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Research on the Influencing Factors of Low-Carbon Cold Chain of Agricultural Products in Guangxi Under Digital Empowerment

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Abstract. In order to effectively help enterprises identify the digital influencing factors of low-carbon cold chain of agricultural products in Guangxi and accelerate the realization of low-carbonization of agricultural products cold chain enterprises, this paper constructs an evaluation index system of low-carbon cold chain of agricultural products in Guangxi under digital empowerment. Based on the data of cold chain energy of agricultural products in 11 cities of Guangxi from 2013 to 2022, the carbon emissions of cold chain of agricultural products in different cities were calculated. The results show that the consumption of cold chain energy of agricultural products in Guangxi is increasing in general from 2013 to 2022. Subsequently, the correlation analysis between the panel data of agricultural product cold chain carbon emissions and the panel data of digital factors in 11 cities in Guangxi was carried out. The results showed that the highest correlation was the degree of digital investment, and the lowest was the level of employee digitization. However, the correlation degree of all digital factors is higher than 0.6, which proves that digital factors have a high correlation with the low-carbon cold chain of agricultural products in Guangxi. This study provides a reference for how to realize low carbon in the cold chain of agricultural products in Guangxi by means of digitization.

Keywords. Digitalization; Guangxi agricultural products cold chain; low carbon; analysis of influencing factors

1. Introduction

In December 2022, the Guangxi government promulgated the ' Implementation Plan for Carbon Peaks in Guangxi Zhuang Autonomous Region ', which proposed that by 2025, the energy consumption and carbon dioxide emissions per unit of GDP in Guangxi Zhuang Autonomous Region will be reduced to ensure the completion of the national

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target. By 2030, the decline in carbon dioxide emissions per unit of GDP in Guangxi Zhuang Autonomous Region will ensure the completion of the national target and achieve carbon peaks in parallel with the whole country. As a major agricultural province, Guangxi should take the lead in opening a low-carbon wave, which can not only help achieve carbon peaks, but also lead other provinces and provide a reference template for other provinces. However, the cold chain of agricultural products in Guangxi started late, the cold chain facilities and equipment are backward, and the carbon dioxide emissions and cargo damage rates generated during the storage and transportation of agricultural products are high.

The emergence of digitization has brought a new direction to the low-carbon cold chain of agricultural products in Guangxi. How to choose the digital elements suitable for the low-carbon development of enterprises is the key to promote the efficient and green development of agricultural products cold chain. Only by clarifying the relationship between digitization and low-carbon can we effectively help the low-carbon development of agricultural products cold chain. By exploring the logical relationship between digital economy and agriculture, Liu Haiqi [1] initially established the development idea of digital agriculture in China; yang Xiaoli [2] found that technological innovation in the digital economy is an important mechanism affecting the circulation efficiency of agricultural products by measuring the panel data of 29 provinces in China. Chen Zeyun [3] explored the development path and mechanism of e-commerce logistics from the perspective of digital village. Zhang [4] believed that government intervention or exogenous coordination mechanism must be introduced to promote the members of the cold chain supply chain of agricultural products to reach a consensus on the digital transformation based on blockchain. Minghong [5] explored the impact of digital trade on the export efficiency of China 's agricultural products and found that it is necessary to continuously improve digital technology and narrow the digital gap to improve the export efficiency of China 's agricultural products. Yang [6] used the fixed effect model to replace the threshold regression model and clarified the positive impact of digital development on technological progress in the wholesale market of agricultural products. With the promulgation of the " double carbon " policy, more and more scholars have begun to explore the relationship between digitization and low-carbon logistics. Zhong Wen [7] found that there is a U-shaped relationship between the digital economy and logistics carbon emissions, and the digital economy can well suppress and evolve the carbon emissions of the logistics industry ; wang [8] studied the impact of carbon emission reduction on the supply chain of fresh agricultural products in the context of digital villages ; in addition, Liu [9] used the two-way fixed effect model and the two-stage least squares method to empirically evaluate the emission reduction effect mechanism of digital economy under the development of local logistics in 31 provinces in China from 2015 to 2019. The empirical results show that the growth of digital economy has an inhibitory effect on pollution emissions.

In summary, at present, scholars mostly focus on the mechanism of action between digitization and agricultural products or logistics, and rarely study the relationship between digitization and low-carbon cold chain of agricultural products and lack empirical research. Secondly, the existing scholars seldom explore the influencing factors of digitization and low-carbon cold chain of agricultural products, and only study whether digitization can reduce the carbon emissions of agricultural products cold chain, and the research combined with the local situation of Guangxi is relatively lacking. This will lead to the low-carbon transformation of Guangxi agricultural products cold chain enterprises only stay in theory, lack of actual data support. In order to solve this problem and better help Guangxi agricultural products cold chain enterprises to take the ' digital express ' to achieve low-carbon transformation, this paper takes Guangxi agricultural products cold chain as the research object, and finds the relationship between the digital factors of 14 cities in Guangxi and the carbon emissions of agricultural products cold chain through the comprehensive grey correlation method, and then explores the digital influencing factors of low-carbon cold chain of agricultural products in Guangxi, so as to help enterprises explore the digital direction of low-carbon transformation of agricultural products cold chain enterprises in the future from an empirical point of view.

2. Construction of digital evaluation index system of cold chain of agricultural products in Guangxi

2.1 Data source

The data of Guangxi agricultural products cold chain enterprises in 2013-2022 in this paper are derived from ' Guangxi Bureau of Statistics ', Wind database, KPMG, ' China Agricultural Products Processing Industry Yearbook ', and statistical yearbooks of various cities. Some of the data may be missing. This paper uses reptile technology and AHP method to process and supplement.

