Scientific and Social Research, 2025, Volume 7, Issue 11
https://ojs.bbwpublisher.com/index.php/SSR
Online ISSN: 2981-9946
Print ISSN: 2661-4332

Research on Demand Forecasting for Cold Chain Logistics of Fresh Agricultural Products in Urban Areas of Qinhuangdao

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Abstract: Based on the current development status of cold chain logistics for fresh agricultural products in urban areas of Qinhuangdao, this study employs the grey forecasting model to predict the consumption of fresh agricultural products in these areas. The forecasting results demonstrate high accuracy, effectively reducing losses and circulation costs of agricultural products, thereby promoting the healthy development of cold chain logistics for fresh agricultural products in Qinhuangdao and providing decision-making support for relevant departments in the city.

Keywords: Grey GM(1,1) model; Fresh agricultural products; Cold chain logistics; Demand forecasting

Online publication: November 14, 2025

1. Introduction

In the new era of socialism with Chinese characteristics, people's quality of life has been significantly improved. As fresh agricultural products form the mainstay of their diet, the demand for such products is also on the rise. Given the high perishability of fresh agricultural products, accurately and timely obtaining high-quality and fresh produce has become a critical issue that consumers hope to resolve [1]. The freshness of fresh agricultural products is a measure of people's dietary quality, necessitating stringent storage requirements in refrigerated environments at every stage of logistics. To ensure that fresh agricultural products are not affected by the environment during circulation and to maintain their high quality and diversity, thereby meeting consumers' demands for high-quality and diverse fresh agricultural products, this study takes Qinhuangdao City as an example. By constructing a grey forecasting model, it predicts the consumption of fresh agricultural products among urban residents in Qinhuangdao, providing data support and a reference basis for the construction of cold chain logistics for fresh agricultural products in Qinhuangdao and similar cities.

In recent years, the academic community has paid significant attention to research on cold chain demand forecasting. Liu Wenhui and Wang Shaoran (2018) selected seven key indicators based on four factors influencing the market demand for fresh agricultural products and established a forecasting optimization model based on the grey GM(1,1) model [2]. Yin Wanqiu (2019) used the GM(1,1) model to forecast the cold chain logistics demand for aquatic products in Qingdao [3]. Huang Kai and Wang Jian (2020) analyzed the demand for cold chain logistics of fresh agricultural products using three methods: GM(1,1), BP neural network, and RBF neural network [1]. Lv Jing and Chen Yushu (2020) combined the GM(1,1) and BP neural network models to predict the demand for cold chain logistics of aquatic products in Dalian [4]. Li Minjie and Wang Jian (2020) used a combination of grey GM(1,1), RBF neural network, and BP neural network models to forecast the demand for cold chain logistics of aquatic products in China [5]. Zhang Lanrui (2021) established an improved grey GM(1,1) model modified by Markov chains to quantitatively forecast the demand for cold chain logistics of fresh agricultural products in Chongqing [6]. Li Xiaoxiang (2022) analyzed the development strategies for cold chain logistics of fresh agricultural products in China under the normalcy of the epidemic using a combined Lasso-BP neural network model [7]. Zeng Hao and Zhu Wenjuan (2022) used the grey GM(1,1) model to forecast the agricultural product output in Hunan Province over the next four years [8]. Li Xiaoling (2022) conducted a predictive study on the demand for cold chain logistics of agricultural products in Guangdong Province using the GM(1,N) model [9]. Li Sicong and Ye Jing (2022) studied the market demand prospects for cold chain logistics in China under the “dual circulation” background, employing a combined model of grey forecasting and multiple linear regression [10].

Regarding demand influencing factors and forecasting, domestic scholars have rarely used “agricultural product consumption” as an indicator when selecting forecasting indicators for the logistics demand of fresh agricultural products, despite its ability to fully reflect changes in people’s demand for fresh agricultural products. This paper takes the logistics demand for fresh agricultural products in urban areas of Qinhuangdao as the research object, forecasts it using the grey forecasting method, conducts empirical analysis, and proposes relevant countermeasures and measures. The research conclusions hold significant importance for decision-making and implementation by relevant departments.

