

Time Series Analysis of Grains Commodity Futures Price Trends

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Abstract. This study delves into forecasting commodity price trends, explicitly utilizing the ETS and SARIMA models to analyze grains-Soybeans, Corn, Wheat and Soybean Meal. The research underscores the intrinsic seasonal and cyclical attributes of these commodities. While the ETS model provides initial predictions, it reveals limitations in accuracy. Subsequently, the SARIMA model, incorporating seasonal parameters, emerges as a more dependable predictor of price trends. The study emphasizes the significance of considering external factors, such as geopolitics and alterations in transport routes, especially concerning high-value commodities like soybeans. By enhancing forecast precision, the paper underscores the necessity for meticulous model selection, acknowledging the intricate dynamics of seasonal fluctuations in commodity futures prices. In conclusion, the SARIMA model stands out for its superior ability to capture and predict the nuances of seasonal patterns, providing valuable insights for investors and researchers navigating the complex landscape of commodity markets. Its comprehensive analysis of seasonal trends and precise forecasting capabilities make it a preferred choice for understanding and anticipating the complexities of commodity price movements.

Keywords: Commodity futures, commodity price, grains, seasonal trend.

1. Introduction

Commodities are one of the most fundamental and significant categories of market trade. Due to their sensitivity to market demand and supply, the issue of commodity price fluctuations has been of particular concern. Since the supply and demand of commodities are characterized by certain seasonal variations, i.e., the trend of increase or decrease in the supply or demand of commodities is relatively stable with the change of seasons, the prices of these commodities also exhibit seasonal variations. In the case of grains, which are typically sown in a particular season of the year, after growth and maturity, and then harvested in another season, this cycle of growth makes grains more susceptible to seasonal fluctuations than industrial metals or energy. Investors in the study of grain price trends often refer to its seasonal fluctuation pattern.

However, as the financial characteristics of the commodities market have increased in recent years, the stability of the seasonal fluctuation pattern of agricultural commodity prices has weakened. This paper uses the ETS model and SARIMA model to examine the change in commodity prices. By comparing the two models, we would like to select the most practical forecasting model and results that can more effectively and accurately predict the trend of commodity price fluctuations and seasonal cycles, thus facilitating investors' and researchers' subsequent investment and research.

The volatility and seasonal trends of commodity prices have attracted the attention of researchers in financial economics, who have conducted numerous studies on commodity futures prices. Richter and Sørensen attempted to estimate stochastic volatility continuously using panel data on soybean futures and options as early as 2002 [1]. The results demonstrated seasonal patterns in commodity market price levels and volatility. When discussing estimated seasonal patterns of agricultural prices, Sørensen simultaneously investigates the inventory perspective and provides empirical evidence on storage theory [2]. His article predicts a negative correlation between inventories and convenience yields. Todorova examined the dynamics of petroleum oil and natural gas futures prices in 2004 [3]. After determining the presence of seasonality by analyzing the variance structure of natural gas prices,

he seasonally adjusted the prices. He attempted to estimate a model using the de-seasonalized data, with results broadly aligned with expectations.

In 2013, Brooks investigated whether the predictive ability of commodity futures could be attributed to the degree of seasonality they exhibit [4]. They discovered more evidence of seasonality in the basis than previous studies, supporting the storage theory. In addition, it was demonstrated that the predictive ability of commodity futures could not be attributed to their degree of seasonality, which spawned a new line of inquiry in later years. Fama and French proposed a new storage theory after being inspired by Fama's work [5]. They discovered evidence that the basis varies with seasonal changes in interest rates and convenience yields, explaining the difference between contemporaneous futures and spot prices (the basis) in terms of changes in storage costs, interest rates, and convenience yields.

