analysis [6]. Wenliang Bian et al. developed an evaluation model to assess the competitiveness of the national logistics industry. The model considers three key factors: logistics effectiveness, logistics strength, and logistics potential. The researchers of this document utilized factor analysis to objectively measure the competitiveness of the logistics industry in various countries [7]. Tai Zhou and his colleagues defined regional logistics capacity and developed an evaluation system for regional logistics capacity based on four aspects: infrastructure support capacity, business management operation capacity, information system guarantee capacity, and development environment support capacity [8]. Xin Jiang conducted an empirical analysis by constructing a low-carbon logistics environment, evaluating the strength and potential of low-carbon logistics, and utilizing the fuzzy material element method. The data used for the analysis were collected from the Yangtze River Delta and the eight provinces and one city in the central region. The study identified the weak links in logistics development and proposed suggestions for improvement [9]. Li Li developed a regional low-carbon logistics evaluation index system, which includes elements such as the low-carbon logistics environment, low-carbon logistics capabilities, low-carbon logistics potential, and the level of low-carbon logistics. Li Li then conducted an empirical analysis using data from the Beijing–Tianjin–Hebei region as an example [10]. Xu Xu believes that low-carbon logistics aims to achieve low energy consumption, low pollution, and low emissions in the logistics process, using energy-efficient technology, renewable energy technology, waste recovery, logistics system optimization, and other methods to achieve low carbonization throughout the logistics operation process and logistics management [11]. Ma Shihua and associated scholars based logistics capability on logistics operation capability and logistics element capability, and analyzed the competitive relationship in the supply chain from the perspectives of having or not having capability constraints, identifying the most competitive supply chain [12]. After examining these papers, it is evident that scholars have conducted in-depth analyses of logistics' comprehensive competitiveness from the perspectives of enterprises [4,5], regions [6–11], or supply chains [12,13]. However, the research on measuring the low-carbon competitiveness of regional cold chain logistics is not extensive enough, and there are fewer and less in-depth studies on this topic. The existing literature has notable issues in constructing an evaluation index system for low-carbon competitiveness in cold chain logistics and in data processing. Further research and exploration are needed to address these issues. The existing literature on the competitiveness of regional cold chain logistics lacks flexibility in modeling and evaluating the constructed model. The evaluation language is rigid, which restricts the ability to convey pertinent evaluation information. This fixed evaluation level restricts experts from selecting options based on their preferences. Therefore, further research is needed to address these limitations and explore pertinent issues within the existing research context.

Based on the analysis of existing papers and considering the characteristics of low-carbon cold chain logistics, this paper constructs a regional low-carbon competitiveness index evaluation system for cold chain logistics from four aspects: low-carbon environmental conditions, low-carbon flow service capability, cold chain logistics efficiency, and low-carbon energy transition. The paper uses the triangular fuzzy number gray correlation analysis method to measure the logistics low-carbon competitiveness index of evaluation objects within the region. Based on the scatter plot of this index, the evaluation objects are ranked and classified. Finally, the paper analyzes logistics' low-carbon competitiveness based on Henan's data. According to the competitiveness index values of the 18 cities in Henan, they are divided into four hierarchical levels. The diamond model is adopted to analyze the development of low-carbon logistics in cities at different levels of growth. The model proposed in this paper expands the traditional 7 fixed basic evaluation levels to 28 levels. This expansion allows the capture of fuzzy and uncertain data, making the evaluation language simple and easy to operate. It can describe expert decision-making thoughts in any situation, demonstrating substantial completeness.

2. Regional Cold Chain Logistics Low-Carbon Evaluation Index System Construction

When evaluating the low-carbon competitiveness of cold chain logistics, constructing a scientific and reasonable indicator system is very crucial. Based on the research of related scholars, this part mainly introduces the construction principles of the indicator system and the key factors to be considered when evaluating the low-carbon competitiveness of cold chain logistics.

2.1. Principles of Index System Construction

To ensure an accurate assessment of the level of development in low-carbon cold chain logistics competitiveness, we have constructed an evaluation system for such development. This system is based on the principles of representativeness, certainty, independence, and operability [13]. This system considers various aspects, including the cold chain logistics environment, the capacity of cold chain logistics services, the energy consumption level in cold chain logistics, and the energy transition within the cold chain logistics industry. It serves as the guiding framework for evaluating the development of cold chain logistics. Among them, operability indicates that the index system should be constructed with careful consideration of the actual situation to prevent data from becoming inaccessible. According to the aforementioned guidelines, Table 1 illustrates the low-carbon evaluation index system of cold chain logistics in this paper.

2.2. Analysis of the Low-Carbon Evaluation Index System for Cold Chain Logistics

2.2.1. Low-Carbon Development Environment for Cold Chain Logistics

The development environment of cold chain logistics is an external factor that affects the level of low-carbon development in this industry. It encompasses three major aspects: the economic environment, the social environment, and the regional transportation environment. The regional economic environment is determined by the per capita Gross Domestic Product (GDP) and the total regional GDP, which are directly related to the level of development of the regional logistics cold chain. The level of cold chain logistics services is higher in economically developed regions, which enhances the competitiveness of low-carbon logistics. The social environment mainly includes policies that govern low-carbon logistics, such as financial and tax support, mandatory policies for achieving energy saving and emission reduction targets, and laws and regulations related to low-carbon logistics, among others. The relevant low-carbon policies and regulations play a guiding or mandatory role in improving the implementation of low-carbon practices in the logistics industry. Superior geographic location and transportation conditions also contribute to enhancing the low-carbon competitiveness of the logistics industry.

Table 1. Evaluation index system for the low-carbon development of cold chain logistics.

Goal	Primary Index	Secondary Index	Method	Value Direction
Low-Carbon Competitiveness of Cold Chain Logistics	A_1 low-carbon environment	B_1 Low-carbon logistics social environment	Qualitative	+
		B_2 Regional traffic environment	Qualitative	+
		B_3 Regional GDP	Quantitative	+
		B_4 Per capita GDP	Quantitative	+
	A_2 low-carbon flow service capability	B_5 Logistics Infrastructure	Qualitative	+
		B_6 Intelligent Transportation System Application Level	Qualitative	+
		B_7 Advanced Transportation Mode Application Degree	Qualitative	+
	A_3 energy consumption in cold chain logistics	B_8 Energy consumption per unit output value of cold chain logistics industry	Qualitative	+
	A_4 low-carbon energy transition	B_9 Renewable Energy Usage	Qualitative	+
		B_{10} Renewable Packaging Usage	Qualitative	+

2.2.2. Cold Chain Logistics Service Capability

Low-carbon development of regional cold chain logistics requires the efficient and low-cost completion of logistics services through the coordinated and mutually supportive interaction of relevant facilities and support. The material prerequisites for reducing logistics carbon emissions are the investment and utilization of fixed assets in the logistics industry, such as road and postal mileage. Expanding the number of cold chain logistics parks can effectively centralize goods from various regions, leading to enhanced transportation efficiency and reduced transportation costs. The extensive network of well-maintained highways and postal routes indicates favorable road conditions in the region, which significantly reduces the risk of traffic congestion in logistics transportation and enhances operational efficiency. The platform and service investment in the development of cold chain logistics can significantly improve logistics transport efficiency and enhance the service capability of the logistics industry. For example, Intelligent Transportation Systems (ITS), which integrate functions such as the Global Positioning System (GPS), Electronic Toll Collection System (ETC), and Geographic Information System (GIS), can efficiently plan the optimal transportation route, avoiding detours by transport vehicles. The ITS system can enable cold chain transportation vehicles to have real-time awareness of road conditions, helping them avoid traffic congestion and find the shortest transportation route to improve efficiency. Users can also access real-time visibility of the status and location of goods, as well as estimated delivery times. As a result, the ITS system significantly enhances logistics efficiency.

