Forecasting Supply and Demand Balance of Agricultural Products Market Before and After the Epidemic in China Based on SARIMA Model and Optimizing Industry Chain Integration

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Abstract: Since the outbreak of the new crown epidemic, it has had a far-reaching impact on the supply-demand relationship and the operation of the industrial chain in China's agricultural products market. The epidemic restricted rural labor mobility, delaying sowing. Moreover, strict prevention measures limited transportation, resulting in poor circulation of agricultural products. On the other hand, the problem of mismatch between supply and demand has caused more irregular changes in the price of agricultural products, which directly affects the consumer's purchasing behavior. Farmers and enterprises in the market will also be subject to information asymmetry and other problems of interference, and thus can not make accurate judgments about the market situation they face. Therefore, based on the SARIMA time series model, this paper models and predicts the supply and demand data of China's major agricultural markets in the year before and after the epidemic. Specific strategies for the integration and optimization of the agricultural industry chain from production, distribution and consumption are proposed, aiming to optimize the structure of agricultural production through accurate forecasting, and to improve the industry's risk-resistant ability and market adjustment efficiency. The study provides important theoretical support and practical reference for the government and enterprises to deal with emergencies.

Keywords: SARIMA; Supply and Demand Balance; Industrial Chain Integration and Optimization; Price Fluctuation; Information Asymmetry

1. Introduction

With the rapid development of China's economy, the market demand for agricultural products is growing, and guaranteeing the supply and demand balance of the agricultural products market has become an important task of national macro-control. Since the outbreak of the new crown epidemic in 2020, China's agricultural products market has suffered an unprecedented impact, affecting the production strategy and efficiency of the supply side. It directly affects logistics and transportation, alters consumer behavior, and reshapes the market structure. The supply and demand relationship in the agricultural market tends to be complicated. The traditional experience-dependent static analysis method exposes obvious limitations in terms of response speed and forecasting accuracy.

In view of the seasonal fluctuation pattern of the agricultural market, the SARIMA model can be used to derive the time series data of the agricultural market, including seasonal changes, trends and cyclical fluctuations, while dealing with the non-stationary and seasonal variations of the data. However, the current research on modeling and forecasting the supply and demand of China's agricultural market in the context of the epidemic still needs to effectively combine multiple methods, especially the empirical analysis combined with industry chain optimization.

Therefore, this research question takes the time of the epidemic as the basis of division, takes Chinese cabbage as an example, and uses the SARIMA model to model the price of Chinese cabbage from January 2019 to June 2021, and compares the fitted value of the output with the actual value. Identify whether there is a potential structural imbalance risk in Chinese cabbage. On this basis, the supply chain optimization plan is further proposed in combination with the results of the supply and demand forecast. Through the optimization of logistics, warehousing, transportation and other links to reduce the cost of agricultural products in the supply chain circulation process, improve the efficiency of distribution, in order to ensure the stability of market supply. The study not only enriches the cross perspective of agricultural economic forecasting and industry chain research, but also provides a feasible path for building a resilient agricultural supply system. It aims to improve the stability of the agricultural industry chain.