2.2 Determination of evaluation index

In this paper, through literature research and investigation of agricultural products cold chain enterprises in various provinces of Guangxi, the links and effects of digital development of agricultural products cold chain enterprises are preliminarily explored, and the data are sorted out and summarized. As well as the "Evaluation Index of Digital Level of Small and Medium-sized Enterprises (2022 Edition)" issued by the General Office of the Ministry of Industry and Information Technology, the first-level index of digital evaluation of agricultural products cold chain enterprises was obtained. The four key factors of digital foundation, business process digitization, personnel technology digitization and digital performance are taken as the first-level indicators and further analyzed.

Table 1 Digital evaluation index of agricultural products cold chain

first grade indexes	second index	type	Indicator explanation
Digital foundation	Digital hardware equipment(A)	+	Digitization of hardware equipment mainly refers to the ratio of digital hardware equipment to the number of overall hardware equipment.
	Digitalization of Software(B) equipment	+	Digitization of software equipment refers to the ratio of digital software equipment to the total number of software equipment.
	safety of Network(C)	+	Whether the use of industrial network security products and services, the establishment of network security system and a series of operations.
Digitization of business processes	Procurement and Supply(D) digitization	+	Digital procurement operations
	Warehouse(E) digitization	+	Digitalization of inbound and outbound operations

	Transport(F) digitization	+	In-transit management digitization
	Circulation(G) processing digitization	+	Digitization of processing operations
	Digital(H) distribution	+	Path optimization digitization
Personnel technology digitization	Degree of Digital(I) investment	+	Funds invested by enterprises in digitalization
	Employee(J) digital awareness	+	Employees ' understanding of digitization
	Digital level of Employees(K)	+	Employees ' familiarity with the operation of digital systems
Digital performance	Annual revenue(L)	+	Revenue from digitalization
	Annual return(M)	+	Profits from digitalization

In order to facilitate the writing of the following tables, the digital evaluation indicators appearing in the subsequent tables are replaced by the letters in ( ).

3. Calculation of cold chain carbon emissions of agricultural products in Guangxi cities

3.1. Calculation of cold chain energy consumption of agricultural products

According to the information and data released by China Energy Statistical Yearbook and agricultural products cold chain enterprises, the main energy consumption of agricultural products cold chain enterprises is gasoline, natural gas, heat and other eight kinds of energy. On this basis, the data calculated in this paper are based on the eight kinds of energy consumption of agricultural products cold chain in 11 cities of Guangxi Zhuang Autonomous Region. Due to the different types of energy, in order to more easily count the energy consumption of the cold chain of agricultural products in 11 provinces of Guangxi, this paper is based on the conversion coefficient of 8 kinds of energy standard coal given by the National Bureau of Statistics, as shown in table 2 below.

Table 2 Conversion coefficients of 8 kinds of energy standard coal

energy type	**Conversion coefficient (tons of standard coal)**
Coal (tonnes)	0.71430
Gasoline (tons)	1.47140
Kerosene (tons)	1.47140
Diesel (tons)	1.45710
Fuel oil (tonnes)	1.42860
Natural gas (ten thousand cubic meters)	1.33000
Thermal (millions of kilojoules)	0.03412
Electricity (kilowatt-hour)	0.12290

The calculation formula is shown in (1).

$$E=\sum_{i}^{n} C_i \times e_i \quad i=1,2,\cdots,8 \tag{1}$$

Among them, E is the total energy consumption, is the i-th energy, is the i-th energy consumption.

According to the energy consumption of agricultural products cold chain enterprises in Guangxi Zhuang Autonomous Region from 2013 to 2022, the consumption of various energy sources converted into standard coal is calculated by Formula (1), as shown in Table 3 and Table 4.

Table 3 Energy consumption of agricultural products cold chain enterprises in Guangxi Zhuang Autonomous Region from 2013 to 2017 (unit: 10,000 tons of standard coal)

year	2013	2014	2015	2016	2017
Nan ning	2569.12	2832.83	3061.65	3258.84	3615.52
Liu zhou	2265.76	2507.61	2803.02	2991.51	2641.58
Gui lin	710.36	955.83	847.65	868.97	903.60
Wu zhou	355.39	632.24	724.57	1489.37	838.75
Bei hai	344.73	413.09	471.93	639.94	920.45
FangChenggang	135.66	147.35	183.48	294.83	343.88
Qin zhou	298.42	667.81	505.81	1141.28	1332.14
Gui gang	968.93	1148.04	1225.80	1274.53	1096.16
Yu lin	662.59	669.84	764.01	878.20	715.71
Bai se	1307.65	1217.37	1481.75	1547.01	1517.46
He zhou	802.98	934.22	999.07	1457.24	1332.40
He chi	448.96	431.48	498.79	597.01	466.40
Lai bin	692.30	1396.31	2043.90	2064.29	1905.60
Chong zuo	132.27	153.50	191.88	244.93	324.73
Total	11695.12	14107.52	15803.31	18747.95	17954.38

Table 4 Energy consumption of agricultural products cold chain enterprises in Guangxi Zhuang Autonomous Region from 2018 to 2022 (unit: 10,000 tons of standard coal)

year	2018	2019	2020	2021	2022	mean value
Nan ning	3814.59	3958.52	4170.81	5318.05	5516.48	3811.64
Liu zhou	2767.17	2971.56	2974.79	4610.77	5211.75	3174.55
Gui lin	951.55	995.15	1034.06	1483.72	1703.67	1045.46
Wu zhou	1000.34	1107.69	933.16	1063.36	1146.44	929.13
Bei hai	1076.47	1313.19	1369.61	1721.00	1901.88	1017.23
Fang Chenggang	402.30	1507.54	1439.77	1934.01	2099.74	848.86
Qin zhou	1390.47	1440.91	1322.83	2039.39	2189.58	1232.86
Gui gang	1189.96	1470.80	1515.81	1529.05	2129.70	1354.88
Yu lin	766.15	818.07	811.53	895.99	985.62	796.77
Bai se	1798.74	1348.35	1065.60	1140.79	1203.10	1362.78
He zhou	1561.64	1594.14	1717.28	2170.13	2375.21	1494.43
He chi	537.11	86.86	80.61	85.32	91.25	332.38
Lai bin	1458.11	1468.58	1957.13	2002.73	2110.78	1709.97
Chong zuo	335.09	313.40	342.12	152.62	319.58	251.01
Total	19049.69	20394.76	20735.11	26146.93	28984.78	19361.96