Cold chain logistics information platforms based on internet technology can connect vehicle and goods sources effectively, reducing the randomness of searching for cars or goods. Therefore, logistics information technology, advanced transportation methods, and other logistics platforms play a crucial role in enhancing the low-carbon competitiveness of logistics. Advanced transportation methods such as drop-and-pull and multi-modal transportation can significantly increase the loading rate and utilization efficiency of transportation tools, thereby further improving logistics operational efficiency.

2.2.3. Efficiency of Cold Chain Logistics

Logistics efficiency mainly refers to external indicators of logistics socialization and internal indicators of operational efficiency. These indicators include logistics efficiency and carbon emission levels. The level of socialization in cold chain logistics refers to the proportion of employees involved in cold chain logistics compared to the total number of employees in the tertiary industry. It serves as an indicator for measuring the level of socialization in the logistics industry. Generally, the higher the level of socialization in cold chain logistics, the greater the level of development, and consequently, the higher the efficiency of the cold chain logistics. The measurement of carbon emissions in logistics primarily involves calculating the carbon emissions per unit of GDP and the energy consumption per unit of output value in the cold chain logistics industry. The carbon emissions per unit of GDP are an indicator for measuring low-carbon economic development. It is related to the scale of the economy, energy structure, and level of industrialization. This indicator serves as a measure of the external low-carbon environment for the development of low-carbon logistics. It can be calculated by converting GDP, comprehensive energy consumption, and carbon emission coefficients. The energy consumption per unit of output value in the cold chain logistics industry is calculated by dividing the energy consumption by the value added.

2.2.4. Energy Transition

Cold chain logistics is an industry with relatively high carbon emissions. With the emergence of renewable energy sources, there is a need for structural adjustments in the energy requirements for the development of cold chain logistics in order to significantly reduce greenhouse gas emissions. It involves utilizing environmentally friendly energy sources and packaging materials to decrease carbon emissions in logistics, encourage the adoption of energy-saving technologies and equipment in logistics parks, actively promote the growth of eco-friendly warehousing, and facilitate the installation of "rooftop photovoltaic power stations" in logistics parks and trading markets to establish a self-sustaining energy system for logistics. It fully implements the national standard for eco-friendly packaging in express delivery, promotes the use of recycled materials for packaging, and reduces unnecessary and excessive packaging.

3. Evaluation Model for Low-Carbon Competitiveness of Regional Cold Chain Logistics

In this part, based on the elaboration of the extension of the evaluation language level, the calculation steps of the triangular fuzzy–gray correlation evaluation model are described in detail, and the process of clarifying the fuzzy evaluation language level is shown step by step. Its specific details are as follows:

3.1. Evaluation Ratings Based on Triangular Fuzzy Numbers

3.1.1. Triangular Fuzzy Numbers and Evaluation Semantics

In expert group decision making, the rating level can generally be set to seven. This can be expressed using a triangular fuzzy number, as shown in Table 2. The graphical representation of the triangular fuzzy evaluation level is shown in Figure 1. If the evaluation grade considers a scheme good, it specifies, by a certain indicator, that the degree has to take a value between five and nine. The most likely value is seven, and the triangular evaluation representation value can be methodical (5,7,9).

3.1.2. Triangular Fuzzy Evaluation Rating Extension

In the actual comprehensive evaluation group, decision-making experts may think that the evaluation results of a judgment object are between "very poor" and "poor"; in this case, the traditional seven-level evaluation language fixed in Table 1 can not meet the evaluation requirements of this type of leapfrog. And so, with "very poor" as the left boundary and "poor" as the right boundary, the composition of a new fuzzy evaluation level of "very poor–poor", notated as D_{13}, is produced. Accordingly, the extended fuzzy evaluation level can be defined as $D_{ij} = (i, j = 1, 2, 3, 4, 5, 6, 7; i \leq j)$. The traditional 7 fixed basic evaluation levels mentioned above can be expanded to include a total of 28 evaluation levels.

Table 2. Triangular fuzzy number representation of evaluation levels.

Sign	Grade	Triangular Fuzzy Number Representation
D_{11}	pretty poor	(0,0,1)
D_{22}	very poor	(0,1,3)
D_{33}	poor	(1,3,5)
D_{44}	ordinary	(3,5,7)
D_{55}	well	(5,7,9)
D_{66}	very well	(7,9,10)
D_{77}	pretty well	(9,10,10)

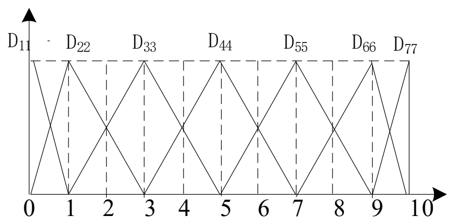

Figure 1. Expression of triangular fuzzy rank.

3.1.3. Possible Scenarios after Extension of Evaluation Ratings

The following are the general possibilities for expert evaluation of an alternative object in a comprehensive assessment:

The evaluation level belongs completely to D_{ii}, which can be expressed as $\{(D_{ii}, 1.0)\}$. In a spanning situation, the evaluation level of an alternative object is considered to belong to $D_{ij}(i \leq j)$ completely, and it is recorded as $\{(D_{ij}, 1.0)\}$. A distributed evaluation situation, where the evaluation is considered to span the two neighboring levels, is recorded as $\{(D_{ii}, \alpha), (D_{i+1i+1}, \beta)\}$ and $\alpha + \beta = 1$. Ineffective evaluation refers to the evaluation result of a certain indicator that does not belong to D_{ij} at all. Ineffective evaluation also includes the situation of $\{(D_{17}, 1.0)\}$, which does not contain any information. Invalid evaluations should be eliminated from the evaluations.

3.1.4. Clarification of Fuzzy Evaluation Ratings

The method for clarifying fuzzy numbers is described in reference [14]. The triangular fuzzy number clarification method is similar to the rectangular fuzzy number. It involves a triangular fuzzy set $\widetilde{A}$ on the domain $X = [X^-, X^+]$, with an affiliation distribution function as:

$$\mu_{\widetilde{A}}(x) = \begin{cases} 0 & X^- \leq x \leq a \\ L(x) & a < x \leq b \\ R(x) & b < x \leq c \\ 0 & c < x \leq X^+ \end{cases}$$

In the given equation, $L(x)$ and $R(x)$ represent the affiliation degrees of the left and right sides of the triangular fuzzy numbers, respectively. $L(x)$ is a strictly increasing function, while $R(x)$ is a strictly decreasing function. The graph of the affiliation function for the triangular fuzzy set $\widetilde{A}$ is shown in Figure 2. According to the literature [14], the equation for clarifying a triangular fuzzy number is $C = C^-/(C^- + C^+)$, where $C^- = \int_0^1 [R^{-1}(\mu) - X^-] d\mu$ and $C^+ = \int_0^1 [X^+ - L^{-1}(\mu)] d\mu$. Using this clarification equation, the clarification table for the triangular fuzzy number is obtained, as shown in Table 3.