2. Literature Review

At present, some scholars at home and abroad have carried out a series of studies on the development of the agricultural industry.Y. Liu (2020), in the context of agricultural modernization, in response to the problem of the lagging development of agricultural standardization, used agricultural production and market data, based on the big data analysis method, and obtained the result that agricultural standardization can improve the quality and market competitiveness of agricultural products[1]. Lin Dongsheng and Wang Tong (2022), in response to current problems in the supply-demand interface of agricultural products, such as the lack of close channels and low consumer trust, and proposed strategies such as strengthening information sharing, professional guidance and collaboration in order to improve the efficiency of the supply-demand interface and the quality of circulation of agricultural products[2]. Chen Meng and Fu Linxuan (2017) analyzed the necessity and effect of the construction of agricultural products information sharing platform through game theory under the background of "Internet +", pointing out that information sharing can effectively solve the problem of information asymmetry, promote the construction of agricultural informationization and improve the efficiency of agricultural products circulation[3]. Kabato, W et al. (2025) used precision agriculture and other ways to predict climate change, enhance agricultural productivity and sustainable development, especially for developing countries' agricultural barriers to output effective countermeasures[4]. Hua, Shuchun, et al. (2022) scholars, in the context of the new Crown Pneumonia outbreak, address the imbalance between supply and demand of agricultural products, and put forward strategies such as the implementation of health insurance for public health events, the increase of temporary subsidies for distribution of agricultural products, the targeted release of information on the risk level of the outbreak. and the development of training for practitioners in the prevention of epidemiological capacity, in order to ensure the effective functioning of the supply chain of agricultural products and the stabilization of the agricultural industry chain[5]. The above literature focuses on the use of technological innovation and information sharing to optimize the supply chain management of agricultural products to improve the efficiency of supply-demand matchmaking and the quality of distribution, which can effectively respond to the challenges in the supply chain management of agricultural products. However, these researches are not able to accurately predict the data using the original supply chain management strategy in response to sudden situations such as global public health events, where the structure of supply and demand is significantly impacted. SARIMA has good stability in price prediction due to its strong adaptability to time trends and cyclical fluctuations. Domestic scholars, Gong Xiao hui(2023), used the SARIMA model to predict the price fluctuation of hogs, and the results show that the model has good prediction accuracy[6]. Lin Liu(2023) predicted by SARIMA model and concluded that the predicted value of the wholesale price of cucumber from January 2019 to December 2019 is very close to the real value[7]. Using the SARIMA model for supply and demand prediction, combining the key factors affecting the supply and demand of the agricultural market during the epidemic, discussing the methods of optimizing supply chain management, and proposing supply chain resilience management strategies adapted to emergencies to improve the stability of the agricultural market.

3. Research Design

3.1 Data Sources

This paper adopts the historical data published by the National Bureau of Statistics on the price of Chinese cabbage (yuan/kg) in China's marketplace from January 2019 to June 2021 for short-term forecasting, in which the data from January 2019-December 2020 are used for modeling, and the data from January 2021-June 2021 are used for future trend forecasting.

3.2 Research Methodology

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a time series forecasting method that can deal with non-stationary and seasonal fluctuations at the same time, which can accurately portray the characteristics of the time series and realize effective medium- and long-term forecasts.

The resulting model can be shown in equation **(1)**:

$$\text{SARIMA}(p, d, q)(P, D, Q)\ s \quad (1)$$

The completed expression can be shown as equation **(2)**:

$$\Phi_P(B^s)\phi_p(B)\nabla^d = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad (2)$$

Where ∇^d represents the non-seasonal difference operator for removing trend; ∇_S^D represents the seasonal difference operator for removing cyclical fluctuations. d is the non-seasonal difference order; D is the seasonal difference order; s is the seasonal difference step. ε_t is the white noise error term; $\phi_p(B)$ represents the non-seasonal autoregressive term polynomial; $\Phi_P(B^s)$ represents the seasonal autoregressive term polynomial of order P with lag period s. p is the non-seasonal autoregressive order; P is the seasonal autoregressive step. $\theta_q(B)$ *represents* the non-seasonal sliding average term polynomial; $\Theta_Q(B^s)$ represents the seasonal sliding average term polynomial of order Q with a lag period of s. q is the sliding average order; Q is the seasonal sliding average order. yt observations at time t; the white noise error term.

The SARIMA model is able to capture the trend and seasonal structure in the non-stationary time series at the same time, and can effectively identify the long-term trend behind the price fluctuations, which has a strong explanatory power in portraying the time series characteristics of the cabbage price before and after the epidemic.

4. Research results

4.1 Time Series

Based on the sequence chart of Chinese cabbage price trend from January 2019 to December 2020 (Figure 1), it can be seen that the price of Chinese cabbage fluctuates greatly and demonstrates a more intuitive seasonal fluctuation characteristic. In the fall, there is a clear downward trend in price, and in winter, there is a clear upward trend in price.

