Research on Forecasting the Consumption of Fresh Agricultural Products Based on DGM (1, 1)

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Abstract. With the improvement of residents' consumption level, the requirements for freshness and quality of agricultural products are becoming increasingly high Therefore, it is necessary to plan and promote the cold chain logistics of fresh agricultural products, and scientifically predicting the consumption of fresh agricultural products can help make accurate decisions for the development of cold chain logistics. This article selects six types of fresh agricultural products, including vegetables, fruits, meat, dairy products, eggs, and aquatic products, and uses the DGM (1,1) model to predict the consumption of fresh agricultural products. The results indicate that the consumption of fresh agricultural products continues to increase, and the demand for cold chain logistics is very high in the future. It is necessary to gradually improve the cold chain logistics infrastructure and equipment, increase cold storage capacity, enhance logistics technology and services, and improve logistics efficiency to promote the development of fresh agricultural products.

Keywords: Fresh agricultural products, cold chain logistics, DGM (1,1) model

1 Introduction

In recent years, China has not only achieved better development in logistics facilities and equipment, but also gradually increased the variety and output of agricultural products. The production of fresh vegetables, fruits, fresh aquatic products, meat, eggs, milk and other fresh agricultural products in China has increased from 288.6129 million tons in 2016 to 362.6428 million tons in 2023. Consumers not only have requirements for the category of fresh agricultural products, but also have higher demands for quality and freshness. Fresh agricultural products are perishable foods, so there are very high temperature requirements for transportation, storage, distribution, and other aspects, resulting in relatively high transportation and facility equipment costs. The increasing demand for fresh agricultural products from consumers is driving the development of cold chain logistics.

In order to effectively avoid excessive or insufficient supply capacity of cold chain logistics in the future, it is necessary to predict the demand for cold chain logistics of fresh agricultural products and provide scientific and accurate development suggestions

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for cold chain logistics. This article predicts the future consumption of fresh agricultural products based on historical data, helping to better plan the development of cold chain logistics and fresh agricultural products in the future.

Many scholars have conducted research on cold chain logistics demand forecasting methods.

Zhang Jiaqi (2023) designed the grey prediction model, BP neural network model and grey neural network model to compare the prediction effects of the three models and select the grey neural network model with higher accuracy to forecast the demand for fresh agricultural products cold chain logistics in the next five years [1].

Peng Xiuxiu (2023) uses grey correlation analysis to select some influencing factors that can affect the national cold chain logistics indicators. Using the relevant data of national cold chain logistics demand from 2013 to 2020, the GM (1, N) grey prediction model is established by selecting the total social logistics cost and the total demand for cold chain logistics in China[2].

Li Tingting (2024) applies the gray GM(1, 1) model to forecast the demand for cold chain logistics of agricultural products in Guizhou Province from 2022 to 2031. The results show that the constructed model passed the validity test and accuracy test, and the demand for agricultural cold chain logistics in this province is increasing year by year [3].

Zheng Xingtong (2024) screened out seven key indicators by random forest algorithm, and then constructed a multi-layer BiLSTM model for prediction. At the same time, the GM(1, 1) model, BPNN model and LSTM model were constructed for empirical comparative research. It is found that the multi-layer BiLSTM model has the lowest value and the best prediction effect. Finally, the multi-layer BiLSTM model is used to predict the cold chain logistics demand value of fresh agricultural products in Fujian Province from 2023 to 2027 [4].

Gong Yingmei (2024) establishes a combined prediction model by assigning weights to three single prediction models: grey prediction GM (1,1), time series ARIMA method, and quadratic smoothing index method using entropy method. Using the production data of six types of fresh agricultural products in Yunnan Province from 2009 to 2020, the article predicts the relevant logistics volume from 2021 to 2030. The prediction results show that the combined prediction method has better prediction accuracy than the three single prediction methods [5].

Liu Xueli (2024) selects ten basic indicators from the three levels of product supply, logistics scale, and social economy. Utilizing the SPSS software, a multiple regression model is constructed to forecast the demand for cold chain logistics of fresh agricultural products in Hebei Province. The study analyses the impact of each indicator on the demand for cold chain logistics in Hebei Province and predicts the changing trends of these indicators over time through curve regression. Finally, the future demand for cold chain logistics of fresh agricultural products in Hebei Province over the next five years is calculate [6].