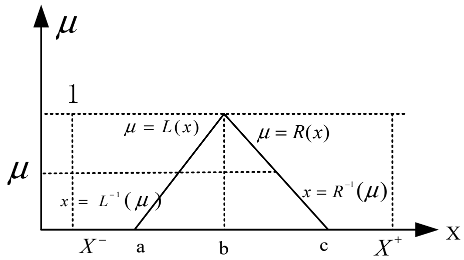

Figure 2. The membership of fuzzy triangular.

Table 3. Clarification of triangular fuzzy rank.

d_{11} = 0.048	d_{12} = 0.167	d_{13} = 0.286	d_{14} = 0.375	d_{15} = 0.444	d_{16} = 0.487	d_{17} = 0.500
	d_{22} = 0.174	d_{23} = 0.296	d_{24} = 0.387	d_{25} = 0.457	d_{26} = 0.500	d_{27} = 0.512
		d_{33} = 0.333	d_{34} = 0.429	d_{35} = 0.500	d_{36} = 0.523	d_{37} = 0.556
			d_{44} = 0.500	d_{45} = 0.571	d_{46} = 0.613	d_{47} = 0.625
				d_{55} = 0.667	d_{56} = 0.704	d_{57} = 0.714
					d_{66} = 0.826	d_{67} = 0.833
						d_{77} = 0.952

3.2. Decision-Making Model Based on Triangular Fuzzy Number–Gray Correlation Analysis

Gray correlation analysis was first proposed by Professor Deng Julong in 1982 and was initially used in control theory [15]. Later, it has been widely used by many scholars in engineering [16–19], economics [20,21], management [22,23], and other related fields. It mainly compares the decision-making object with the ideal solution and the anti-ideal solution based on curve similarity to construct the decision matrix. The basic idea is that the correlation is greater when the curve shape of the decision-making solution set is closer to the ideal solution, and vice versa when it is closer to the anti-ideal solution. Combined with the challenges of collecting relevant data to measure the competitiveness of cold chain logistics, as well as dealing with fuzzy and uncertain data, this paper proposes a measurement and evaluation model that utilizes a combination of triangular fuzzy number–gray correlation analysis. The specific steps for decision making are outlined as follows.

3.2.1. Determine the Original Evaluation Matrix $\widetilde{X}$

In fuzzy group decision making, the set of expert personnel is denoted as $A_l(l = 1,2,\cdots,L)$, the set of alternative objects is denoted as $O_m(m = 1,2,\cdots M)$, and the set of judgment indicators is denoted as $Y_n(n = 1,2,\cdots,N)$. The result of a fuzzy rank judgment made by the expert A_l on the alternative object O_m, based on the indicator Y_n, can be denoted as $\left\{(D_{ij}, y^l_{ij}(O_m, Y_n))i, j = 1,2,\cdots 7; i \leq j\right\}$. Here, $y^l_{ij}(O_m, Y_n)$ represents the degree of affiliation of expert A_l, who considers the alternative object O_m to be rated D_{ij} in relation to the indicator Y_n. Let the weight of each expert A_l be λ_l, which denotes the importance of the evaluator in the evaluation, and $\sum_{l=1}^{L} \lambda_l = 1$. The fuzzy comprehensive evaluation results, made by A_l experts based on n indicators for m objects, are as follows:

$$\begin{aligned} \widetilde{X}_m(n) = \Big\{&(D_{ij}, y_{ij}(O_m, Y_n))(i, j = 1,2,\cdots,7; i \leq j, \\ &m = 1,2,\cdots,M; n = 1,2,\cdots,N)\Big\} \end{aligned} \tag{1}$$

where $y_{ij}(O_m, Y_n) = \sum_{l=1}^{L} \lambda_l y_{ij}^l(O_m, Y_n)$. Equation (1), when written as a matrix, can be expressed as:

$$\widetilde{X} = \begin{bmatrix} \widetilde{X_1}(1) & \widetilde{X_1}(2) & \cdots & \widetilde{X_1}(N) \\ \widetilde{X}_2(1) & \widetilde{X}_2(2) & \cdots & \widetilde{X}_2(N) \\ \vdots & \vdots & \vdots & \vdots \\ \widetilde{X}_M(1) & \widetilde{X}_M(2) & \cdots & \widetilde{X}_M(N) \end{bmatrix} \quad (2)$$

3.2.2. Clarification of Fuzzy Matrices

$$\begin{aligned} & X_M(N) = \sum_i \sum_j d_{ij}\, y_{ij}(O_m, Y_n)(i, j = 1, 2, \cdots, 7 \\ & i \leq j, m = 1, 2, \cdots, M; n = 1, 2, \cdots, N) \end{aligned} \quad (3)$$

In the expression of Equation (2), $\widetilde{X}_M(N)$ is a quantity that requires clarification. The value of d_{ij} is provided in Table 1. According to Equation (3), the clarification evaluation matrix can be obtained as Equation (4).

$$X = \begin{bmatrix} X_1(1) & X_1(2) & \cdots & X_1(N) \\ X_2(1) & X_2(2) & \cdots & X_2(N) \\ \vdots & \vdots & \vdots & \vdots \\ X_M(1) & X_M(2) & \cdots & X_M(N) \end{bmatrix} \quad (4)$$

3.2.3. Calculate the Weighted Normalization Matrix

Determination of the weights of the evaluation indicators: let us consider the fuzzy triangular fuzzy weight assigned by expert A_l to the evaluation indicator Y_n is $\widetilde{\omega}_n^l = (\omega_{na}^l, \omega_{nb}^l, \omega_{nc}^l)(n = 1, 2, \cdots, N; l = 1, 2, \cdots, L)$. The evaluation weights assigned by all experts to the indicator Y_n can be determined and expressed as follows:

$$\omega_n = \sum_l \lambda_l \widetilde{\omega} = \left(\sum_l \lambda_l \omega_{na}^l, \sum_l \lambda_l \omega_{nb}^l, \sum_l \lambda_l \omega_{nc}^l \right) \quad (5)$$

The method for clarifying the weights is similar to the method for clarifying the evaluation matrix. This method produces the clarified weights ω_n for the indicator Y_n, which are then normalized to determine the weights of the indicator Y_n:

$$\overline{\omega}_n = \omega_n / \sum_n \omega_n (n = 1, 2, \cdots N) \quad (6)$$

Calculate the weighted normalization matrix:

$$X' = (\overline{\omega}_n X) = \begin{bmatrix} X_1(1)' & X_1(2)' & \cdots & X_1(N)' \\ X_2(1)' & X_2(2)' & \cdots & X_2(N)' \\ \vdots & \vdots & \vdots & \vdots \\ X_M(1)' & X_M(2)' & \cdots & X_M(N)' \end{bmatrix} \quad (7)$$