2. Research methodology

Grey prediction is a forecasting method within the framework of grey system theory, suitable for predicting systems with high levels of uncertainty. Based on known data and patterns of change, under certain constraints, grey prediction aims to minimize the mean squared error and uses grey models to forecast future trends. Among these, the GM(1,1) model is the most commonly used grey prediction model. It is a predictive model constructed based on a randomly generated original time series, by accumulating the data to form a new time series, and under the condition of first-order linear differential equations. The GM(1,1) model is derived through mathematical deduction from a first-order differential equation based on the data. The main approach of this model involves accumulating the original data sequence, averaging the accumulated generated sequence, and establishing a differential equation model for prediction. The advantage of grey prediction lies in its ability to handle situations with small sample sizes, incomplete data, and uncertain data changes.

The steps for the grey GM(1,1) model are as follows: Assume there is an existing original non-negative data sequence:

$$X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \ldots, X^{(0)}(n)\}$$

Perform a first-order accumulation operation on the original data sequence to generate a new first-order accumulated sequence:

$$X^{(1)} = \{X^{(1)}(1), X^{(1)}(2), X^{(1)}(3), \ldots, X^{(1)}(n)\}$$

where,

$$X^{(1)}(n) = \sum_{i=1}^{n} X^{(0)}(n) \tag{1}$$

Model the new sequence to obtain the corresponding differential equation for the GM(1,1) model:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{2}$$

where, a and b are undetermined coefficients, with a being the development coefficient that primarily controls the system's development trend, and b being the grey action quantity, whose magnitude reflects the relationship of data changes.

Solve for the coefficient matrix $\hat{a}$, where $\hat{a}=\begin{Bmatrix} a \\ b \end{Bmatrix}$, and estimate $\hat{a}$ using the least squares method, resulting in

$$\hat{a} = (B^{r}B)^{-1}B^{T}Y$$

Where,

$$B = \begin{bmatrix} -\frac{1}{2}\left(X^{(1)}(1) + X^{(1)}(2)\right) & 1 \\ -\frac{1}{2}\left(X^{(1)}(2) + X^{(1)}(3)\right) & 1 \\ \cdots & \cdots \\ -\frac{1}{2}\left(X^{(1)}(n-1) + X^{(1)}(n)\right) & 1 \end{bmatrix}$$

$$Y = \{X^{(0)}(2), X^{(0)}(3), \ldots, X^{(0)}(n)\}$$

By solving according to the formula, the GM(1,1) prediction model can be obtained:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a}, k = 1,2,\ldots,n \tag{3}$$

Perform inverse accumulation on $\hat{X}^{(1)}(k+1)$ to obtain the restored predicted value:

$$\hat{X}^{(1)}(k+1) = \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k) = (1 - e^{a})\left[X^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a} \tag{4}$$

The future forecast data is calculated using the aforementioned steps, followed by an analysis of the reliability of the forecast data. This analysis is primarily based on the development coefficient “a” and residuals, as detailed below:

2.1. Matching degree test between the development coefficient “a” and the model applicability range

When assessing the accuracy of the forecast data, it is essential to consider the development coefficient “a” to determine the applicability of the model. The specific applicability range is outlined in **Table 1**.

Table 1. Applicability range of the grey prediction model

Range of $\|a\|$	Model Applicability
$\|a\| \geq 2$	The model is meaningless.
$\|a\| \leq 0.3$	Suitable for medium to long-term forecasting.
$0.3 < \|a\| \leq 0.5$	Can be used for short-term forecasting; use with caution for medium to long-term forecasting.
$0.5 < \|a\| \leq 0.8$	Should be used with great caution, even for short-term forecasting.
$0.8 < \|a\| \leq 1$	The residual-corrected GM(1,1) model should be adopted.
$\|a\| > 1$	The GM(1,1) model is not suitable for forecasting.