Using an EGARCH model, Debashish studied the seasonality and spillover effects of futures and spot prices of several actively traded agricultural commodities in 2018 [6]. He found that the effect of seasonality on volatility cannot be ignored because it is significant, and asymmetry is present across all commodities. Statistically, the prevalence of seasonality and structural breaks in the variance equation can slightly reduce volatility. In the same year, Hevia. et al. also emphasized the significance of seasonality, indicating that these seasonal fluctuations cannot be predicted entirely and that stochastic seasonal fluctuations represent a source of risk [7]. To analyze the impact of stochastic seasonal fluctuations on commodity futures pricing and risk premiums, they devised models allowing for stochastic variations in seasonality.

In 2020, Divakara. et al. used the SARIMA model to model and forecast the price of red lentils [8]. Schneider and Bertrand introduced a multifactor model that takes stochastic volatility into account with seasonal mean reversion levels for the study in 2021 [9]. In 2022, Ewald et al. discovered the existence of a little-mentioned seasonality in energy futures contracts known as trading time seasonality [10]. This seasonality is revealed by the timing of futures transactions, as opposed to their expiration dates or associated spot prices. They engaged in informal conversations regarding the effect's potential causes and identified seasonal hedging pressures and market sentiment. In their study of commodity futures prices conducted in 2023, Figueiredo and Saporito utilized machine learning to examine commodity price movements with seasonal trends [11]. These studies show that researchers are increasingly turning to machine learning to study commodity futures prices with seasonality, indicating that the field of study is entering a new era.

2. Methodology

2.1. Selection of Dataset

The dataset is taken from Eurex monthly prices for the decade 2003-2023 from Kargle. The dataset contains prices of 23 commodities with high Usability. In this paper, the broad category of cereals is selected from it for time series analysis.

2.2. Model Selection

This paper use time series plots with seasonal trends, the decomposition method, the ETS model, and the SARIMA model as the primary research methods for analysis and forecasting. The ETS (Error, Trend, Seasonal) model and SARIMA (Seasonal Autoregressive Integrated Moving Average) model are used for time series analysis and forecasting. ETS models directly model error, trend, and seasonality, offering simplicity but potentially less flexibility in handling complex seasonal patterns. On the other hand, SARIMA builds upon the ARIMA model by introducing seasonal components, making it suitable for time series with strong seasonality. The primary model is the SARIMA model, which can be expressed as follows: $ARIMA(p, d, q)(P, D, Q)_m$. The part (p, d, q) represents the non-seasonal part of the model, and $(P, D, Q)_m$ represents the seasonal part of the model.

3. Seasonal Trends in Grain Prices

The main types of commodities are divided into these four, and for further study, we have selected the datasets with grain prices for analysis and forecasting. This paper selected four groups of variables: soybeans, corn, wheat, and soybean meal shown as figure 1. Because the fluctuation ranges of each group of variables are not the same, these lines are too far apart on the y-axis. In order to avoid price differences from affecting the observation and analysis, this paper normalized the data so that these variables moved between 0 and 1, making it easy to determine whether the price trends were consistent.