3.2.4. Determination of Ideal and Anti-Ideal Solutions

The ideal solution is:

$$\begin{aligned} Y_0^+ &= \left\{ (\max_{1 \leq m \leq M} Y_m(\overline{\omega}_n n)' \middle| n \in N^+), (\min_{1 \leq m \leq M} Y_m(n)' \middle| n \in N^-) \right\} \\ &= \left(Y_0^+(1), Y_0^+(2), \cdots, Y_0^+(n), \cdots, Y_0^+(N) \right) \end{aligned} \quad (8)$$

The anti-ideal solution is:

$$\begin{aligned} Y_0^- &= \left\{ (\min_{1\le m\le M} Y_m(n)' \middle| n \in N^+), (\max_{1\le m\le M} Y_m(n)' \middle| n \in N^-) \right\} \\ &= \left(Y_0^-(1), Y_0^-(2), \cdots, Y_0^-(n), \cdots, Y_0^-(N)\right) \end{aligned} \tag{9}$$

where N^+ is the set of indicators for which a more enormous value is better, and N^- is the set of indicators for which a smaller value is better.

3.2.5. Calculate the Correlation Coefficient of the O_m Decision with the Ideal and Anti-Ideal Solutions

The weighted normalization matrix X' is obtained from Equation (7). This matrix serves as the foundation for calculating the gray correlation coefficient between the O_m scenario and the ideal scenario in relation to the Y_n indicator, as shown in Equation (10).

$$r_{mn}^+ = \frac{\min\limits_m \min\limits_n \left|Y_0^+(n)' - Y_m(n)'\right| + \zeta \max\limits_m \max\limits_n \left|Y_0^+(n)' - Y_m(n)'\right|}{\left|Y_0^+(n)' - Y_m(n)'\right| + \zeta \max\limits_m \max\limits_n \left|Y_0^+(n)' - Y_m(n)'\right|} \tag{10}$$

ζ is the discrimination coefficient, which is generally taken as $\zeta = 0.5$ [16,21,23]. The matrix of correlation coefficients between the alternative and the ideal solution is given by Equation (11).

$$R^+ = \begin{bmatrix} r_{11}^+ & r_{12}^+ & \cdots & r_{1n}^+ \\ r_{21}^+ & r_{22}^+ & \cdots & r_{2n}^+ \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1}^+ & r_{m2}^+ & \cdots & r_{mn}^+ \end{bmatrix} \tag{11}$$

The gray correlation between the O_m alternative and the ideal alternative is:

$$R_m^+ = \frac{1}{n} \sum_{n=1}^{N} r_{mn}^+, (m = 1, 2, \cdots M) \tag{12}$$

The gray correlation coefficient between the O_m scenario and the anti-ideal scenario, in relation to the Y_n indicator, is:

$$r_{mn}^- = \frac{\min\limits_m \min\limits_n \left|Y_0^-(n)' - X_m(n)'\right| + \zeta \max\limits_m \max\limits_n \left|Y_0^-(n)' - Y_m(n)'\right|}{\left|Y_0^-(n)' - Y_m(n)'\right| + \zeta \max\limits_m \max\limits_n \left|Y_0^-(n)' - Y_m(n)'\right|} \tag{13}$$

Then, the matrix of correlation coefficients between the alternative and the anti-ideal program is:

$$R^- = \begin{bmatrix} r_{11}^- & r_{12}^- & \cdots & r_{1n}^- \\ r_{21}^- & r_{22}^- & \cdots & r_{2n}^- \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1}^- & r_{m2}^- & \cdots & r_{mn}^- \end{bmatrix} \tag{14}$$

The gray correlation between the O_m alternative and the anti-ideal alternative is:

$$R_m^- = \frac{1}{n} \sum_{n=1}^{N} r_{mn}^-, (m = 1, 2, \cdots M) \tag{15}$$

The gray correlation closeness of the decision object is calculated as $D_m^* = R_m^+ / (R_m^+ + R_m^-)(m = 1, 2, \cdots, M)$. The magnitude of its value indicates the proximity of the decision object to the ideal or anti-ideal scheme. In the shape of the curve changes, the larger the value of the decision object, the better it becomes. Conversely, the smaller the value of the relative closeness of the decision object, the worse it becomes.

4. Empirical Research—Henan as an Example

As a central province connecting home and abroad, spanning the east and west of the country, and running through the north and south, Henan enjoys a prominent position as a transportation hub. As a major agricultural province, Henan is still prominent in the national issues of agriculture, rural areas, and farmers. Taking Henan as an example, the planning and construction of regional cold chain logistics base has a demonstration and leading effect. Furthermore, it should be noted that the model proposed in this paper exhibits universal adaptability and is not constrained by terrain and climate conditions.

4.1. Analysis and Measurement of Regional Cold Chain Logistics Competitiveness in Henan Province

Based on the full investigation and review of the statistical yearbook of Henan Province in 2022, this part uses the previous measurement decision model to find three senior experts to score the selected indicators through a questionnaire survey. The expert weights are obtained in the same manner as the indicator importance, through a questionnaire, and are expressed using triangular fuzzy numbers. The detailed data processing of the expert weights is described in Section 3.2.3. To simplify the steps in the example validation and with reference to [14], specific values were assigned to the indicator weights to facilitate processing. The resulting measurement information table is shown in Table A1 (Appendix A).

According to Equation (3), the weights of indicators and evaluation results in Table A1 are clarified and normalized, and the results are shown in Table 4. On this basis, the weighted standardized matrix can be obtained according to Equations (5)–(7), as shown in Table 5.

Table 4. Comprehensive evaluation information of clarified table.

Measurement Index	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}
Comprehensive index weight	0.1	0.1	0.106	0.089	0.104	0.089	0.102	0.094	0.104	0.1
Zhengzhou	0.699	0.699	1	0.958	0.925	0.889	0.715	0.667	0.826	0.667
Kaifeng	0.55	0.55	0.201	0.509	0.81	0.5	0.584	0.5	0.634	0.467
Luoyang	0.667	0.667	0.429	0.738	0.927	0.826	0.667	0.617	0.747	0.634
Pingdingshan	0.55	0.55	0.212	0.518	0.81	0.5	0.584	0.5	0.634	0.417
Anyang	0.525	0.525	0.192	0.428	0.794	0.5	0.567	0.417	0.634	0.417
Hebi	0.5	0.5	0.084	0.649	0.667	0.45	0.417	0.383	0.417	0.285
Xinxiang	0.55	0.55	0.255	0.498	0.826	0.598	0.558	0.5	0.634	0.634
Jiaozuo	0.5	0.5	0.168	0.58	0.794	0.5	0.55	0.467	0.417	0.5
Puyang	0.333	0.333	0.14	0.451	0.533	0.383	0.45	0.383	0.417	0.333
Xuchang	0.584	0.584	0.288	0.798	0.858	0.615	0.25	0.517	0.334	0.55
Luohe	0.55	0.55	0.136	0.694	0.826	0.598	0.584	0.5	0.584	0.55
Shanmenxia	0.5	0.5	0.125	0.743	0.778	0.5	0.55	0.5	0.634	0.45
Nanyang	0.634	0.634	0.342	0.43	0.889	0.761	0.617	0.584	0.715	0.584
Shangqiu	0.55	0.55	0.243	0.38	0.826	0.598	0.533	0.55	0.584	0.533
Xinyang	0.55	0.55	0.242	0.472	0.826	0.5	0.584	0.55	0.634	0.35
Zhoukou	0.584	0.584	0.275	0.374	0.858	0.663	0.584	0.533	0.634	0.55
Zhumadian	0.55	0.55	0.243	0.424	0.826	0.55	0.584	0.5	0.634	0.45
Jiyuan	0.417	0.417	0.06	1	0.778	0.5	0.5	0.5	0.5	0.417

Table 5. Weighted normalization matrix.