Liu Fangyi (2024) chose Shapley value method to combine the principal component regression prediction model, RBF neural network model, and LSTM model to build a composite prediction model, and the four prediction models are used to predict the cold chain logistic demand of fresh agricultural products in Hebei province from 2010 to 2022 [7].

Xu Chaoyi (2024) collected fresh agricultural product yield data from2001 to 2022 and trained and validated three models: back propagation neural network (BP neural network), long short-term memory (LSTM), and particle swarm optimization long short-term memory (PSO-LSTM). The results showed that the PSO-ISTM model has the highest prediction accuracy and the best fitting effect, and can effectively predict the cold chain logistics demand for fresh agricultural products in Anhui Province [8].

This article applies the DGM (1,1) model to predict the future demand for cold chain logistics of fresh agricultural products based on their consumption.

The Notice of the General Office of the Ministry of Transport on the Implementation of Green Channel Policies for Piglets and Fresh Meat states that fresh agricultural products include fresh vegetables, fruits, aquatic products (only referring to live and fresh), live livestock and poultry, fresh meat, eggs, milk, etc. This article selects six types of fresh agricultural products, namely vegetables, fruits, meat, dairy products, eggs, and aquatic products, for in-depth research and discussion.

2 Grey Residual Correction DGM (1.1) Model

Logistics demand forecasting is based on the development of the logistics industry and related factors, using appropriate forecasting methods and means to predict the future development trend of logistics and form scientific judgments. At present, there are abundant methods for predicting logistics demand, including exponential smoothing, expert prediction, regression analysis prediction, time series prediction, grey prediction, etc. Each prediction method has its own characteristics and usage scenarios.

Grey prediction method is to analyze the correlation between system factors, process raw data to find the rules of system changes, generate regular data sequences, and then establish corresponding differential equation models to predict the future development trend of things. This article chooses the DGM (1,1) model to predict the consumption of fresh agricultural products.

2.1 DGM (1.1) Modelling

The GM (1,1) model, as the core of the grey prediction model, is an approximate differential and difference equation model that views the entire system as a function that changes over time. When modeling, good predictive performance can be achieved even without a large amount of data support, achieving high fitting and prediction accuracy. Small changes in the initial values of the sequence in this model may lead to significant changes in the simulated sequence, which can have a significant impact on the prediction results. Therefore, when the original data sequence has an approximate exponential growth pattern, the prediction results are not ideal. Due to the significant changes in the growth rate of freight volume in recent years, the prediction accuracy of the GM (1,1) grey model is relatively low. Therefore, the discrete grey DGM model is introduced into the prediction [9-10].

Firstly,

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \tag{1}$$

Accumulate the original sequence once and generate a new sequence:

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \tag{2}$$

It is called

$$X^{(0)}(k) + aX^{(1)}(k) = b \tag{3}$$

As the original form of the GM (1,1) model. Among them, the development coefficient is the parameter a, which represents the development law and trend of the sequence; The grey action quantity is the parameter b, which reflects the changing relationship of the sequence.

The whitening equation is:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{4}$$

After improving the GM (1,1) model, the DGM (1,1) model can be obtained.

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2 \tag{5}$$

In the formula, β_1, β_2 are parameters;

If $\hat{\beta} = (\beta_1, \beta_2)^T$ is a parameter column, and $B = \begin{bmatrix} x^{(1)}(1) & 1 \\ x^{(1)}(2) & 1 \\ \cdots & \\ x^{(1)}(n-1) & 1 \end{bmatrix}$, $Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \cdots \\ x^{(1)}(n) \end{bmatrix}$

The least squares parameter estimation parameter column of the grey differential equation (3) satisfies:

$$\hat{\beta} = (B^T B)^{-1} B^T Y \tag{6}$$

$x^{(1)}(k+1)$ estimated value is: $x^{(1)}(k+1) = \beta_1^k x^{(1)}(1) + \frac{1-\beta_1^k}{1-\beta_1}\beta_2$

The predicted value obtained is : $x^{(0)}(k+1) = (1-\beta_1^{-1})\beta_1^k x^{(1)}(1) + \beta_1^{k-1}\beta_2$

2.2 Residual Correction DGM Model

When the prediction accuracy of the DGM (1,1) prediction model is low, residual sequences can be used to establish the DGM (1,1) model, and the predicted values of the original model can be corrected to improve the prediction accuracy [11].