It can be seen from Table 3 and Table 4 that in the Guangxi Zhuang Autonomous Region, the energy consumption of agricultural products cold chain enterprises in Nanning and Liuzhou ranks in the forefront. Among them, Nanning 's average energy consumption in the past decade is as high as 38.1164 million tons, far ahead of other cities. The lowest energy consumption is Chongzuo City, with an average annual consumption of about one-fifth of Nanning. There is a big gap in the development of agricultural products cold chain enterprises among cities in Guangxi, and the average annual consumption of most cities is concentrated between 7 million and 15 million tons. There is an imbalance in its development. On the whole, the total energy consumption of Guangxi continues to rise every year except 2017.

It is worth noting that the consumption of Hechi, Wuzhou, Fangchenggang and other cities has a large span between years, mainly due to the large gap in the use of coal. In the overall agricultural products cold chain enterprises in Guangxi, the main energy use is still mainly dependent on coal, and the amount of carbon dioxide produced by coal is very high. Therefore, it is necessary to carry out low-carbon transformation of Guangxi agricultural products cold chain enterprises.

3.2 Calculation of carbon emissions of agricultural products cold chain

At present, the official statistical agencies do not give specific carbon emissions data, but this paper can estimate the corresponding carbon emissions through the methods in References [10-13]. In this paper, the carbon emission coefficient method is used to calculate. The CO_2 generated by 8 kinds of energy is used as the basis for calculating the cold chain carbon emissions of agricultural products. The calculation formula of CO_2 emissions is as follows:

$$CO_2=\sum_i^n W_i \times P_i \times F_i \times(\frac{44}{12})\times E_i \tag{2}$$

where, represents the carbon content of the unit calorific value of the ith energy, $W_i$represents the average low calorific value of the ith energy, P_i represents the carbon conversion rate of the ith energy, 44 and 12 represent the molecular weight of carbon dioxide and carbon, respectively, and E_i represents the ith energy.

Table 5 Eight kinds of energy CO_2 emission coefficients

energy type	coal	gasoline	kerosene	diesel oil	fuel oil	natural gas	Heating power	electric power
Carbon content per unit calorific value	26.37	18.90	19.50	20.20	21.10	15.30	—	—
Average low calorific value	20908	43070	43070	42652	41816	38931	—	—
carbon oxidation rate	0.94	0.98	0.98	0.98	0.99	0.99	—	—

In the table, this paper can see that there is no index value of heat and electricity. CO_2 emission coefficient is calculated by $W_i \times P_i \times F_i \times(44/12)$. Therefore, this paper directly queries the CO_2 emission coefficients of electricity and heat for the calculation of Equation (3.2), which are 9.46 (TC/TJ) and 10069 (TC/Gwh), respectively. In addition, the energy consumption after conversion into standard coal can also be multiplied by the C emission coefficient of standard coal. According to the above method, the calculation results are shown in Table 6 and Table 7.

Table 6 Carbon emissions of agricultural products cold chain enterprises in guangxi zhuang autonomous region from 2013 to 2017 (unit: ten thousand tons)

year	2013	2014	2015	2016	2017
Nan ning	1747.00	1926.32	2081.92	2216.01	2458.55
Liu zhou	1540.72	1705.17	1906.05	2034.23	1796.27
Gui lin	483.04	649.96	576.40	590.90	614.45
Wu zhou	241.67	429.92	492.71	1012.77	570.35
Bei hai	234.42	280.90	320.91	435.16	625.91
Fang Cheng gang	92.25	100.20	124.77	200.48	233.84
Qin zhou	202.93	454.11	343.95	776.07	905.86
Gui gang	658.87	780.67	833.54	866.68	745.39
Yu lin	450.56	455.49	519.53	597.18	486.68
Bai se	889.20	827.81	1007.59	1051.97	1031.87
He zhou	546.03	635.27	679.37	990.92	906.03
He chi	305.29	293.41	339.18	405.97	317.15
Lai bin	470.76	949.49	1389.85	1403.72	1295.81
Chong zuo	89.94	104.38	130.48	166.55	220.82
Total	7952.68	9593.11	10746.25	12748.61	12208.98

Table 7 Carbon emissions of agricultural products cold chain enterprises in guangxi zhuang autonomous region from 2018 to 2022 (unit: ten thousand tons)

year	2018	2019	2020	2021	2022	mean value
Nan ning	2593.92	2691.79	2836.15	3616.27	3751.21	1762.50
Liu zhou	1881.68	2020.66	2022.86	3135.32	3543.99	1467.91

Gui lin	647.05	676.70	703.16	1008.93	1158.50	483.42
Wu zhou	680.23	753.23	634.55	723.08	779.58	429.63
Bei hai	732.00	892.97	931.33	1170.28	1293.28	470.37
Fang Cheng gang	273.56	1025.13	979.04	1315.13	1427.82	392.51
Qin zhou	945.52	979.82	899.52	1386.79	1488.91	570.08
Gui gang	809.17	1000.14	1030.75	1039.75	1448.20	626.50
Yu lin	520.98	556.29	551.84	609.27	670.22	368.43
Bai se	1223.14	916.88	724.61	775.74	818.11	630.15
He zhou	1061.92	1084.02	1167.75	1475.69	1615.14	691.02
He chi	365.23	59.06	54.81	58.02	62.05	153.69
Lai bin	991.51	998.63	1330.85	1361.86	1435.33	790.69
Chong zuo	227.86	213.11	232.64	103.78	217.31	116.07
Total	12953.79	13868.44	14099.87	17779.91	19709.65	8952.97

From Table 6 and Table 7, it can be concluded that in Guangxi Zhuang Autonomous Region, the growth rate of carbon emissions in Fangcheng Port is the highest, with an increase of 1518 % from 2013 to 2022, followed by Beihai and Qinzhou, which are 552 % and 734 % respectively. This is closely related to the development of port trade in Guangxi. In recent years, Fangcheng Port has made use of the Beibu Gulf port to vigorously develop port trade and has established a good partnership with ASEAN and other places. The carbon emissions of other cities except Baise and Hechi are on the rise. The total carbon emissions of Guangxi increased by 248 % from 2013 to 2022, up to 197.0965 million tons. In order to actively respond to the ' double carbon ' policy and help China realize low-carbon life as soon as possible, Guangxi agricultural products cold chain enterprises should realize low-carbon transformation as soon as possible.