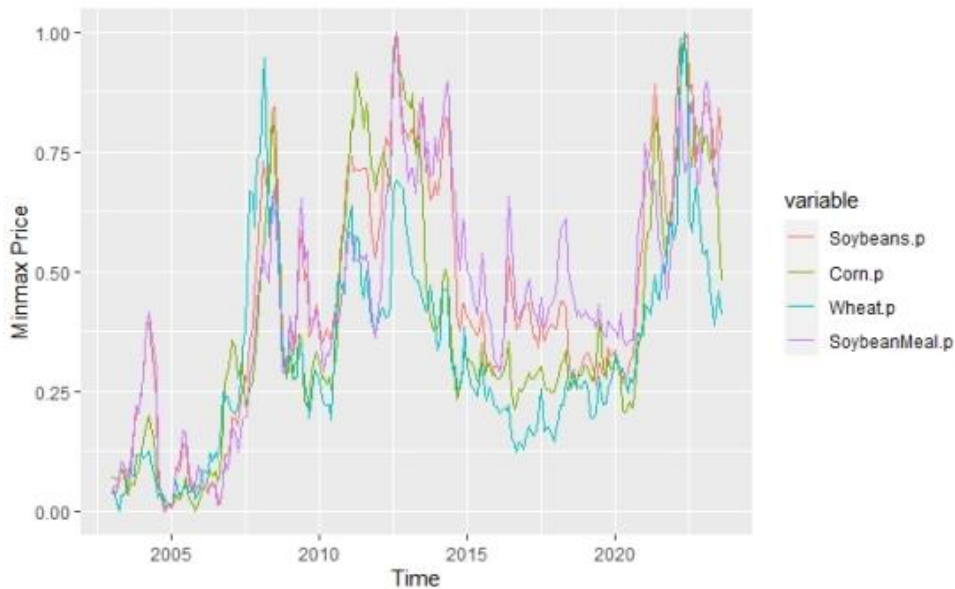


Figure 1. Grains Price Trend Between 2003-2023 (After Adjusted)

Figure 2 below shows a series of time series plots based on the price trends of the four commodities, and it is clear to see that their movements are similar overall, proving that the normalization process works.

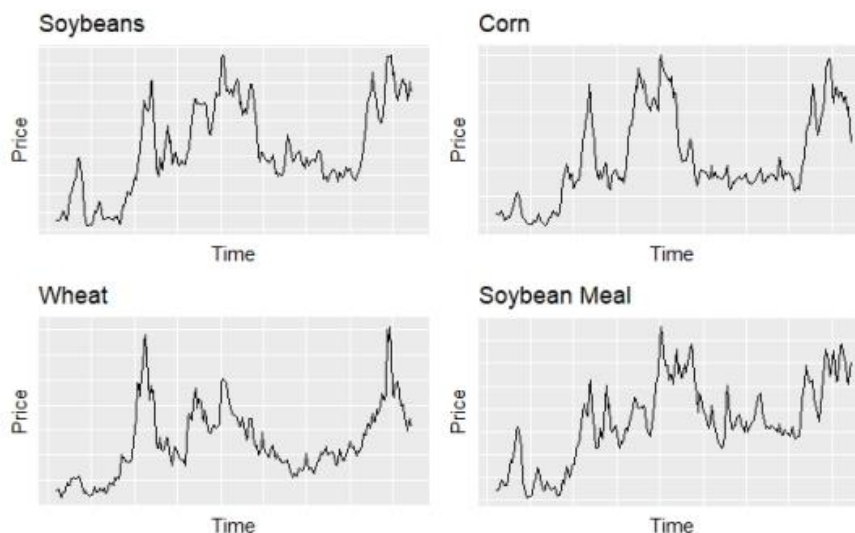


Figure 2. Price trends for four commodities

3.1. Soybeans

From the point of view of the seasonal pattern of soybean planting, soybeans are generally sown in May and June, and soybeans basically enter the harvest period in September. Subject to the cyclical characteristics of soybean growth, soybean in different months of supply and consumption also varies greatly, so the soybean futures price shows the characteristics of seasonal changes.

In October each year, the northern hemisphere soybeans are concentrated on the market, resulting in a seasonal supply peak so that the price reaches a new low. From October to the following February, the price steadily improved, mainly because of the gradual slowdown in supply pressure, and consumption steadily improved. In 2 to 6 months, the northern hemisphere soybeans were gradually being consumed. However, the harvest of soybeans in South America from the second half of March has nearly begun but concentrated on the market to the period in May, the shipping is already June or July for delivery to all countries. This period is also a high consumption period for soybeans, so prices have remained high.

July is a relatively low point, as the arrival of South American soybeans puts real pressure on the price of soybeans in July. On the other hand, with the arrival of summer, palm oil began to peak in consumption, and the substitution of soybean oil began to appear, thus suppressing the demand for soybeans.