2.2. Residual test for the Grey GM(1,1) model

Calculations are performed based on the original data and forecast values to derive the absolute error $\hat{E}^{(0)}(i) = \hat{X}^{(0)}(i) - X^{(0)}(i)$, relative error $F(i) = \frac{\hat{E}^{(0)}(i)}{\hat{X}^{(0)}(i)} \times 100\%$, and average relative error $\bar{F}(i) = \frac{\sum_{i=1}^{n}|F(i)|}{n}$, where i = 1, 2, ..., n.

The accuracy of the model is expressed as: $\eta = (1 - \bar{F}(i)) \times 100\%$. Generally, when $\eta > 80\%$, the model’s forecast results can be deemed satisfactory. When $\eta > 90\%$, the forecast accuracy is considered high.

3. Forecasting demand for cold chain logistics of fresh agricultural products in urban areas of Qinhuangdao

3.1. Selection of forecast categories

Through research, it has been found that with the rising consumption levels of urban residents in Qinhuangdao, the demand for cold chain logistics of fresh agricultural products is increasing. Due to the characteristics of different agricultural products, vegetables, fruits, meats, etc., have higher storage requirements for whether refrigeration measures are taken during transportation and circulation, which directly affects the quantity and loss rate of spoilage. As essential daily necessities, fresh agricultural products like vegetables and fruits have a high consumption volume, leading to a significant demand for cold chain transportation. Therefore, this paper focuses on vegetables, fruits, meats, aquatic products, and dairy products as the primary research objects.

3.2. Processing of forecast demand data

The availability of data is the foundation of forecasting research. To ensure the reliability and accuracy of the data, the forecasting indicator data in this paper are sourced from the “Hebei Statistical Yearbook”, the sixth section on

“People’s Livelihood” in the “Qinhuangdao Statistical Yearbook”, and the “Qinhuangdao Economic and Social Development Statistical Bulletin.” The consumption volume of fresh agricultural products among urban residents in Qinhuangdao City is used as the original forecasting data. Furthermore, given that the “2022 Qinhuangdao Statistical Yearbook” had not been officially released during the research period, an empirical analysis was conducted on five major agricultural products based on historical statistical data from 2017 to 2021. Specific statistical data is shown in **Table 2**.

Table 2. Consumption of fresh agricultural products by urban residents in Qinhuangdao City

Year	Vegetables (kg)	Fruits (kg)	Meat (kg)	Dairy (kg)	Aquatic Products (kg)
2017	104.12	62.72	23.41	23.02	8.25
2018	96.65	63.34	23.04	20.77	7.86
2019	102.97	71.48	27.14	21.51	7.61
2020	106.99	80.08	24.48	20.47	9.97
2021	118.95	83.02	25.18	23.67	9.88

3.3. Forecasting consumption of fresh agricultural products among urban residents

3.3.1. Vegetables

Model parameters: a = -0.067; b = 85.653

Grey forecasting model: $\widehat{X}^{(1)}(k+1) = 1382.522985e^{0.067k} - 1278.402985$

The forecasted values for vegetable consumption among urban residents from 2022 to 2026 are shown in **Table 3**.

Table 3. Forecasted values for vegetable consumption among urban residents from 2022 to 2026

Year	2022	2023	2024	2025	2026
Predicted Consumption (kg)	125.473	134.211	143.557	153.554	164.247

3.3.2. Fruits

Model parameters: a = -0.089; b = 56.311

Grey forecasting model: $\widehat{X}^{(1)}(k+1)$ =695.427865e^0.089t - 632.707865

The forecasted values for fruit consumption among urban residents from 2022 to 2026 are shown in Table 4.