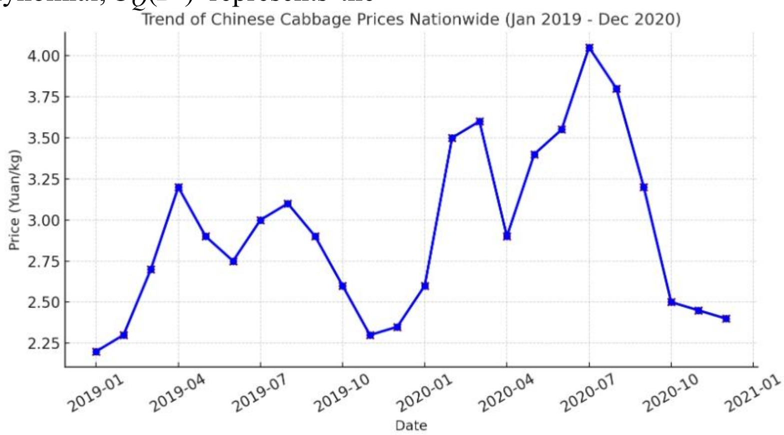

Figure 1. Chinese Cabbage Price Time Series Chart

4.2 Smoothness test

Augmented Dickey-Fu¹ler Test

data:price_ts

Dickey-Fu1ler =-3.5971,Lag order =2,p-value =0.05041

alternative hypothesis:stationary

Due to the large fluctuations in Chinese cabbage prices and a certain trend, the ADF method is used to verify its smoothness. Based on the results of the above ADF test , which concluded that the P value is greater than the significance level of 0.05, the ADF test results show that the Chinese cabbage is a non-stationary time series.

Augmented Dickey-Fu¹ler Test

data:diff_price_ts

Dickey-Fu1ler =-5.1522,Lag order =2,p-value =0.01

alternative hypothesis:stationary

Therefore, the first-order period-by-period differencing was applied to cabbage, resulting in a new ADF test result with a surface P-value = 0.01 < 0.05. This indicates that the first-order differencing succeeded in eliminating the fluctuating tendency in the series and making it smooth.

Based on Table 1 yields a seasonal ADF test statistic of -1.6159 while the 5% critical value is -3.00, -1.6159> -3.00, therefore, the null hypothesis cannot be rejected indicating that the time series is not smooth at 5% level of significance and there may be a unit root. Further seasonal differencing of the time series is required to ensure smoothness.

Table 1. Seasonal ADF test

	T–value	significant level		
		1%	5%	10%
ADF text	-1.6159	-3.75	-3	-2.63
Lag term test	1.7962	7.88	5.18	4.12

The following ADF seasonal first-order differencing yields a p-value = 0.02218 < 0.05, indicating that the first-order differencing removes the trend of seasonal fluctuations to make it smooth. Therefore it can be determined that the d and D orders in the model are 1.

Augmented Dickey-Fuller Test
data:seasonal_diff
Dickey-Fu1ler = -4.0309, Lag order = 2, p-value = 0.02218
alternative hypothesis:stationary

4.3 Model Selection

Based on the ACF-PACF plot in Figure 2 and Table 2, both ACF and PACF values change drastically after the lag order is 3 and gradually converge to 0. Therefore, we can focus on p=3, q=3. There is a small positive correlation between the ACF and PACF plots of order 1-2 and the value is significantly non-zero, therefore, we can also consider the model with p=2, q=2. Model. The ACF value at lag order 12 (seasonal cycle) is 0.143, which is a relatively low value indicating that the autocorrelation of seasonal variations is not too strong. At order 12, the PACF value is -0.076, which is also a relatively small value indicating that the seasonal autoregressive component is similarly not strong. Therefore, let P=0, Q=0.