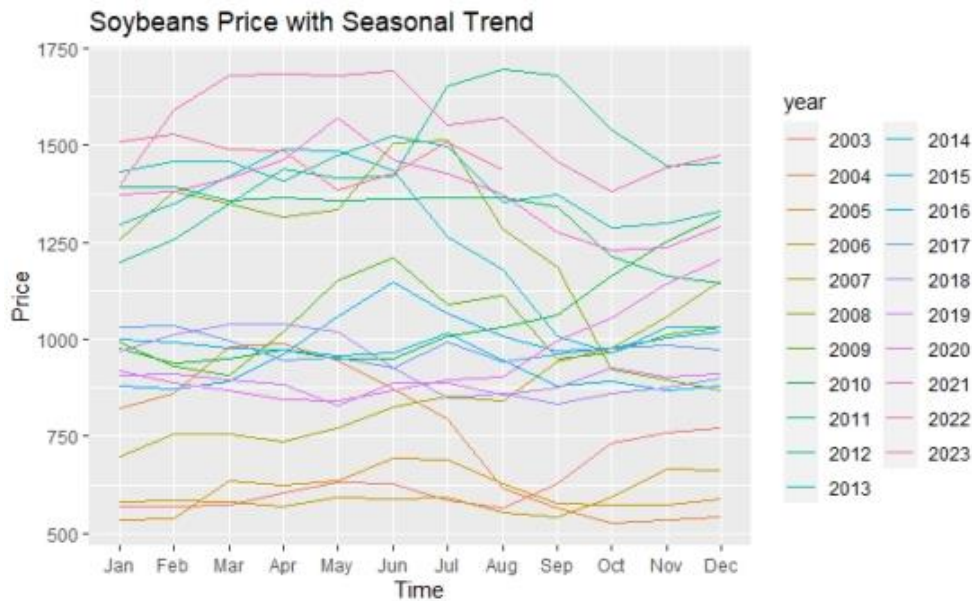


Figure 3. Seasonal Trends of Soybeans prices

In Figure 3 and Figure 4, it is evident from the supply side that in October, soybeans in the northern hemisphere predominantly aligned with the market's supply period, exerting a substantial impact. South American soybean listing in July on the price of a relatively light degree of impact, corresponding to October and July respectively, the two lows, the price of October is even lower; new soybeans on the market before the supply of a relative shortage of period, corresponding to the relative highs in September and May respectively, the price of May is higher.

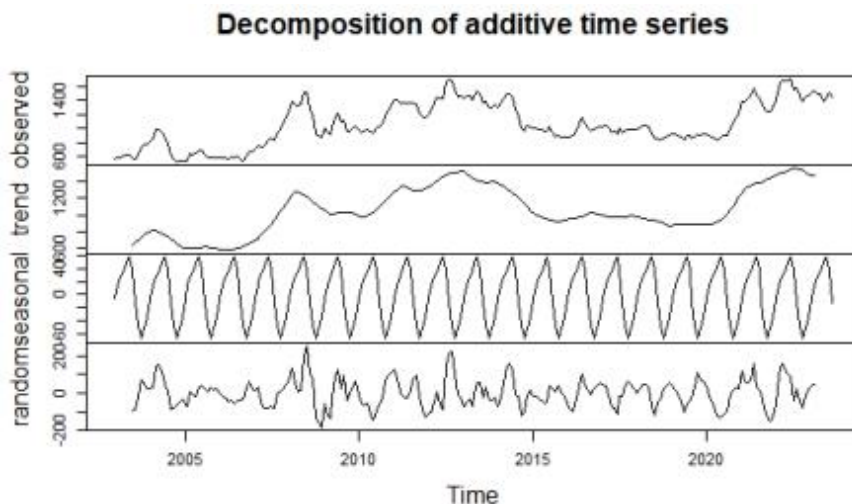


Figure 4. Decomposition of Soybeans Price Time Series

3.2. Corn

Figure 5 reveals that the price of corn is divided into two levels: At the lower price level, production of corn is less than total demand in May-July, when an upward trend usually develops, and then stays down until September. At the higher price level, the price of corn peaks in April-May and September-October.