Table 4. Forecasted values for fruit consumption among urban residents from 2022 to 2026

Year	2022	2023	2024	2025	2026
Predicted Consumption (kg)	92.616	101.277	110.749	121.106	132.432

3.3.3. Meat

Model parameters: a = -0.015; b = 23.892

Grey Prediction Model: $\widehat{X}^{(1)}(k+1) = 1616.21e^{0.015t}$ –1592.8

The predicted values of meat consumption by urban residents from 2022 to 2026 are shown in **Table 5**.

Table 5. Predicted values of meat consumption by urban residents from 2022 to 2026

Year	2022	2023	2024	2025	2026
Predicted Consumption (kg)	25.888	26.27	26.658	27.052	27.452

3.3.4. Dairy products

Model Parameters: a = -0.036; b = 19.237

Grey Prediction Model: $\widehat{X}^{(1)}(k+1) = 557.381111e^{0.036t} - 534.361111$

The predicted values of dairy product consumption by urban residents from 2022 to 2026 are shown in **Table 6**.

Table 6. Predicted values of dairy product consumption by urban residents from 2022 to 2026

Year	2022	2023	2024	2025	2026
Predicted Consumption (kg)	23.633	24.505	25.411	26.349	27.322

3.3.5. Aquatic products

Model Parameters: a = -0.095; b = 6.458

Grey Prediction Model: $\widehat{X}^{(1)}(k+1) = 76.228947e^{0.095t} - 67.978947$

The predicted values of aquatic product consumption by urban residents from 2022 to 2026 are shown in **Table 7**.

Table 7. Predicted values of aquatic product consumption by urban residents from 2022 to 2026

Year	2022	2023	2024	2025	2026
Predicted Consumption (kg)	11.135	12.25	13.476	14.825	16.309

Analysis reveals that the model parameter a for the consumption of fresh agricultural products by urban residents all satisfy $-a \leq 0.3$, indicating, according to **Table 1**, that this paper is suitable for medium- to long-term predictions.

3.4. Error inspection for predicted consumption of urban residents

An error inspection was conducted on the predicted values and original data for the consumption of five types of fresh agricultural products by urban residents in Qinhuangdao, yielding the accuracy of the predicted values. The relative errors and prediction accuracies are shown in **Tables 8**, **9**, **10**, **11**, and **12**, respectively.

Table 8. Relative errors between predicted and actual values for vegetables

Year	Observed Value	Fitted Value	Absolute Error	Relative Error (%)
2017	104.12	104.12	0	0
2018	96.65	95.853	0.797	0.825
2019	102.97	102.528	0.442	0.43
2020	106.99	109.667	-2.677	2.502
2021	118.95	117.304	1.646	1.383

Table 9. Relative errors between predicted and actual values for fruits

Year	Observed Value	Fitted Value	Absolute Error	Relative Error (%)
2017	62.72	62.72	0	0
2018	63.34	64.771	-1.431	2.259
2019	71.48	70.828	0.652	0.912
2020	80.08	77.452	2.628	3.282
2021	83.02	84.695	-1.675	2.018

Table 10. Relative errors between predicted and actual values for meat

Year	Observed Value	Fitted Value	Absolute Error	Relative Error (%)
2017	23.41	23.41	0	0
2018	23.04	24.414	-1.374	5.962
2019	27.14	24.774	2.366	8.717
2020	24.48	25.14	-0.66	2.696
2021	25.18	25.511	-0.331	1.316

Table 11. Relative error between predicted and actual values of dairy products

Year	Observed Value	Fitted Value	Absolute Error	Relative Error (%)
2017	23.02	23.02	0	0
2018	20.77	20.441	0.329	1.584
2019	21.51	21.196	0.314	1.46
2020	20.47	21.979	-1.509	7.371
2021	23.67	22.791	0.879	3.715

Table 12. Relative error between predicted and actual values of aquatic products

Year	Observed Value	Fitted Value	Absolute Error	Relative Error (%)
2017	8.25	8.25	0	0
2018	7.86	7.602	0.258	3.277
2019	7.61	8.363	-0.753	9.901
2020	9.97	9.201	0.769	7.716
2021	9.88	10.122	-0.242	2.447

The prediction accuracy for vegetables, fruits, meat, dairy products, and aquatic products is 98.97%, 98.31%, 96.26%, 97.17%, and 95.33%, respectively, all exceeding 90%. This indicates that the model exhibits high prediction accuracy.