Residual refers to the difference between the original and predicted values of data, and the residual sequence is as follows:

$$\varepsilon^{(0)}(k) = \left(\varepsilon^{(0)}(1), \varepsilon^{(0)}(2), \dots, \varepsilon^{(0)}(n)\right) \tag{7}$$

Among them:

$$\varepsilon^{(0)}(k) = x^{(0)}(k) - \bar{x}^{(0)}(k) \tag{8}$$

To ensure the non negativity of the residual sequence, the following processing should be applied:

(1) When the values in the residual sequence are all positive, directly establish a grey DGM (1,1) prediction model;

(2) When all the values in the residual sequence are negative, take the absolute values of all the numbers and establish a DGM (1,1) model. After obtaining the results, add a negative sign;

(3) When there are positive and negative numbers in the residual sequence, normalization must be performed first. Each number in the residual sequence is added with the absolute value of the smallest negative number in the sequence; Then establish the DGM (1,1) model; After obtaining the result, subtract the absolute value of the smallest negative number.

After processing, use the residual sequence to establish a grey DGM (1,1) model, and obtain the correction quantity.

Finally, obtain the revised prediction result:

$$\bar{x}^{(0)\prime}(k) = \bar{x}^{(0)}(k) + \delta(k) \tag{9}$$

3 Prediction of Consumption of Fresh Agricultural Products

The formula for calculating the total consumption of fresh agricultural products by residents is as follows:

Total consumption of fresh agricultural products by residents=total population of the year × per capita consumption of fresh agricultural products by residents of the year

After calculation, the total consumption of six types of fresh agricultural products in China from 2016 to 2023 is calculated. Taking the total consumption of fresh products by residents in Beijing as an example, the raw data is shown in Table 1.

Table 1. Raw Data of Total Consumption of Fresh Products by Residents in Beijing (Unit: 10000 tons).

Year	2016	2017	2018	2019
consumption volume	497.1675	486.8486	562.0288	612.324
Year	2020	2021	2022	2023
consumption volume	631.3076	621.676	545.5632	572.7320

The prediction steps are as follows:

Step 1: Calculate the accumulated vector to obtain the generated column.

$$X^1 = (497.1675, 984.0161, 1546.0449, 2158.3689, \\ 2789.6765, 3411.3525, 3956.9157, 4529.6477)$$

Step 2: Calculate the model parameters in EXCEL:

$$\beta_1=1.0131,\ \beta_2=547.3813;$$

Step 3: Calculate the predicted value to obtain the forecast data of the total consumption of fresh products by residents.

The comparison between the actual and predicted values of the total consumption of fresh products by residents in Beijing is shown in Table 2.

Table 2. Comparison of Actual and Predicted Consumption of Fresh Products by Residents in Beijing (Unit: 10000 tons).

Year	2016	2017	2018	2019
actual value	497.1675	486.8486	562.0288	612.324
predicted value	497.1675	553.8881	561.1372	568.4811
error	0.00%	13.77%	-0.16%	-7.16%
Year	2020	2021	2022	2023
actual value	631.3076	621.676	545.5632	572.7320
predicted value	575.9212	583.4587	591.0948	598.8308
error	-8.77%	-6.15%	8.35%	4.56%

From Table 3, it can be seen that the prediction data has a large error, so residual correction is necessary.

According to formula 7, the residual sequence of the total consumption of fresh products by residents is obtained as follows:

$$\varepsilon^{(0)}(k) = (0, -56.7206, -74.2886, -6.4523,\ 36.4028, 47.8489, 30.5812, -53.2676)$$

Due to the positive and negative nature of the numbers in the sequence, normalization is required: add 74.2886 to all the numbers in the sequence to obtain a new sequence:

$$\varepsilon^{(0)}(k) = (74.2886, 17.5680, 0, 67.8362,\ 110.6913, 122.1375, 104.8698, 21.0209)$$

Establish a DGM (1,1) model, obtain the predicted values of the residual sequence, subtract 74.2886 from all the numbers to obtain the corrected value sequence:

$$\delta^{(0)}(k) = (0, -19.6690, -16.4792, -13.1030\ -9.5297, -5.7477, -1.7448, 2.4919)$$

According to formula 9, the corrected predicted value can be obtained.