4. Grey relational model construction

4.1 Basic definition

The panel data structure is relatively rich, from the vertical observation is the time series, from the horizontal observation is the cross-section data, that is, the description of the dynamic trend of multiple object indicators. In addition, the panel data also includes the time dimension and the index dimension, which can more comprehensively express all aspects of the data. Let the index set $A=\{a_0,a_1,\cdots,a_I\}$(where a_0 is the reference index, the other is the comparison index), the object set $B=\{b_1,b_2,\cdots,b_M\}$, the time level $C=\{c_1,c_2,\cdots,c_N\}$, and write u^i_{mn} as the value of the mth object of the ith index at the nth time, then the panel data can be represented by three tables, as shown in Table 8.

Table 8 Three-dimensional table of panel data

idex	**0**					⋯	**i**					⋯	**I**				
object	Time					⋯	Time					⋯	Time				
	1	⋯	n	⋯	N	⋯	1	⋯	n	⋯	N	⋯	1	⋯	n	⋯	N
1	u^0_{11}	⋯	u^0_{1n}	⋯	u^0_{1N}	⋯	u^i_{11}	⋯	u^i_{1n}	⋯	u^i_{1N}	⋯	u^I_{11}	⋯	u^I_{1n}	⋯	u^I_{1N}
⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮
m	u^0_{m1}	⋯	u^0_{mn}	⋯	u^0_{mN}	⋯	u^i_{m1}	⋯	u^i_{mn}	⋯	u^i_{mN}	⋯	u^I_{m1}	⋯	u^I_{mn}	⋯	u^I_{mN}
⋮	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮	⋱	⋮
M	u^0_{M1}	⋯	u^0_{Mn}	⋯	u^0_{MN}	⋯	u^i_{M1}	⋯	u^i_{Mn}	⋯	u^i_{MN}	⋯	u^I_{M1}	⋯	u^I_{Mn}	⋯	u^I_{MN}

Due to the different units of each index, the data may belong to the benefit index, cost index or moderate index. If the direct calculation of Table 4 is directly used, it will lead to the distortion of the correlation analysis results in the modeling process. Therefore, the data needs to be preprocessed. The digital evaluation indexes of agricultural products cold chain constructed in this paper are all benefit oriented. Therefore, this paper takes benefit oriented as an example.

Definition 1 [14] Let $X=(X_1,X_2,\cdots,X_N)$ be the index behavior sequence of panel data, where X_i is the matrix of panel data under index b_i. If b_m is a benefit index, then the decision grey target under index b_m is $u^i_{mn} \in [u^i_{n_0m_0}, \max_m \max_n u^i_{mn}]$, where $u^i_{n_0m_0}$ is the critical value of u^i_{mn}.It is called

$$x^i_{mn}=\frac{u^i_{mn}-u^i_{n_0m_0}}{\max_m \max_n u^i_{mn}-u^i_{n_0m_0}} \tag{3}$$

It is a benefit index effect measure function.

In order to be able to describe the geometric characteristics of panel data, this paper uses the method of literature [15].

Definition 2 Let $x_i(s,t)$ be the value of index i with respect to the object s in time t.

$$X_i=\begin{bmatrix} x_i(1,1) & x_i(1,2) & \dots & x_i(1,N) \\ x_i(2,1) & x_i(2,2) & \dots & x_i(2,N) \\ \cdots & \cdots & \ddots & \cdots \\ x_i(M,1) & x_i(M,2) & \dots & x_i(M,N) \end{bmatrix} \tag{4}$$

X_i is the behavior matrix of index i, abbreviated as $X_i=(x_i(s,t))_{M\times N}$,$X=(X_1,X_2,\cdots,X_I)$is the sample sequence of panel data.

4.2 Model construction

In order to reasonably evaluate the impact of digital indicators of agricultural products cold chain on carbon emissions of agricultural products cold chain, this paper constructs data models on two-dimensional, three-dimensional and four-dimensional planes from the perspectives of similarity and similarity. In this paper, similarity is to describe the degree of similarity between two entities, and to solve it in the form of derivative. Similarity describes the ' distance ' between two entities, which is more inclined to the size of the entity value. For example, the area of a rectangle and a circle is $1\,m^2$. this paper think that it has high similarity and poor similarity. It can be seen that if this paper only relies on similarity or proximity to solve the correlation degree, it will lead to one-sidedness of the results. The following table shows the composition of similarity and similarity correlation in this paper.

Table 9 The composition of similarity and similarity correlation degree

degree of association	composition	dimensional	feature
the similarity relational degree	Displacement correlation degree	two dimensions	The distance is solved for the time dimension of panel data.
	Speed correlation degree	two dimensions	First-order derivation is performed on the time dimension of panel data.
	Acceleration correlation degree	two dimensions	Second-order derivation is performed on the time dimension of panel data.
Similarity correlation degree	Grey projection area correlation degree	three dimensions	The time dimension and object dimension of panel data are considered.
	Tetrahedral network correlation degree	four dimensions	The time dimension of panel data is considered and compared in pairs.