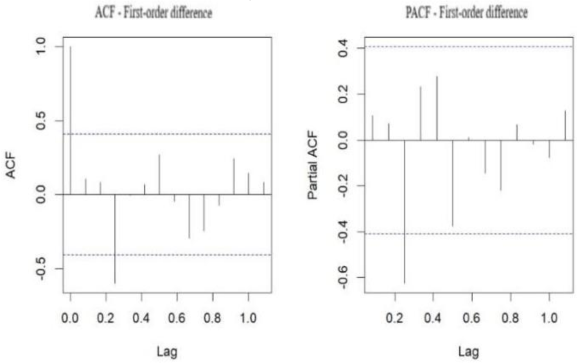

Figure 2. ACF-PACF Plot

Table 2. ACF and PACF Values

(Lag)	ACF value	PACF value
1	0.107	0.107
2	0.082	0.071
3	−0.598	−0.625
4	−0.003	0.232
5	0.066	0.277
6	0.271	−0.374
7	−0.046	0.011
8	−0.296	−0.143
9	−0.244	−0.218
10	−0.073	0.068
11	0.244	−0.018
12	0.143	−0.076
13	0.083	0.126

Thus, we attempted to build the model combination as described below:

SARIMA (3, 1, 3) (0, 1, 0) $_{12}$
SARIMA (3, 1, 2) (0, 1, 0) $_{12}$
SARIMA (2, 1, 3) (0, 1, 0) $_{12}$
SARIMA (2, 1, 2) (0, 1, 0) $_{12}$

Table 3. Model Comparison Result

	AIC	BIC	Ljung-Box Q*	p-value
SARIMA (3,1,3) $(0,1,0)_{12}$	10.98	18.93	6.4205	0.09285
SARIMA (3,1,2) $(0,1,0)_{12}$	10.51	17.33	7.0435	0.07053
SARIMA (2,1,3) $(0,1,0)_{12}$	13.96	20.78	11.436	0.009588
SARIMA (2,1,2) $(0,1,0)_{12}$	15.16	20.84	10.42	0.01531

As can be seen from Table 3, the statistics of Ljung-Box Q* test for residuals of SARIMA(2,1,3)(0,1,0)$_{(12)}$ and SARIMA(2,1,2)(0,1,0)$_{12}$models are 11.436 (p<0.05) and 10.42 (p<0.05), respectively, which show strong autocorrelation, so these two models are not considered. In the remaining two models, Ljung-Box Q* are both close to 6 and 7, and the p-value is greater than 0.05, which means that there is no significant autocorrelation of the residuals of the two models, and they both have a relatively good fitting effect, but SARIMA (3, 1, 2)(0, 1, 0)$_{12}$has the smallest AIC and BIC values, and therefore SARIMA (3, 1 2,0, 1, 0)$_{12}$is chosen as the optimal model.

4.4 Model Testing

The Ljung-Box test is used to ensure that the residual series are white noise and SARIMA (3, 1, 2) (0, 1, 0)$_{12}$is the optimal model selected. Ljung-Box test statistic = 7.0435, corresponding to p-value = 0.07053> 0.05. Having a small

Q-value and p> 0.05 means that the residuals of the model are consistent with white noise and there is no significant autocorrelation. It shows that the model fits well and can be judged as significantly valid.

4.5 Model Prediction

SARIMA (3, 1, 2) (0, 1, 0)$_{12}$was used to compare the actual and fitted values for January 2019-December 2020, as shown in Figure 3, and the overall fit is good.

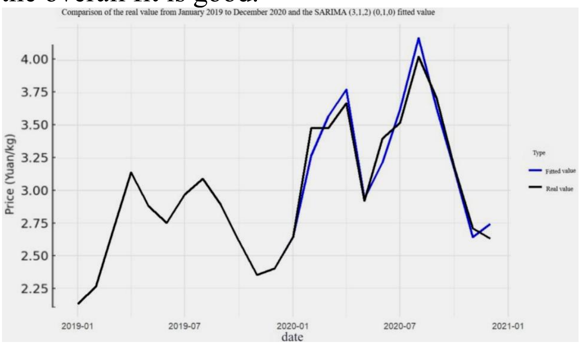

Figure 3. Comparison of the Real Value from January 2019 to December 2020 and the SARIMA (3.1.2) (0.1.0) Fitted Value