3.5. Demand forecast results

The results of the error tests demonstrate that the proposed forecasting method has achieved favorable predictive outcomes with high accuracy. The forecasted consumption of five types of fresh agricultural products among urban residents in Qinhuangdao from 2022 to 2026 is detailed in Table 13.

Table 13. Forecasted consumption of fresh agricultural products by urban residents from 2022 to 2026

Year	Vegetables	Fruits	Meat	Dairy	Aquatic Products	Total
2022	125.47	92.62	25.89	23.63	11.14	278.75
2023	134.21	101.28	26.27	24.51	12.25	298.52
2024	143.56	110.75	26.66	25.41	13.48	319.86
2025	153.55	121.11	27.05	26.35	14.83	342.89
2026	164.25	132.43	27.45	27.32	16.31	367.76

Table 13 reveals that the logistics consumption of the aforementioned five categories of fresh agricultural products is projected to increase annually from 2022 to 2026. Notably, the demand for vegetables and fruits is expected to rise significantly, as they remain consistently popular among consumers. The total logistics demand for fresh agricultural products in 2022 is estimated to reach 278.75 kilograms, with an average annual increase of 5.6% in logistics consumption of fresh agricultural products in Qinhuangdao over the five-year period from 2022 to 2026.

A comprehensive analysis indicates that the consumption of fresh agricultural products in Qinhuangdao is increasing year by year, leading to a gradual rise in logistics demand. This trend can be attributed to two main factors: Firstly, within the overall economic development of Qinhuangdao, the disposable income of permanent residents has been steadily rising, and consumer attitudes have kept pace with the times. This is reflected in the increasingly diversified consumption patterns of agricultural products, with a growing demand for fresh and green produce. Consumers' perceptions of major fresh agricultural products have gradually shifted from quantity to quality. Secondly, from the perspective of government support, the state has been continuously strengthening its policy, project, and financial support for fresh produce cold chain logistics. Qinhuangdao City's cold chain logistics have also received corresponding policy support, security guarantees, and project support, all of which have played a crucial role in promoting demand growth and ensuring supply. On this basis, the fresh produce cold chain logistics system in Qinhuangdao City has been further improved, steering it towards standardization, normalization, and specialization.

4. Research conclusions and recommendations

4.1. Research conclusions

Based on relevant domestic and international literature and theoretical research, combined with the current development status of fresh produce logistics in Qinhuangdao's urban areas, this paper selects relevant types of agricultural products for study and employs the gray GM(1,1) forecasting method to predict the logistics demand for fresh produce in Qinhuangdao's urban areas over the next five years. The conclusions indicate that the demand for cold chain logistics of fresh produce in Qinhuangdao's urban areas is showing a year-on-year increase, particularly for vegetables and fruits. By 2026, the total demand for cold chain logistics of fresh produce in Qinhuangdao's urban areas is projected to reach 367.76 kilograms.

4.2. Recommendations

Based on the forecast results and Qinhuangdao's current development and needs, recommendations are proposed to promote the development of agricultural product cold chain logistics in Qinhuangdao and meet its demands. These recommendations provide a reference for the rational construction of Qinhuangdao's cold chain logistics system, the long-term development of the fresh produce market, and the improvement of Qinhuangdao's cold chain logistics industry chain.