(1) Similarity correlation degree

Definition 3 (displacement correlation degree) Let the reference matrix be X_0, and the comparison matrices $x_i(s,t)$ and $x_0(s,t)$ are the values of the index i and the reference index with respect to the sample s at time t and the vulnerability index, respectively. Then the displacement correlation degree of X_0 and X_i at time t is:

$$r_{0i}^{(0)}=\frac{1}{M\times N}\sum_{m=1}^{M}\sum_{n=1}^{N}\exp(-|x_i(s,t)-x_0(s,t)|) \tag{5}$$

The displacement correlation degree is the overall proximity between the digital index i of agricultural products cold chain and the carbon emission index of agricultural products cold chain. The greater the $r_{0i}^{(0)}$, the greater the impact of the cold chain digitization index i and the cold chain carbon emissions of agricultural products.

Definition 4 (speed correlation degree) Let the reference matrix X_0, the comparison matrix X_i, $x_i'(s,t)$and $x_0'(s,t)$ are the first-order difference quotients of the index i and the reference index with respect to the sample s at time t and the first-order difference quotient of the vulnerability index value, respectively. Then the bit speed correlation degree of X_0 and X_i at time t is:

$$r_{0i}^{(1)}=\frac{1}{M\times(N-1)}\sum_{m=1}^{M}\sum_{n=1}^{N-1}\exp(-|x_i'(s,t)-x_0'(s,t)|) \tag{6}$$

Which

$$x_i'(s,t)-x_0'(s,t)=(x_i(s,t+1)-x_i(s,t))-(x_0(s,t+1)-x_0(s,t))$$

$$x_i'(s,t)=\frac{x_i(s,t+1)-x_i(s,t)}{\Delta t}$$

$$x_0'(s,t)=\frac{x_0(s,t+1)-x_0(s,t)}{\Delta t}$$

The speed correlation degree is the proximity between the digital index i of agricultural products cold chain and the carbon emission index of agricultural products cold chain. The greater the $r_{0i}^{(1)}$, the greater the impact of the cold chain digitization index i and the cold chain carbon emissions of agricultural products.

Definition 5 (acceleration correlation degree) Let the reference matrix beX_0,The comparison matrices X_i, $x_i''(s,t)$ and $x_0''(s,t)$ are the second-order difference quotient of the index i and the reference index with respect to the sample s in time t and the second-order difference quotient of the vulnerability index value, respectively. Then the correlation between X_0 and X_i at time t is:

$$r_{0i}^{(2)}=\frac{1}{M\times(N-2)}\sum_{m=1}^{M}\sum_{n=1}^{N-2}\exp(-|x_i''(s,t)-x_0''(s,t)|) \tag{7}$$

Which

$$x_i''(s,t)-x_0''(s,t)=(x_i(s,t+2)-2x_i(s,t+1)+x_i(s,t))-(x_0(s,t+2)-2x_0(s,t+1)+x_0(s,t))$$

$$x_i''(s,t)=\frac{x_i'(s,t+1)-x_i'(s,t)}{\Delta t}$$

$$x_0''(s,t)=\frac{x_0'(s,t+1)-x_0'(s,t)}{\Delta t}$$

The acceleration correlation degree is the degree of proximity between the digital index i of agricultural products cold chain and the carbon emission index of agricultural products cold chain. The greater the $r_{0i}^{(2)}$, the greater the impact of the digital index i of cold chain and the carbon emission of agricultural products cold chain.

Definition 6 (similarity correlation degree) Let the reference matrix be X_0 and compare matrix X_i, then the correlation degree between X_0 and X_i at time t is:

$$r_{oi}=\frac{r_{0i}^{(0)}+\left(\frac{r_{0i}^{(1)}+r_{0i}^{(2)}}{2}\right)}{2} \tag{8}$$

(2) Similarity correlation degree

Definition 7[16] Let the behavior matrix of the i th index in the panel data be X_i, then the projection area functions of X_i in the time plane and the object plane are:

$$F_i(s,t)=\frac{1}{2}[|x_i(s+1,t)-x_i(s,t)|+|x_i(s+1,t+1)-x_i(s,t+1)|] \tag{9}$$

$$G_i(s,t)=\frac{1}{2}[|x_i(s+1,t+1)-x_i(s+1,t)|+|x_i(s,t+1)-x_i(s,t)|] \tag{10}$$

Definition 8 Suppose the panel data are X_i and X_j, then this paper says:

$$\xi_{ij}^{F}(s,t)=\frac{1}{1+|F_i(s,t)-F_j(s,t)|} \tag{11}$$

is the three-dimensional gray projection area correlation coefficient on the time plane from (s, t) to (s, t + 1), which is called:

$$\xi_{ij}^{G}(s,t)=\frac{1}{1+|G_i(s,t)-G_j(s,t)|} \tag{12}$$

is the three-dimensional gray projection area correlation coefficient on the object plane from (s, t) to (s + 1, t).

Definition 9 Let $\xi_{ij}^{F}(s,t)$ and $\xi_{ij}^{G}(s,t)$ be the three-dimensional grey projection area correlation coefficient of the panel data X_i and X_j on the time and object plane, respectively. Then ξ_{ij}^{F} , ξ_{ij}^{G} , ξ_{ij} are called the three-dimensional grey projection area correlation degree of X_i and X_j on the time and object plane, and the three-dimensional grey projection area correlation degree of X_i to X_j. The calculation process is as follows.

$$\xi_{ij}^{F}=\frac{\sum_{t=1}^{n-1}\sum_{s=1}^{m-1}\xi_{ij}^{F}(s,t)}{(n-1)(m-1)} \tag{13}$$

$$\xi_{ij}^{G}=\frac{\sum_{t=1}^{n-1}\sum_{s=1}^{m-1}\xi_{ij}^{G}(s,t)}{(n-1)(m-1)} \tag{14}$$

$$\xi_{ij}=\frac{1}{2}(\xi_{ij}^{F}+\xi_{ij}^{G}) \tag{15}$$

Definition 10 Let $X_i=(x_i(s,\ t))_{M\times N}$ be the behavior matrix of index i, and the object set is $B=\{b_1,b_2,\cdots,b_M\}$.Any two objects in B are marked as b_{j_1} and b_{j_2}, where j_1 and j_2 are any two different numbers in $\{1,2,\cdots,M\}$, then $\{b_{j_1},b_{j_2}\}$ is called a binary combination of the object set. Then all possible binary object combinations are:

$$M_B^2=\{\{b_{j_1},b_{j_2}\}|j_1\neq j_2\in\{\{1,2,\cdots,M\}\}$$

The data corresponding to objects b_{j_1} and b_{j_2} construct a 2×N matrix, denoted as $X_{i(j_1,j_2)}$, which represents the behavior matrix X_i of binary objects b_{j_1} and b_{j_2} of matrix xa, as shown below.