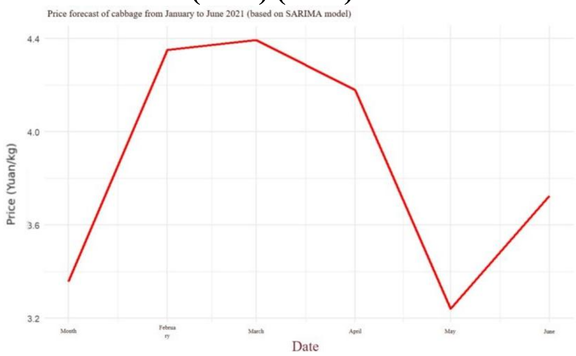

Figure 4. Price Forecast of Cabbage from January to June 2021 (Based on SARIMA Model)

Table 4. Comparison of Predicted and Actual Values of Cabbage Prices for January 2021-June 2021

Time	Predictive_Value	Actual_Value	Relative_Error
2021—01	3.388958	3.40	0.33%
2021—02	4.332434	3.02	43.63%
2021—03	4.414322	3.01	46.69%
2021—04	4.126807	2.93	40.66%
2021—05	3.247522	2.82	15.21%
2021—06	3.684619	2.94	25.33%
RMSE=0.99		MAE=0.85	MAPE=28.63%

Figure 4. shows the model prediction of the price output of Chinese cabbage from January 2021-June 2021 based on SARIMA (3, 1, 2) (0, 1, 0)$_{12}$. Using the real value of the price of cabbage in January-June 2021 published by the National Bureau of Statistics, as shown in Table 4, in which the predicted value and the actual value of the RMSE = 0.99, MAE = 0.85, which belongs to the lower standard, MAPE = 28.63%, the model's predicted value and the actual value of the deviation, which belongs to the range of 20% to 50%, which only indicates that the prediction is reasonable (Yang Zhenhao 2021)[8].

5. Supply Chain Optimization

In this study, cabbage prices before and after the epidemic were forecasted based on the SARIMA (3,1,2)(0,1,0)$_{12}$ model. Although the model performs well in trend capture, the MAPE value is 28.63%, indicating that the supply and demand fluctuations triggered by the epidemic have disrupted the original supply and demand rhythms, resulting in untimely information transfer generating an information lag (the market change has already occurred, and the data is only delayed in reflecting it). This has resulted in logistics and production adjustments not being able to keep up, thus hindering and deviating from actual and forecast prices. This, combined with factors such as changes in consumption patterns, weakens the overall forecasting accuracy of the model. To deal with this problem, it is necessary to reduce the interference of external shocks on prices through supply chain co-optimization schemes after price forecasting, so as to effectively reduce the forecasting error. Therefore, the core logic of supply chain optimization is to reduce the information lag, shorten the response time, and increase the redundancy capacity, so as to reduce the uncertainty of market fluctuations, and make the prediction model closer to the real trend.

5.1 Information Transparency

First of all, it is necessary to detect changes in supply and demand in advance by improving information transparency (letting models and decision makers know earlier that the market is going to change). It can be used to build a national agricultural supply and demand information platform, integrating multiple sources of information such as wholesale market prices, sowing area of origin, agricultural progress, logistics status, epidemic risk level, weather data, and so on. Reduce the information lag, so that the prediction is based on the "latest real market state". The introduction of blockchain and IoT technology enables real-time tracking of the circulation chain of Chinese cabbage from origin to retail, ensuring the integrity and reliability of the data, and at the same time enhancing the trust of market participants in the information, providing real-time and verifiable data sources for the prediction model. If the impact and sealing control generated by the epidemic leads to the obstruction of logistics in a certain production area, the platform will monitor the reduction of transportation vehicles in real time, and the prediction system will instantly adjust the parameters of supply in the area, and correct the predicted price through the relationship between supply and demand.