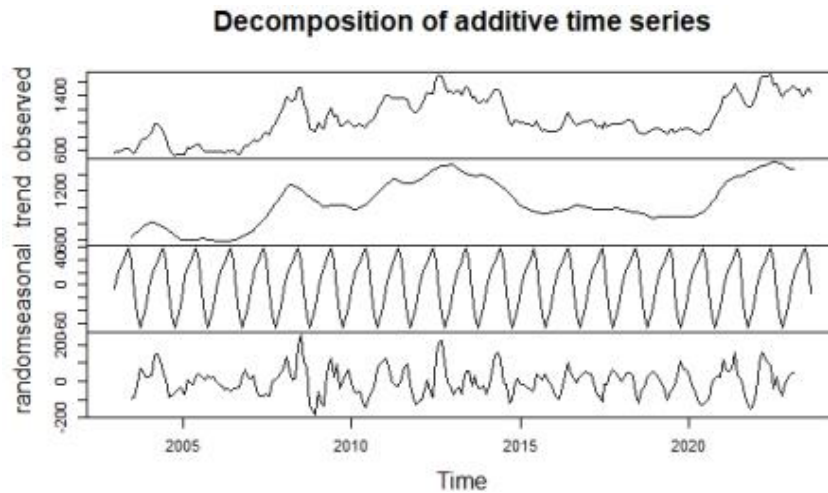


Figure 5. Decomposition of Corn Price Time Series

3.3. Wheat

The impending supply increase ahead of a bumper wheat harvest led to a price drop, but wheat futures prices recovered upwards.

They gradually stabilized as the market eased expectations of a spike in supplies for the upcoming harvest season. Moreover, prices gradually climbed from relative lows to highs as stocks were being depleted. So, the wheat market tends to fall between the spring and July harvest periods. Pick up from the harvest lows through the autumn and winter months (Figure 6).

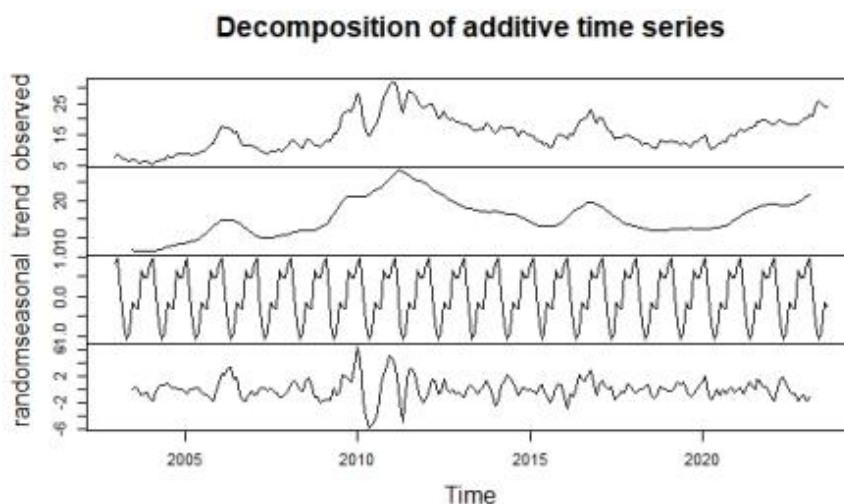


Figure 6. Decomposition of Wheat Price Time Series

3.4. Soybean Meal

Soybean meal is a by-product obtained from the extraction of soybean oil from soybeans and is an excellent source of protein that is widely used in areas such as the feed and food industries. The seasonality of soybean meal is closely related to soybeans and soybean oil, so, naturally, a price trend differs from the two. For example, June to August is the main stage of soybean meal prices and an essential node of speculation. Any favorable news will lead to soybean prices, thus driving up the price of soybean meal. Furthermore, November to December is the South American soybean planting

period. Soybean prices will also be affected by weather factors and fluctuations, this time near the end of the year. The output of the oil mills is generally higher, and soybean meal stocks will slowly increase. During this period, soybean meal has a certain probability of rising, but the yield is limited due to the suppression of inventory.