$$X_{i(j_1,j_2)}=\begin{bmatrix}x_i(j_1,1) & x_i(j_1,2) & \cdots & x_i(j_1,N)\\ x_i(j_2,1) & x_i(j_2,2) & \cdots & x_i(j_2,N)\end{bmatrix} \tag{16}$$

According to the permutation and combination, there are m (m-1) / 2 possibilities for the binary combination of M different objects, that is to say, the binary object behavior matrix of X_i has m (m-1) / 2.

Definition 11 Let $X_{i(j_1,j_2)}$ be the behavior sub-matrix of the binary objects b_{j_1} and b_{j_2} of matrix X_i , and connect the four adjacent points $(1,t,\ x_i(j_1,t))$,$(2,t,\ x_i(j_2,t))$,$(1,t+1,\ x_i(j_1,t+1))$, $(2,t,\ x_i(j_2,t+1))$($(1,t,\ x_i(j_1,t))$ corresponding to $X_{i(j_1,j_2)}$ as the points in the three-dimensional space projected by the values in $X_{i(j_1,j_2)}$, $t=1,2,\cdots,N-1$). The aggregate $T_i(j_1,j_2,t)$ is the tetrahedron when $X_{i(j_1,j_2)}$ is at t, and $T_i(j_1,j_2)$ is the set of all tetrahedrons composed of $X_{i(j_1,j_2)}$, which is called the tetrahedron network of $T_i(j_1,j_2)$ is $X_{i(j_1,j_2)}$.

Definition 12[17] Let the volume of $T_i(j_1,j_2,t)$ tetrahedron be $V_i(j_1,j_2,t)$, then the directed volume of $T_i(j_1,j_2,t)$ is

$$V_i(j_1,j_2,t)=\begin{cases} \overline{V}_i(j_1,j_2,t) & \check{x}_i(j_1,j_2,t) > \check{x}_i(j_2,j_1,t) \\ 0 & \check{x}_i(j_1,j_2,t) = \check{x}_i(j_2,j_1,t) \\ -\overline{V}_i(j_1,j_2,t) & \check{x}_i(j_1,j_2,t) < \check{x}_i(j_2,j_1,t) \end{cases} \tag{17}$$

Which

$$\check{x}_i(j_1,j_2,t)=x_i(j_1,t)+x_i(j_2,t+1)$$

$$\check{x}_i(j_2,j_1,t)=x_i(j_2,t)+x_i(j_1,t+1)$$

$$\overline{V}_i(j_1,j_2,t)=\frac{1}{6}|\check{x}_i(j_1,j_2,t)-\check{x}_i(j_2,j_1,t)|$$

In general, the tetrahedron formed by panel data is very thin, and its discrimination is not large. Therefore, in this paper, when calculating the volume, the front coefficient 1 / 6 is removed, and the formula becomes: : $\overline{V}_i(j_1,j_2,t)=|\check{x}_i(j_1,j_2,t)-\check{x}_i(j_2,j_1,t)|$.

Definition 13 $X_0=(x_i(s,t))_{M\times N}$ be the reference index behavior matrix, $X_i=(x_i(s,t))_{M\times N})$ is the index behavior matrix, $X_{0(j_1,j_2)}$ and $X_{i(j_1,j_2)}$ are the behavior sub-matrices of binary objects X_0 and X_1 of b_{j_1} and b_{j_2}, $V_0(j_1,j_2,t)$ and $V_i(j_1,j_2,t)$ are the directed volumes of tetrahedrons $T_0(j_1,j_2,t)$ and $T_i(j_1,j_2,t)$ at time t, respectively. Then $\varepsilon_{0i}(j_1,j_2,t)$ is called the grey tetrahedral network correlation coefficient of X_0 and X_i with respect to objects b_{j_1} and b_{j_2} at time t, and the formula is as follows.

$$\varepsilon_{0i}(j_1,j_2,t)=\frac{1}{1+|V_0(j_1,j_2,t)-V_i(j_1,j_2,t)|} \tag{18}$$

Definition 14 Let $X_0=(x_i(s,t))_{M\times N}$ be the reference index behavior matrix, $X_i=(x_i(s,t))_{M\times N}$ be the index behavior matrix, $\varepsilon_{0i}(j_1,j_2,t)$ be the grey tetrahedral network correlation coefficient of X_0 and X_i with respect to objects b_{j_1} and b_{j_2} at time t, then ε_{0i} is called the grey tetrahedral network correlation degree of X_0 and X_i.

$$\varepsilon_{0i}=\frac{2}{m(m-1)(n-1)}\sum_{b_{j_1},b_{j_2}\in M_B^2}\sum_{t=1}^{n-1}\varepsilon_{0i}(j_1,j_2,t) \tag{19}$$

Definition 14 Let ξ_{0j} be the three-dimensional grey projection area correlation degree of X_0 to X_j, ε_{0i} is the grey tetrahedral network correlation degree of X_0 and X_i, then the similarity correlation degree of X_0 to X_j is α_{oi}, and the specific formula is as follows.

$$\alpha_{0i}=\frac{1}{2}(\xi_{0j}+\varepsilon_{0i}) \tag{20}$$

(3) Comprehensive grey correlation degree

The comprehensive grey correlation degree of panel data X_0 and X_j is obtained by weighted average of similarity correlation degree and similar correlation degree. The similarity correlation degree is obtained by weighted average of displacement correlation degree, velocity correlation degree and acceleration correlation degree. A similar correlation degree is obtained by weighted average of three-dimensional grey projection area correlation degree and grey tetrahedron network correlation degree. When the difference of different correlation degree is large, it will lead to the distortion of comprehensive grey correlation degree and make the result unreliable. Therefore, this paper introduces the entropy value of grey correlation degree to describe the difference between correlation degrees and sets the weight of similarity correlation degree and similar correlation degree according to the degree of difference, so as to construct a comprehensive and reasonable comprehensive grey correlation degree.