Measurement Index	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}
Zhengzhou	0.07	0.102	0.106	0.086	0.096	0.079	0.073	0.062	0.086	0.067
Kaifeng	0.055	0.089	0.021	0.045	0.084	0.045	0.059	0.047	0.066	0.047
Luoyang	0.067	0.096	0.046	0.066	0.097	0.074	0.068	0.058	0.078	0.063
Pingdingshan	0.055	0.089	0.023	0.046	0.084	0.045	0.059	0.047	0.066	0.042
Anyang	0.053	0.086	0.02	0.038	0.083	0.045	0.058	0.039	0.066	0.042
Hebi	0.05	0.074	0.009	0.058	0.07	0.04	0.042	0.036	0.043	0.029
Xinxiang	0.055	0.091	0.027	0.045	0.086	0.053	0.057	0.047	0.066	0.063
Jiaozuo	0.05	0.086	0.018	0.052	0.083	0.045	0.056	0.044	0.043	0.05
Puyang	0.033	0.07	0.015	0.04	0.056	0.034	0.046	0.036	0.043	0.033
Xuchang	0.058	0.095	0.031	0.071	0.089	0.055	0.025	0.048	0.035	0.055
Luohe	0.055	0.091	0.014	0.062	0.086	0.053	0.059	0.047	0.061	0.055
Shanmenxia	0.05	0.088	0.013	0.066	0.081	0.045	0.056	0.047	0.066	0.045
Nanyang	0.063	0.096	0.036	0.038	0.093	0.068	0.063	0.055	0.075	0.058
Shangqiu	0.055	0.091	0.026	0.034	0.086	0.053	0.054	0.051	0.061	0.053
Xinyang	0.055	0.091	0.026	0.042	0.086	0.045	0.059	0.051	0.066	0.035
Zhoukou	0.058	0.091	0.029	0.033	0.089	0.059	0.059	0.05	0.066	0.055
Zhumadian	0.055	0.091	0.026	0.038	0.086	0.049	0.059	0.047	0.066	0.045
Jiyuan	0.042	0.088	0.006	0.089	0.081	0.045	0.051	0.047	0.052	0.042

According to the standardized matrix and Equations (8) and (9), the ideal solution of the decision matrix is:

$$Y_0^+ = (0.07, 0.102, 0.106, 0.089, 0.097, 0.079, 0.089, 0.062, 0.086, 0.067).$$

The anti-ideal solution is:

$$Y_0^- = (0.033, 0.07, 0.006, 0.033, 0.051, 0.006, 0.025, 0.036, 0.035, 0.029)$$

According to Equations (10)–(15), the correlation matrices R^+ and R^- are calculated sequentially. The correlation coefficients r_m^+ and r_m^- between each region and the ideal and anti-ideal solutions are then calculated. Based on the equation of gray correlation proximity, it is possible to calculate the relative gray correlation decision values and rankings of the 18 cities and municipalities in Henan Province. The specific results are shown in Table 6.

Table 6. Low-carbon competitiveness ranking of cold chain logistics in 18 cities of Henan province.

Region	**Zhengzhou**	**Kaifeng**	**Luoyang**	**Pingdingshan**	**Anyang**	**Hebi**	**Xinxiang**	**Jiaozuo**	**Puyang**
R_m^+	0.99	0.5039	0.75	0.499	0.472	0.394	0.55	0.468	0.359
R_m^-	0.33	0.2	0.281	0.315	0.222	0.281	0.254	0.258	0.224
D_m^*	0.75	0.48	0.66	0.48	0.44	0.348	0.52	0.45	0.29
class	I	III	II	III	III	III	II	III	III
ranking	1	9	2	12	16	17	4	15	18
Region	**Xuchang**	**Luohe**	**Shanmenxia**	**Nanyang**	**Shangqiu**	**Xinyang**	**Zhoukou**	**Zhumadian**	**Jjyuan**
R_m^+	0.53	0.535	0.495	0.65	0.518	0.508	0.5528	0.51	0.508
R_m^-	0.053	0.261	0.05	0.065	0.253	0.228	0.367	0.345	0.214
D_m^*	0.48	0.51	0.48	0.59	0.49	0.48	0.52	0.49	0.47
class	III	II	III	II	III	III	II	III	III
ranking	10	6	13	3	7	11	5	8	14

4.2. Analysis of Results and Discussion

With thresholds of 0.75, 0.5, and 0.25, the low-carbon competitiveness level of regional logistics in Henan is divided into levels I, II, III, and IV (Figure 3). From previously calculation results, it can be seen that the low-carbon competitiveness of cold-chain logistics varies widely in different regions of Henan. Zhengzhou is ranked at the highest level of competitiveness, with a significant lead over the second-ranked city. No city is at the fourth level. As the economy and level of informatization continue to develop, the disparities in cold chain logistics development among different regions, in terms of transportation environment, logistics infrastructure, and the application of logistics technology, are gradually narrowing.

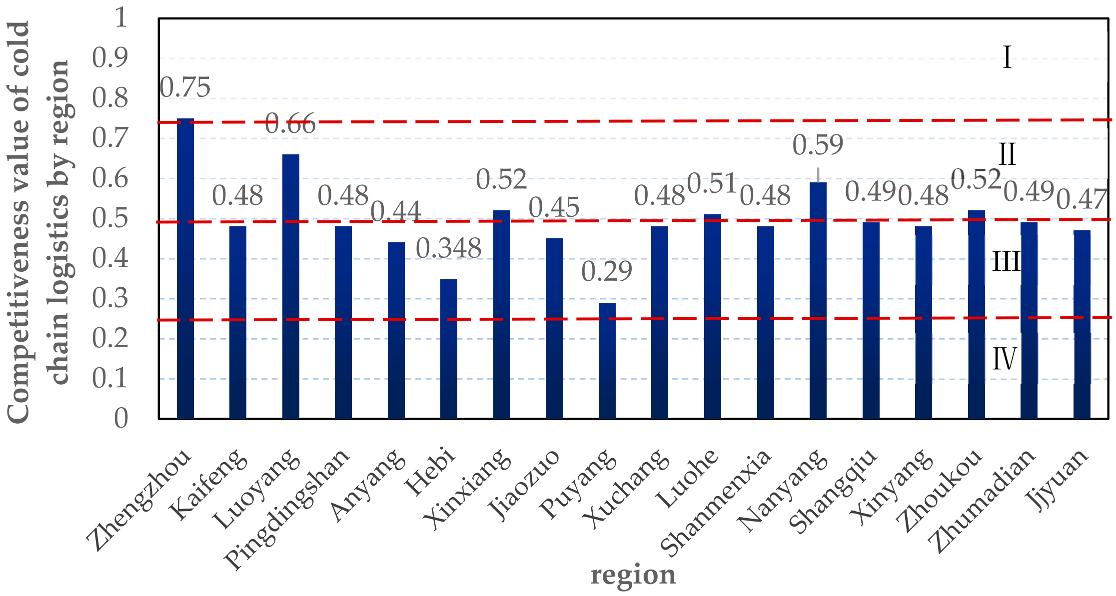

Figure 3. Henan regional logistics low-carbon competitiveness index and hierarchical class.