5.2 Supply Chain Layered Management and Full Collaboration

Li Yixin (2024) emphasizes that the supply chain of agricultural products is a complex network from the production of raw materials to the final consumer, which is affected by seasonality and involves production, processing, storage, transportation, wholesale, retail and other links[9]. Agricultural products are usually fresh products, which are prone to decay and spoilage. Particular attention needs to be paid to the storage, transportation and handling of products to ensure freshness and quality.

Therefore, in the case of an epidemic, it is necessary to ensure the smooth flow of information, logistics and capital through supply chain hierarchical management (origin-transit-marketing) and the whole collaborative mechanism, so as to realize the synchronous adjustment of each link and avoid the overall imbalance due to the interruption of local links.

5.2.1 (Production-marketing synergy)

Production-Sales Coordination (Production-Sales Coordination) refers to the information sharing and action synchronization between the production link and the sales link in terms of time, quantity, variety and quality, etc. Through contractualization, informatization and organization, order agriculture is implemented in the field of agricultural products: orders are placed by enterprises and others before the planting season according to the forecasted demand, and contracts are signed with producers to specify the planting area, variety and quality., specifying the planting area, varieties, quality standards, delivery time and price range. For example, enterprises based on SARIMA cabbage price forecasts and historical sales data, calculate the demand for cabbage in each sales cycle, can be passed to the production side of the cabbage will be in the next cycle of the price and demand is how much for the planting program as a reference. Therefore, the production side can be planted in the previous planting season more or less cabbage supply to stabilize prices.

5.2.2 (Cold chain and transportation optimization)

Cold Chain Optimization (Cold Chain Optimization) refers to the introduction of low-temperature control and information management tools in the whole process of production, storage, transportation and distribution of agricultural products to precisely regulate the temperature and humidity, logistic paths, inventory status, etc., so as to prolong the freshness period of perishable agricultural products, reduce losses, and maintain a stable supply capacity in the event of changes in market demand or unforeseen events. The following are some examples of perishable agricultural products that can be stored for a longer period of time. Examples include fresh fruits, vegetables and meats such as cabbage. Maintaining proper temperature and humidity levels is critical to maintaining product quality. In the supply chain of such perishable agricultural products, distributed cold chain storage nodes should be laid out between the main production areas, wholesale markets and core consumption areas, and combined with SARIMA forecasts, inventory can be transferred to cold storage near consumption areas in advance of the peak demand period to shorten the transportation time; IoT sensors can be introduced to monitor the temperature, humidity and location of the goods in real time during the transportation and storage process, and the transportation routes and storage conditions can be optimized through the cold chain management platform dynamically; in addition, the temperature and humidity levels of fresh fruits, vegetables and meats should be maintained to maintain product quality. In addition, the cold chain optimization plan should be formulated in parallel with the order agriculture and production and marketing alliance, so as to increase the capacity and storage capacity of the cold chain in advance when the forecast shows that the demand surge or the epidemic may lead to the interruption of logistics, and to open up the "green channel" for the perishable agricultural products in order to guarantee the smooth transportation. In the off-season, the transportation capacity and storage capacity should be reduced in order to lower the cost.

5.2.3 (Inventory management)

Inventory Management (Inventory Management) refers to the process of regulating supply and demand, smoothing price fluctuations, reducing storage costs, minimizing losses and smoothing market fluctuations in the supply chain by rationally controlling the quantity, structure and flow rate of inventory. And it should adopt the forecast data as the basis, combined with the demand cycle, seasonal characteristics and storage conditions, to dynamically adjust the inventory level. For example, establishing safety stock before the peak season and moderately reducing inventory occupancy in the off-season to reduce capital deposition and resource waste. Such changes can be predicted by using the SARIMA model to forecast the demand trend. At the same time , they can rely on cold chain preservation technology, the inventory of cabbage according to the maturity of graded storage, and expected sales time in batches out of the warehouse, to extend the sales cycle, to mitigate the impact of centralized listing on the price. Finally, distributed inventory nodes covering the major consumption areas of such agricultural products based on the domestic spatial dimension can be formed to form a cross-regional adjustment mechanism for rapid replenishment in the event of localized demand surges or supply disruptions.