Definition 15 Let the panel data X_0 and X_j, the displacement correlation degree is $r_{0i}^{(0)}$, the velocity correlation degree is $r_{0i}^{(1)}$ and the acceleration correlation degree is $r_{0i}^{(2)}$, then the grey correlation distribution of panel data X_0 and X_j is mapped as follows :

$$P_{ij}^{r0}=\frac{|r_{0i}^{(0)}|}{P_{ij}} \tag{21}$$

$$P_{ij}^{r12}=\frac{|r_{0i}^{(1)}+r_{0i}^{(2)}|}{P_{ij}} \tag{22}$$

Which

$$P_{ij}=|r_{0i}^{(0)}| + |r_{0i}^{(1)}+r_{0i}^{(2)}|$$

Similarly, $T_{ij}^{r}=-\ln P_{ij}^{r0} - P_{ij}^{r12}\ln P_{ij}^{r12}$ is the test coefficient of the similar grey correlation degree of the panel data X_0 and X_j . $T_{ij}^{\xi\varepsilon}=-\ln P_{ij}^{\xi} - P_{ij}^{\varepsilon}\ln P_{ij}^{\varepsilon}$ is the test coefficient of the similar grey correlation degree of the panel data X_0 and X_j. Based on the above analysis, the larger the test coefficient, the smaller the difference, which means the higher the credibility.

Definition 16 Let the panel data X_0 and X_j, r_{oi} is the similarity correlation degree between X_0 and X_j, α_{0i} is the similarity correlation degree between X_0 and X_j, T_{ij}^{r} and $T_{ij}^{\xi\varepsilon}$ are the similarity between panel data X_0 and X_j, and the test coefficients of similar grey correlation degree. Then the comprehensive grey correlation degree γ_{0j} of X_0 and X_j is as follows.

$$\gamma_{0j}=w_1 r_{oi}+w_2\alpha_{0i} \tag{23}$$

Which

$$w_1=\frac{T_{ij}^{r}}{T_{ij}^{r}+T_{ij}^{\xi\varepsilon}},\ w_2=\frac{T_{ij}^{\xi\varepsilon}}{T_{ij}^{r}+T_{ij}^{\xi\varepsilon}}$$

5. Grey correlation degree calculation and analysis

5.1 Grey correlation degree calculation

According to the relevant data and the above formulas, this section calculates by MATLAB and obtains the gray correlation degree between the digital index and the cold chain carbon emissions of agricultural products. The results are shown in Table 10.

Table 10 Various grey correlation degrees between digital indicators and carbon emissions from cold chain of agricultural products

	$r_{0i}^{(0)}$	$r_{0i}^{(1)}$	$r_{0i}^{(2)}$	r_{oi}	ξ_{ij}	ε_{0i}	α_{0i}
A	0.5380	0.9184	0.8608	0.7138	0.9154	0.5976	0.7565
B	0.5436	0.9013	0.8384	0.7067	0.9091	0.5908	0.7500
C	0.6995	0.7406	0.6131	0.6882	0.8169	0.4738	0.6454
D	0.6910	0.7566	0.6024	0.6853	0.8352	0.4924	0.6638
E	0.5247	0.9536	0.9279	0.7327	0.9081	0.6073	0.7577
F	0.6258	0.8105	0.6891	0.6878	0.8603	0.5255	0.6929
G	0.6415	0.8153	0.7014	0.6999	0.8596	0.5354	0.6975
H	0.6412	0.7954	0.6763	0.6885	0.8566	0.5236	0.6901
I	0.5803	0.9175	0.8700	0.7370	0.9999	0.6428	0.8214
J	0.6693	0.7083	0.5451	0.6480	0.8140	0.4676	0.6408
K	0.6359	0.7785	0.6741	0.6811	0.5723	0.5115	0.5419

L	0.5264	0.9309	0.8932	0.7192	0.5743	0.5953	0.5848
M	0.5614	0.8495	0.7577	0.6825	0.6004	0.5445	0.5725

By using the formula (23) to deal with the above table, the comprehensive grey correlation degree between the digital index and the carbon emission of agricultural products cold chain is obtained, and the ranking is carried out according to the numerical value. The ranking results are shown in Table 11.

Table **11** Comprehensive grey correlation degree between digital indicators and carbon emissions of agricultural products cold chain

index	γ_{0j}	**rank**
A	0.7285	3
B	0.7217	4
C	0.6720	9
D	0.6771	8
E	0.7412	2
F	0.6897	6
G	0.6990	5
H	0.6891	7
I	0.7664	1
J	0.6453	11
K	0.6243	13
L	0.6676	10
M	0.6398	12

It can be seen from the above table that the comprehensive grey correlation degree between the digitization degree of agricultural products cold chain and its carbon emissions in 14 cities of Guangxi is ranked as follows : employee digitization level < annual profit < employee digitization consciousness < annual revenue < network security < procurement and supply digitization < distribution digitization < transportation digitization < circulation processing digitization < software equipment digitization < hardware equipment digitization < warehousing digitization < digital investment degree.