The strength of low-carbon competitiveness in cold chain logistics in Henan is closely related to factors such as GDP per capita, transportation environment, logistics infrastructure, the utilization of advanced transportation modes, and the adoption of new types of energy (Figure 4). Currently, only Zhengzhou exhibits a high level of cold chain logistics competitiveness, while Luoyang, Xinxiang, Nanyang, and Zhoukou are at a medium level of development. The remaining 13 cities are at a low level of development (Figure 5). Zhengzhou's cold chain logistics competitiveness index is approximately 2.6 times higher than that of Puyang, the city with the lowest index.

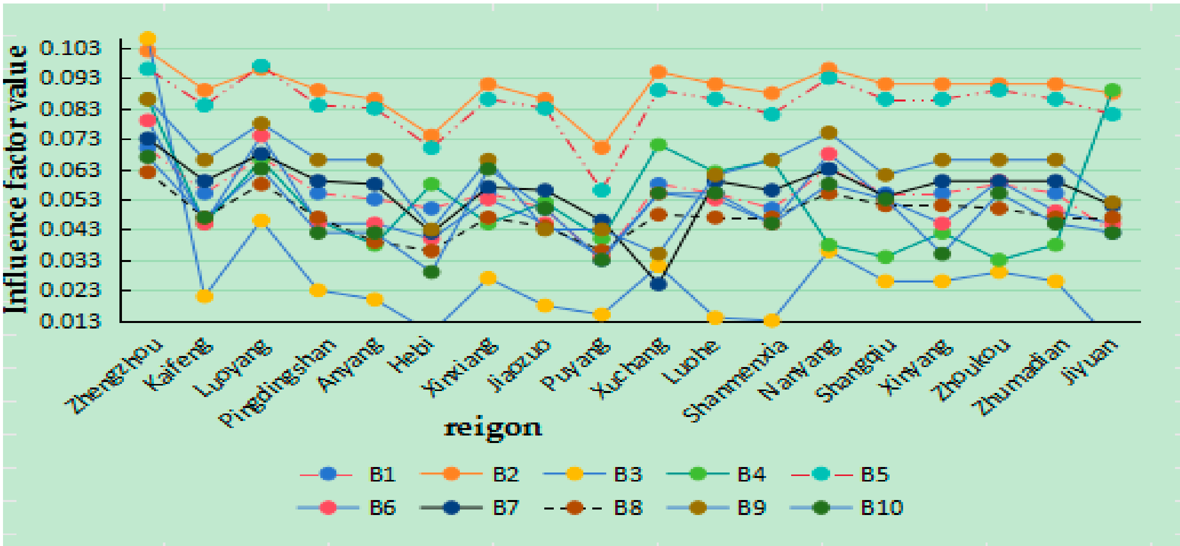

Figure 4. Impact of indicators on the low-carbon competitiveness of regional logistics.

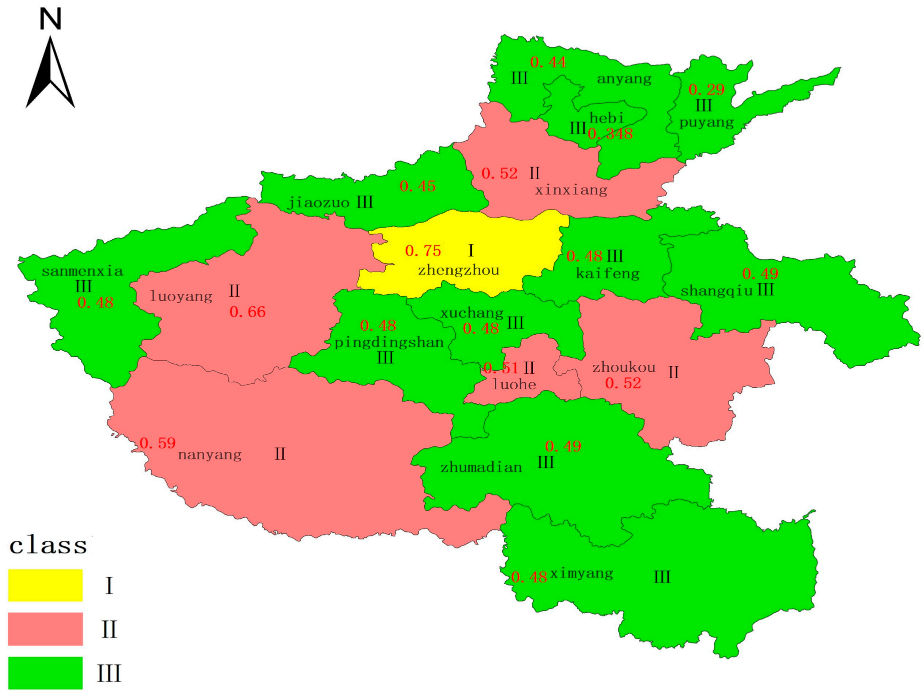

Figure 5. Competitiveness of cold chain logistics in Henan.

China's "14th Five-Year" Cold Chain Logistics Development Plan emphasizes the establishment of approximately 100 national backbone cold chain logistics bases. The plan focuses on utilizing advantageous agricultural production areas, key distribution centers, and primary marketing areas. Zhengzhou, Xinxiang, Luoyang, Shangqiu, and Luohe are ranked among the top 100 cities. After receiving national strategy support, these regions are actively developing eco-friendly warehousing, promoting the use of sustainable building materials, energy-saving technologies, and equipment in logistics parks and large-scale warehousing facilities. They are also promoting energy contract management and other energy-saving strategies, and supporting the development of logistics parks, trading markets, and other facilities for "rooftop photovoltaic power stations" to establish a self-sufficient energy system based on "distributed photovoltaic + energy storage + micro-grid" logistics. They fully implement the national standard for eco-friendly packaging in express delivery, promote the use of recycled materials for packaging, and reduce excessive and redundant packaging. The existence of relevant policies and financial support makes these areas more suitable for the development of low-carbon cold chain logistics compared to other cities in Henan.