4.2.1. Comprehensive planning for fresh produce logistics

The cold chain logistics of agricultural products must adapt to economic and social development. In overall planning, the impact of regional economic development on the cold chain logistics of agricultural products should be fully considered. Firstly, accurately position agricultural cold chain logistics based on the actual situation of Qinhuangdao City. Then, comprehensively arrange cold chain logistics in accordance with the overall agricultural production pattern and economic development level of Qinhuangdao City, with a focus on centralized areas of high-quality and specialty agricultural products, to facilitate industrial layout. Finally, ensure well-coordinated planning by actively collaborating with relevant functional departments and enterprises to promote the implementation of standards. Additionally, implement various safeguard measures to accelerate the rapid development of agricultural cold chain logistics in Qinhuangdao City and enhance the overall development level of agricultural cold chain logistics.

4.2.2. Strengthen infrastructure construction for cold chain logistics

For a long time, Qinhuangdao City has not attached importance to the construction of cold chain logistics, resulting in a significant lag in the city's cold chain logistics equipment level. To change this situation, it is necessary to increase investment in cold chain equipment and improve the overall level of the entire cold chain logistics equipment. Furthermore, the principle of distribution according to needs should be adopted to avoid overinvestment and resource waste. In regions with abundant agricultural resources, equipment investment should be increased, while investment in areas with scarce agricultural resources should be reduced. For example, based on the theory of collaborative management, investment in cold chain-related equipment can be increased in production bases such as Qinglong chestnuts, Lulong walnuts, Changli grapes, Shanhaiguan big cherries, and Changli bulk vegetables. Small-scale storage equipment can be constructed in the fields to enable reasonable storage of agricultural products after maturity and ensure that they remain at a controlled temperature during transportation, thereby reducing losses of agricultural products. This holds significant practical importance for improving the circulation efficiency of agricultural products, facilitating the "first kilometer" for farmers to leave the village, and greatly enriching farmers' "vegetable baskets."

4.2.3. Enhance the informatization level of agricultural product cold chain logistics

The application of network technology in agricultural product cold chain logistics can play a positive role in promoting its development. On the one hand, as the Internet increasingly penetrates households, consumers' acceptance of online shopping for agricultural products has grown, significantly driving the development of cold chain logistics for fresh agricultural products in Qinhuangdao City. On the other hand, leveraging big data platforms and information technology built on the Internet can improve the level of information exchange during the cold chain distribution of agricultural products, thereby helping to reduce losses of agricultural products.

Through the construction of information systems, the study aims to enhance technological support for the transportation and supply of cold-chain agricultural products, gradually establish a comprehensive and reliable product traceability system and a quality control system for agricultural products, continuously improve the standards for cold-chain transportation and distribution of agricultural products, strengthen quality supervision, ensure the implementation of relevant production technologies, norms, and standards, and refine the market access mechanism.

4.2.4. Strengthening the cultivation of talents in cold-chain logistics for agricultural products

The development of modern cold-chain logistics for agricultural products relies on the support of intelligence, information, and automation technologies. It also requires knowledge in areas such as agricultural product storage and preservation, as well as an understanding of relevant logistics laws and regulations, agricultural product policies, and marketing strategies. In terms of training professionals in cold-chain logistics for agricultural products, the following approaches can be taken: Firstly, Qinhuangdao should leverage university resources to connect cold-chain logistics companies in need with relevant universities, forming an organized and planned training system. Secondly, cold-chain logistics enterprises should be guided to fully utilize the advantages of high-quality educational resources from universities, organizing professional training for on-the-job employees, with a focus on frontline staff in cold-chain logistics companies. Finally, attention should be paid to policy support, formulating development and deployment plans for top talents in the logistics industry, creating favorable conditions for attracting top talents in cold-chain logistics, and providing preferential treatment policies for introduced talents in terms of work and living conditions.

Disclosure statement

The authors declare no conflict of interest.

Funding

University-level Research Project of Hebei University of Environmental Engineering, grant number [XJXM-QN-2024006]; Soft Science Project of Qinhuangdao Science and Technology Bureau (202301A376); Natural Science Fund Project of Hebei Provincial Department of Science and Technology (Project Number: G2023415001); Humanities and Social Sciences Research Project in Colleges and Universities of Hebei Province (Project Number: SD2021084).

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