5.2 Results analysis

First of all, from table 9, it can be concluded that among the many digital factors, the degree of digital investment has the highest impact on the carbon emissions of Guangxi agricultural products cold chain. With the increase of digital investment, the ability of enterprises to purchase hardware facilities and software facilities will be greatly improved, so that the overall digitization of agricultural products cold chain will increase, and carbon emissions will decrease. Therefore, the degree of digital investment is the basis of other digital factors and the core of reducing carbon emissions of agricultural products cold chain. Secondly, the order of hardware equipment digitization and software equipment digitization is third and fourth respectively. Hardware equipment digitization and software equipment digitization are the overall evaluation of the digitization of agricultural products cold chain business links, which play an important role in the operation of agricultural products cold chain. It is worth noting that in the business link, the digitization of warehousing links ranks second, which exceeds the digitization of hardware equipment and software equipment. In real life, the cost of agricultural products cold chain warehousing is huge. Agricultural products stay in the warehouse for a long time and need to maintain a certain temperature, so in the whole business link. The carbon emissions and cargo damage rates generated by the storage process are very high.

For the digitization of transportation, distribution, circulation processing, procurement and other links, although there is no large correlation between warehousing links and carbon emissions, it also plays a certain role. Finally, the correlation between digital factors such as network security, employees ' digital awareness, employees ' digital level, digital annual revenue, digital annual profit and carbon emissions of agricultural products cold chain is not high, but they are all greater than 0.6, which confirms that these factors have a high degree of correlation with carbon emissions.

In the future, the cold chain of agricultural products in Guangxi can increase the degree of digital investment. By purchasing digital equipment, establishing digital systems, and increasing the training of employees ' digital awareness and ability, the digital degree of cold chain of agricultural products can be improved. In the context of low-carbon, Guangxi agricultural products cold chain enterprises build a low-carbon transformation plan for agricultural products cold chain according to relevant digital influencing factors, help enterprises achieve low-carbon transformation and help achieve the goal of ' double carbon '.

5.3 Comparative analysis

Table 12 shows the ranking results from two-dimensional angle, three-dimensional angle, four-dimensional angle, similarity, similarity and the methods used in this paper.

Table 12 Sorting results of different perspectives

index	Two – dimensional / similarity	three-dimension	four-dimensional	proximity	This paper
A	4	2	3	3	3
B	5	3	5	4	4
C	8	9	12	9	9
D	10	8	11	8	8
E	2	4	2	2	2
F	9	5	8	6	6
G	6	6	7	5	5
H	7	7	9	7	7
I	1	1	1	1	1
J	13	10	13	10	11
K	12	13	10	13	13
L	3	12	4	11	10
M	11	11	6	12	12

First of all, from the perspective of two-dimensional, three-dimensional and four-dimensional, this paper can find that no matter from which perspective, the degree of digital investment ranks first, and the ranking of most indicators is not much different, but the gap between annual revenue and annual profit is large. For annual revenue, two-dimensional and four-dimensional are compared and analyzed from the perspective of time. From the formula, this paper can see that the calculation process includes the data of the previous time period minus the data process of the current time period (Formula 5 and Formula 17), and the three-dimensional perspective is not only from the perspective of time (Formula 10). The angle of the object is also considered (Formula 9). The annual profit is the same in the two-dimensional and three-dimensional, which is different from the four-dimensional ranking. Although the two-dimensional, three-dimensional and four-dimensional all consider the time dimension, the four-dimensional is compared between multiple objects, and in the calculation process, the comparison results between different objects of the same index are integrated (Formula 19), while the three-dimensional only considers the gap between the previous object and the current object and does not compare any objects. Secondly, starting from the similarity and similarity, this paper can see that in addition to the annual revenue, the ranking of other indicators is basically the same, and the similarity is a combination of three-dimensional and four-dimensional. The gray correlation degree of three-dimensional and four-dimensional annual revenue is 0.5743 and 0.5953, respectively. However, in the three-dimensional, the largest gray correlation index is 0.999, and the largest gray correlation degree of four-dimensional is 0.6428. Therefore, in the process of synthesis, the gray correlation degree of annual revenue similarity is not high. Finally, the scheme proposed in this paper comprehensively considers the characteristics of two-dimensional, three-dimensional and four-dimensional. Compared with other single angles, it is more able to synthesize the advantages of different angles and make a comprehensive judgment to avoid the result being too one-sided.

In the above discussion, this paper finds that the ranking gap is concentrated in the index of annual revenue. It can be seen from Table 3-7 that the two-dimensional angle combines the displacement correlation degree, the velocity correlation degree and the acceleration correlation degree. The displacement correlation degree is the subtraction of the time perspective, while the velocity correlation degree and the acceleration correlation degree are the first derivative and the second derivative on the basis of the displacement correlation degree. It can be seen from the results that the displacement correlation degree of annual revenue ranks 12th, which is basically the same as the ranking order of three-dimensional and this paper, while the annual revenue order of velocity correlation degree and acceleration correlation degree is the first, which makes the final similarity correlation degree rank high. The method proposed in this paper avoids this situation.

6. Conclusion

Firstly, this paper clarifies the purpose and principle of constructing the digital evaluation index system of cold chain of agricultural products in Guangxi. According to the ' Evaluation Index of Digital Level of Small and Medium-sized Enterprises (2022 Edition) ' issued by the General Office of the Ministry of Industry and Information Technology and related literature, the digital evaluation index of cold chain of agricultural products in Guangxi is obtained. Secondly, the energy consumption and carbon emissions of agricultural products cold chain in 14 cities of Guangxi are calculated. On the whole, the carbon emissions of agricultural products cold chain in cities of Guangxi are on the rise. Finally, through the two-dimensional perspective to construct the similarity gray correlation degree and the three-dimensional perspective and the four-dimensional perspective to construct the similarity gray correlation degree, the correlation degree of the digital factors on the carbon emission of the cold chain of agricultural products in Guangxi is quantitatively analyzed. The grey correlation model fully excavates the panel data, integrates the advantages of different dimensional perspectives, and enriches the grey correlation theory. Applying this model to the cold chain of agricultural products in Guangxi provides theoretical and practical data support for exploring the relationship between digitization and carbon emissions in the cold chain of agricultural products in Guangxi, and also points out the development direction of digitization for enterprises to achieve low-carbon transformation in the future.

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