Zhengzhou, Luoyang, Nanyang, and Xinxiang are economically developed areas in Henan Province. The developed economy in these areas ensures investment in research and development of low-carbon technology and new energy application technology, which significantly improves the level of low-carbon cold chain logistics equipment. Furthermore, cities such as Zhengzhou and Luoyang have strengthened their low-carbon logistics policy guidance, resulting in a much higher utilization of advanced transportation modes such as inter-modal and multi-modal transport compared to other cities. It is important to emphasize the role of the government in enhancing the low-carbon competitiveness of cold chain logistics. In the current stage of low-carbon economic development, governments play an important role in promoting the development of low-carbon competitiveness in regional cold chain logistics. The government can provide guidance to enterprises through financial and tax support, as well as by implementing relevant policies and regulations on emission reduction technology. Additionally, efforts can be made to encourage research and development of low-carbon logistics equipment, with a focus on promoting advanced modes of transportation and increasing the adoption of energy-efficient trucks. These measures aim to reduce energy consumption per unit of output value in the logistics industry and enhance the low-carbon competitiveness of regional logistics.

4.2.1. Strategies for the Development of Low-Carbon Logistics in Regions with Solid Competitiveness

The intensely competitive region (Class I) includes only Zhengzhou. Zhengzhou is one of the national central cities and serves as the capital of Henan Province. It is also the central city of the Central Plains City Cluster and a national comprehensive transportation hub, boasting a unique location and excellent transportation infrastructure. In recent years, investment in fixed assets in the logistics industry in Zhengzhou has been steadily increasing. The number of CNG filling stations has also been increasing, making it one of the first cities to pilot the construction of tram charging stations. As a result, the infrastructure for low-carbon logistics has been improving. Additionally, the social division of labor and cooperation has led to an increase in the outsourcing of cold chain logistics businesses, thereby further enhancing collaboration within the cold chain logistics industry. This has laid a solid foundation for the development of low-carbon cold chain logistics in Zhengzhou. The utilization of a significant number of compressed natural gas (CNG) and new, electric-powered energy trucks has optimized the energy composition in cold chain logistics. This optimization has not only significantly reduced logistics costs but has also decreased carbon emissions in cold chain transportation. In recent years, Zhengzhou has increased its support for the development of low-carbon cold chain logistics through technological advancements, the involvement of cold chain enterprises, and policy support. These efforts have made a significant contribution to the development of the low-carbon logistics industry. The constructed cold chain logistics management system integrates intelligent transportation systems and Internet technology, seamlessly connecting with multi-modal transportation, including dump transportation and other advanced transportation modes. This system exhibits characteristics of punctuality and high efficiency, representing a significant advancement in the optimization of cold chain logistics management. From the perspective of regional low-carbon competitiveness indicators in cold chain logistics, Zhengzhou surpasses other cities and municipalities in terms of its competitive environment and capacity for low-carbon logistics services. Vertically, Zhengzhou still needs to vigorously develop third-party cold chain logistics in the next phase. This includes upgrading advanced transportation modes and increasing the level of integration in cold chain logistics. Additionally, there is a need to increase investment in the development of public information platforms for logistics. Simultaneously, there should be increased support for the research, development, and promotion of decarbonization technologies and electric vehicles.

4.2.2. Strategies for Low-Carbon Logistics Development in Moderately Competitive Regions

The medium competitiveness region (Type II) includes Luoyang, Nanyang, Xinxiang, and Zhoukou. Among them, Luoyang and Nanyang are strategically located and serve as the economic centers of Henan Province. They have a high per capita GDP due to their developed processing, manufacturing, and trade service industries. Additionally, they serve as the main cities for the establishment of national second-level logistics parks, making them vital hubs for material distribution in Henan Province. Nanyang and Luoyang have relatively well-developed low-carbon cold chain logistics infrastructure, a strong industrial base, and a positive momentum in the development of high-tech industrial parks. They also have a high level of application of low-carbon logistics technology and equipment, such as new energy trucks and heavy-duty cold chain vehicles, which ensure the low-carbon competitiveness of logistics.

4.2.3. Strategies for Low-Carbon Logistics Development in Regions with Weak Competitiveness

The weakly competitive region (Class III) includes Xinyang, Zhumadian, Jiaozuo, Pingdingshan, Zhoukou, Kaifeng, Xuchang, Anyang, Luohe, Sanmenxia, Puyang, Hebi, and Jiyuan. Among them, Pingdingshan is rich in coal resources, and the electricity and chemical industries are its two key sectors. The development of the industrial economy has led to investments in cold chain logistics infrastructure. However, there are still gaps in the policy regarding low-carbon cold chain logistics and the control of energy consumption per unit of cold chain logistics. Additionally, there is a lack of strong competition in crucial sectors, such as the implementation of alternative energy sources and advanced transportation systems. These issues need to be addressed in order to promote the development of low-carbon cold chain logistics. Xuchang and Anyang are strategically located cities for the establishment of national secondary logistics parks. They are located on the northern and southern routes of the Beijing–Guangzhou Railway and the Beijing–Hong Kong–Macao Expressway. These cities have competitive advantages in terms of low-carbon cold chain logistics infrastructure, integrated transportation modes, and logistics informatization. However, they perform poorly in indicators such as GDP per capita and measures of low-carbon emissions. Jiyuan, located in the mountainous northwestern part of Henan Province, is facing challenges in the development of low-carbon cold chain logistics. Similar weaknesses can be observed in other cities and municipalities, resulting in a low level of competitiveness in the regional cold chain logistics of Henan in terms of low-carbon practices. To address this, cities and municipalities at this level of competitiveness should consider developing their own low-carbon logistics and identifying a key area for improvement. Jiyuan, in particular, is hindered by its location and transportation conditions, which impede the rapid development of low-carbon logistics. It also lacks competitiveness in terms of low-carbon logistics infrastructure, intelligent transportation systems, advanced transportation modes, and the level of logistics integration. The cities at this level of competitiveness should adjust their economic structure, increase the proportion of the tertiary industry in the national economy, and invest more in low-carbon logistics infrastructure.

5. Conclusions and Next Steps in Research

Aiming to address the limitations of previous research on low-carbon logistics, we have developed a regional index system to evaluate the competitiveness of low-carbon logistics. This system considers four aspects: the low-carbon environment, the capacity of low-carbon logistics services, the energy consumption level of cold-chain logistics, and the transition to low-carbon energy. The extended triangular fuzzy evaluation level and the improved gray correlation analysis method were used to calculate the low-carbon competitiveness index of regional cold chain logistics. The extended evaluation language effectively captures fuzzy uncertainty data during the evaluation of low-carbon logistics competitiveness, while minimizing the interference of uncertain information on the evaluation object. The improved gray correlation analysis method was applied to empirically analyze the low-carbon competitiveness of regional logistics in Henan Province. The measurement results align with the actual situation, demonstrating the model's strong applicability. This study presents a system and method for measuring the low-carbon competitiveness of cold chain logistics. Scientific and rational papers can provide a decision-making framework to assist the government in evaluating the extent of low-carbon development in regional cold chain logistics and enhancing the competitiveness of low-carbon cold chain logistics. This is of great significance in transforming the economic development model and promoting the growth of a low-carbon economy.