The comparison between the actual value and the revised forecast value of the total consumption of fresh products by residents is shown in Table 3.

Table 3. Comparison of Actual and Revised Predicted Total Consumption of Fresh Products by Residents (Unit: 10000 tons).

Year	2016	2017	2018	2019
actual value	497.1675	486.8486	562.0288	612.324
Residual correction predicted value	497.1675	534.2190	544.6580	555.3781
Residual correction error	0.00%	-9.73%	3.09%	9.30%

Year	2020	2021	2022	2023
actual value	631.3076	621.676	545.5632	572.7320
Residual correction predicted value	566.3915	577.7110	589.3500	601.3227
Residual correction error	10.28%	7.07%	-8.03%	-4.99%

From Table 3, it can be seen that the prediction accuracy has been improved after residual correction. According to the above calculation method, the predicted total consumption of fresh products by residents can be obtained as shown in Table 4.

Table 4. Predicted Consumption of Fresh Products by Residents (Unit: 10000 tons).

Region	2024	2025	2026	2027	2028
Beijing	613.64	626.33	639.40	652.86	666.75
Tianjin	368.90	363.81	358.85	354.01	349.27
Hebei	2345.77	2529.87	2728.20	2941.58	3170.96
Shanxi	833.96	875.35	920.52	970.00	1024.43
Inner Mongolia	619.95	639.63	661.10	684.28	709.10
Liaoning	1210.50	1249.72	1291.19	1334.63	1379.91
Jilin	537.26	539.92	542.58	545.26	547.96
Heilongjiang	803.94	821.96	840.45	859.42	878.87
Shanghai	646.87	651.89	656.99	662.15	667.38
Jiangsu	2312.62	2442.13	2582.71	2734.00	2895.87
Zhejiang	1862.73	1972.95	2090.60	2216.03	2349.61
Anhui	1595.72	1670.86	1750.80	1835.58	1925.28
Fujian	965.04	998.17	1033.91	1072.04	1112.40
Jiangxi	1222.65	1305.10	1394.10	1489.65	1591.85
Shandong	2629.93	2693.08	2759.99	2830.52	2904.58
Henan	2550.94	2722.12	2907.23	3106.47	3320.24
Hubei	1448.51	1492.67	1539.72	1589.51	1641.90
Hunan	1602.15	1645.68	1691.41	1739.18	1788.88
Guangdong	3084.54	3159.29	3236.20	3315.31	3396.67
Guangxi	977.69	995.56	1014.18	1033.51	1053.50
Hainan	227.94	239.45	251.86	265.16	279.32
Chongqing	953.76	990.80	1030.66	1073.22	1118.41
Sichuan	2024.25	2036.55	2049.26	2062.37	2075.85
Guizhou	640.41	655.05	670.80	687.48	704.96
Yunnan	968.55	1024.10	1082.81	1144.75	1210.05
Xizang	46.42	49.25	52.26	55.47	58.87
Shaanxi	842.10	877.22	914.09	952.75	993.23
Gansu	499.69	506.20	512.87	519.70	526.70
Qinghai	89.31	92.41	95.66	99.05	102.57
Ningxia	160.29	163.59	166.98	170.47	174.05
Xinjiang	535.07	539.21	543.85	548.91	554.33

From the predicted results, it can be seen that the total consumption of six types of fresh agricultural products in each province of China has been increasing year by year. By 2028, the consumption of fresh agricultural products is expected to reach 411.7372 million tons, thus the demand for cold chain logistics will continue to increase.

4 Suggestions

This article uses the DGM (1,1) model to predict the consumption of fresh agricultural products. The results indicate that the consumption of fresh agricultural products continues to increase, and the demand for cold chain logistics is very high in the future. Therefore, it is necessary to vigorously develop cold chain logistics.