5.3 Risk Management and Sustainable Development

Uncertainties arising from facing emergencies such as epidemics, extreme weather, and market fluctuations will largely affect the supply and demand situation and price fluctuations of agricultural products. Therefore, it is necessary to adopt risk management to identify, assess and reduce the uncertainty, and transform the prediction results into a response plan, so as to enhance the resilience and flexibility of the supply chain.

First of all, a multi-dimensional risk monitoring system can be established to integrate and analyze data on weather, epidemic dynamics, market prices, traffic conditions, etc. with SARIMA forecasts to identify potential supply and demand imbalance signals. Emergency response is automatically triggered when price fluctuation magnitude or inventory change rate exceeds the forecast interval. For example, when epidemics or natural disasters affect transportation, priority is given to ensuring smooth transportation of perishable agricultural products and shortening transportation delays. It also adjusts inventory distribution and transportation priorities according to real-time risk levels to ensure that demand in key areas is met. At the same time, risk diversification and buffer measures can be used to set up government- or industry-led emergency stockpiles in producing and consuming areas, and then determine the amount of stockpiles based on predicted demand peaks and risk assessment levels. When the market price exceeds the upper limit, put reserves into the market, and when the price is lower than the lower limit, collect and store to protect the interests of farmers. In addition, diversified cultivation and eco-friendly agricultural models are promoted on the production side to reduce the vulnerability of single-producing areas to disasters or epidemics; and the concept of a green supply chain is introduced into the distribution chain to realize both environmental and economic benefits through energy-saving transportation, reducing packaging waste and lowering carbon emissions. These measures can not only buffer the supply-demand imbalance caused by sudden shocks in the short term, but also build a long-term stable operating foundation for the supply chain, thus providing sustainable external conditions for the price forecasting model, reducing the MAPE value under extreme events such as epidemics and enhancing the resilience of the supply chain.

6. Summary

Taking the Chinese cabbage market as an example, this study discusses the changes in the supply and demand relationship of agricultural products before and after the epidemic, and on the basis of which it proposes a future-oriented supply chain optimization path. It is pointed out that the response lag and information asymmetry of the traditional supply and demand adjustment mechanism are particularly prominent under the impact of sudden public events. Subsequently, based on the cabbage price data from January 2019 to June 2021, a SARIMA model is constructed and validated to fit and predict the price trend before and after the epidemic. The rise of MAPE to 28.63% directly reflects the inadequacy of relying solely on prediction models, which highlights the necessity of supply chain optimization to reduce information lag and enhance market responsiveness.

In response to this challenge, this paper proposes an agricultural supply chain optimization scheme with "prediction-driven decision-making and collaboration to enhance resilience" as the core idea, including three major sections: information transparency, supply chain hierarchical management and whole process collaboration, risk management and sustainable development. In terms of specific strategies, it covers measures such as production and marketing synergy and cold chain layout optimization, aiming to shorten response time through information sharing, reduce mismatch between supply and demand through structural optimization, and smooth price fluctuations through risk buffer. These measures not only serve to respond to extreme scenarios such as epidemics, but also provide a technologized adjustment tool for daily market fluctuations.

This study combines time series forecasting with supply chain optimization, which not only reveals the impact mechanism of emergencies on forecasting accuracy, but also provides a feasible path to optimize the supply chain based on the forecasting results in a reverse direction. In the future, the study can be further extended to the comparative analysis of multi-category agricultural products and cross-regional markets, and combined with machine learning methods to improve the real-time and adaptive nature of forecasting and decision-making, in order to promote a higher level of stability and sustainable development of China's agricultural products market under the uncertainty environment.

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