The low-carbon competitiveness evaluation model presented in this paper compares the evaluation object only with the ideal solution in terms of curve similarity. In order to improve the objectivity of the evaluation model, it is also necessary to compare the evaluation object with the ideal solution using distance as a basis. Several related studies have been conducted on the comparative analysis of evaluating an object in relation to the ideal solution based on distance [8,24–28]. In the subsequent analysis and evaluation of low-carbon competitiveness, it is essential to consider both the proximity of the object being evaluated to the ideal solution and the similarity of the curve to the ideal solution. This will be the next step to be examined in this thesis.

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Appendix A

Table A1. Weight evaluation table for Henan regional cold chain logistics competitiveness index.

Measurement Index	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}
expert weight	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$	$P_1(0.2)$ $P_2(0.3)$ $P_3(0.5)$
index weight	D_{55} D_{55} D_{66}	D_{66} D_{66} D66	D_{55} D_{66} D_{66}	D_{55} D_{55} D_{55}	D_{66} D_{55} D_{66}	D_{55} D_{55} D_{55}	D_{44} D_{66} D_{66}	D_{66} D_{55} D_{55}	D_{66} D_{55} D_{66}	D_{55} D_{55} D_{66}
Zhengzhou	D_{55} D_{55} D_{66}	D_{77} D_{77} D_{77}	12,691.02	100,092	D_{77} D_{77} D_{77}	D_{66} D_{66} D_{77}	D_{55} D_{66} D_{55}	D_{55} D_{55} D_{55}	D_{66} D_{66} D_{66}	D_{55} D_{55} D_{55}
Kaifeng	D_{44} D_{55} D_{44}	D_{66} $(D_{55},0.5;D_{66},0.5)$ D_{66}	2557.03	53,173	$(D_{55},0.5;D_{66},0.5)$ D_{66} D_{66}	D_{44} D_{44} D_{44}	D_{55} D_{55} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{33} D_{44} D_{44}
Luoyang	D_{55} D_{55} D_{55}	D_{66} D_{77} D_{66}	5447.12	77,110	D_{66} D_{77} D_{77}	D_{66} D_{66} D_{66}	D_{55} D_{55} D_{55}	D_{55} D_{44} D_{55}	D_{66} D_{66} D_{55}	D_{44} D_{55} D_{55}
Pingdingshan	D_{44} D_{55} D_{44}	D_{66} $(D_{55},0.5;D_{66},0.5)$ D_{66}	2694.16	54,122	$(D_{55},0.5;D_{66},0.5)$ D_{66} D_{66}	D_{44} D_{44} D_{44}	D_{55} D_{55} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{44} D_{44} D_{33}
Anyang	D_{44} $(D_{44},0.5;D_{55},0.5)$ D_{44}	D_{66} D_{55} D_{66}	2435.47	44,690	D_{55} D_{66} D_{66}	D_{44} D_{44} D_{44}	$(D_{44},0.5;D_{55},0.5)$ D_{55} D_{44}	D_{44} D_{44} D_{33}	D_{44} D_{55} D_{55}	D_{44} D_{44} D_{33}
Hebi	D_{44} D_{44} D_{44}	D_{55} D_{55} D_{55}	1064.64	67,803	D_{55} D_{55} D_{55}	D_{44} D_{33} D_{44}	D_{33} D_{33} D_{44}	D_{44} D_{33} D_{44}	D_{44} D_{44} D_{33}	D_{33} D_{22} D_{33}
Xinxiang	D_{44} D_{55} D_{44}	D_{66} D_{66} D_{66}	3232.53	52,028	D_{66} D_{66} D_{66}	D_{44} D_{66} D_{44}	D_{55} $(D_{44},0.5;D_{55},0.5)$ D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{55} D_{44} D_{44}
Jiaozuo	D_{44} D_{44} D_{44}	D_{66} D_{55} D_{66}	2136.84	60,643	D_{55} D_{66} D_{66}	D_{44} D_{44} D_{44}	D_{44} D_{55}	D_{33} D_{44} D_{44}	D_{44} D_{44} D_{33}	D_{44} D_{44} D_{44}
Puyang	D_{33} D_{33} D_{33}	D_{44} D_{55} D_{55}	1771.54	47,131	D_{55} D_{44} D_{44}	D_{33} D_{44} D_{33}	D_{44} D_{33} D_{44}	D_{44} D_{33} D_{44}	D_{44} D_{33} D_{33}	D_{33} D_{33} D_{33}
Xuchang	D_{55} D_{55} D_{44}	D_{66} D_{66} $(D_{66},0.5;D_{77},0.5)$	3655.42	83,415	D_{66} D_{66} $(D_{66},0.5;D_{77},0.5)$	D_{66} D_{55} D_{44}	D_{55} D_{55} D_{44}	D_{33} D_{55} D_{44}	D_{44} D_{55} D_{55}	D_{44} D_{55} D_{44}
Luohe	D_{44} D_{55} D_{44}	D_{66} D_{66} D_{66}	1721.08	72,560	D_{66} D_{66} D_{66}	D_{44} D_{66} D_{44}	D_{55} D_{55} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{33} D_{44} D_{55}

Table A1. *Cont.*

Measurement Index	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9	B_{10}
Shanmenxia	D_{44} D_{44} D_{44}	D_{55} D_{66} D66	1582.54	77,701	D_{66} D_{55} D_{66}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{44} D_{33} D_{44}
Nanyang	D_{44} D_{55} D_{55}	D_{66} D_{77} D_{66}	4342.22	44,894	D_{66} D_{66} D_{77}	D_{44} D_{66} D_{66}	D_{55} D_{44} D_{55}	D_{44} D_{44} D_{55}	D_{55} D_{66} D_{55}	D_{44} D_{44} D_{55}
Shangqiu	D_{44} D_{55} D_{44}	D_{66} D_{66} D_{66}	3083.32	39,678	D_{66} D_{66} D_{66}	D_{44} D_{66} D_{44}	D_{55} D_{44} D_{44}	D_{44} D_{55} D_{44}	D_{55} D_{55} D_{44}	D_{55} D_{44} D_{44}
Xinyang	D_{44} D_{55} D_{44}	D_{66} D_{66} D_{66}	3064.96	49,345	D_{66} D_{66} D_{66}	D_{44} D_{44} D_{44}	D_{55} D_{55} D_{44}	D_{44} D_{55} D_{44}	D_{44} D_{55} D_{55}	D_{33} D_{44} D_{44}
Zhoukou	D_{55} D_{55} D_{44}	D_{66} D_{66} D_{66}	3496.23	39,126	D_{66} D_{66} $(D_{66},0.5;D_{77},0.5)$	D_{66} D_{66} D_{44}	D_{55} D_{55} D_{44}	D_{55} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{44} D_{55} D_{44}
Zhumadian	D_{44} D_{55} D_{44}	D_{66} D_{66} D_{66}	3082.82	44,266	D_{66} D_{66} D_{66}	D_{44} D_{55} D_{44}	D_{55} D_{55} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{55} D_{55}	D_{44} D_{33} D_{44}
Jiyuan	D_{44} D_{44} D_{33}	D_{55} D_{66} D_{66}	762.23	104,515	D_{66} D_{55} D_{66}	D_{44} D_{44} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{44} D_{44}	D_{44} D_{44} D_{44}	D_{33} D_{33} D_{44}

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