4.1 Reasonably Plan the Spatial Layout of Cold Chain Logistics

The "14th Five Year Plan" for the Development of Cold Chain Logistics has been released, aiming to fully establish a modern cold chain logistics system by 2035.

China will build a national cold chain logistics backbone channel network that connects internal and external channels, and create a "321" cold chain logistics operation system with "three-level nodes, two major systems, and an integrated network". Among them, "3" refers to improving the layout of national backbone cold chain logistics bases, strengthening the construction of production and sales cold chain distribution centers, focusing on the "first kilometer" of production areas and the "last kilometer" of cities, and forming an efficient three-level cold chain logistics node; 2 "refers to the construction of two major cold chain logistics systems that serve domestic production and sales, as well as international import and export; 1 "refers to the construction of a domestic and international integrated cold chain logistics network with intensive facilities, efficient transportation, high-quality services, safety and reliability.

4.2 Improve the Information Technology Level of Cold Chain Logistics

Nowadays, the cold chain circulation rate of agricultural products in developed countries is basically above 95%. In China, the cold chain circulation rate of meat and aquatic products is relatively high, while that of fruits and vegetables is still very weak, resulting in a relatively high loss rate of agricultural products. Therefore, we need to rely on technological innovation to improve supply chain efficiency. At the same time, we should also promote the deep integration of digitization and various links in the fresh agricultural product supply chain, focusing on establishing a refined business process, modular agricultural production, and a digitalized operation system for warehousing and logistics.

4.3 Strengthen the Construction of Cold Chain Logistics Infrastructure

The level of infrastructure and equipment for cold chain logistics directly affects the development level of regional logistics industry and agriculture. By 2025, we aim to establish around 100 national backbone cold chain logistics bases. Although the quantity and quality of cold chain logistics infrastructure equipment such as cold storage, refrigerated trucks, and distribution centers have increased significantly compared to previous years, it is necessary to continue strengthening infrastructure, improving road and railway transportation infrastructure, increasing the circulation rate of fresh agricultural products, increasing cold storage capacity, refrigerated trucks, and other infrastructure to meet the needs of cold chain logistics, promoting standard pallets and turnover boxes, and improving the recycling rate of basic equipment in the context of promoting agricultural modernization. On the other hand, we also need to develop leading enterprises in cold chain logistics to drive the level of economic development and the development of the cold chain logistics industry.

4.4 Increase Policy Support for Cold Chain Logistics

The construction of cold chain logistics is a project with huge investment and engineering volume. Only by relying on the joint efforts of more industries can the development level of cold chain logistics be improved. Internet industries such as big data, Internet of Things, and intelligence, as well as railway and road transportation levels and agricultural development levels, will jointly promote the development of cold chain logistics. Therefore, to improve the development of cold chain logistics, the government needs to vigorously support and support from capital and more aspects, and it needs to introduce support policies conducive to the development of agricultural trade, transportation, and the tertiary industry, so as to provide more possibilities and feasibility for the development of cold chain logistics. In addition, higher requirements should be put forward for enterprises related to cold chain logistics, strictly promoting industry development in accordance with relevant standards and laws and regulations, improving the standardization of cold chain logistics, and implementing fiscal policies such as tax reduction and exemption to encourage more enterprises and talents to join the cold chain logistics industry and make more contributions to the development of fresh agricultural products cold chain logistics industry.

5 Conclusion

This article predicts the consumption of six types of fresh agricultural products: vegetables, fruits, meat, dairy products, eggs, and aquatic products. The results show that the consumption of fresh agricultural products in various provinces of China is on the rise. It is imperative to develop cold chain logistics to better meet consumers' demand for fresh agricultural products. At present, the penetration rate of cold chain logistics in China is only 19%, but the scale of the fresh e-commerce market has exceeded 560 billion yuan, and the huge supply-demand contradiction contains vast room for upgrading. By promoting the intelligence of infrastructure, refinement of industrial chains, and green operation models, connecting the production and sales data of the agricultural sector, logistics enterprises, and retail end, and achieving dynamic matching between demand forecasting and production capacity, we can achieve a leap from "ensuring supply" to "improving quality", and effectively promote the deep integration of rural revitalization and consumption upgrading strategies.

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