Typically, prices rise from March to August and fall from September to November, with the top occurring in August and bottoms forming in March and November. Soybean meal prices mainly were volatile from January to February (Figure 7).

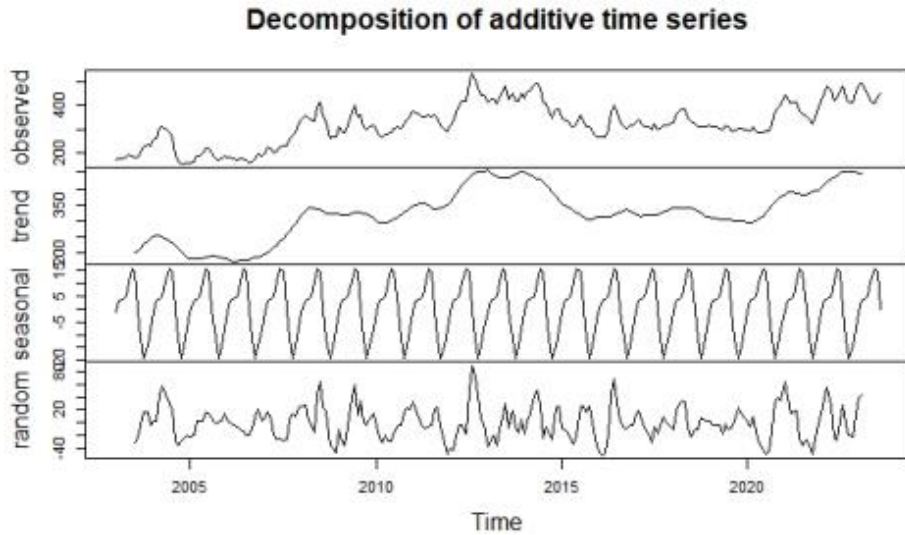


Figure 7. Decomposition of Soybean Meal Price Time Series

4. Forecasting Price Trends with ETS Model

4.1. ETS Model Forecast Results

This paper used the ETS model to predict each set of variables for the next 24 months. The level of model fit with each outcome was also tested to ensure the concordance between the forecasted trends produced by the ETS model and actual price trends (figure 12).

The ETS model's forecasts for soybeans are relatively smooth, around 1500. The model shows horizontal prices over the next 24 months with a wide range of error margins shown as figure 8.

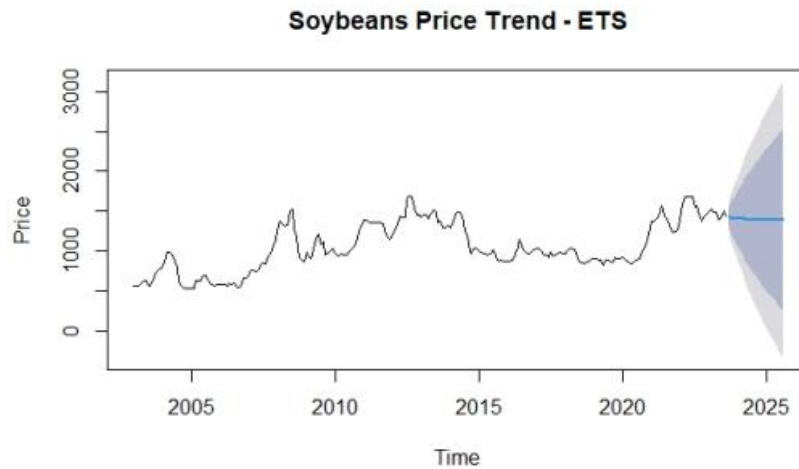


Figure 8. Price trend forecast for Soybeans by ETS model

Corn maintained a downward trend under the ETS model's forecasts for a few months before gradually remaining stable, around 300-500. The margin of error remains significant, and even some forecasts are below zero shown as figure 9.

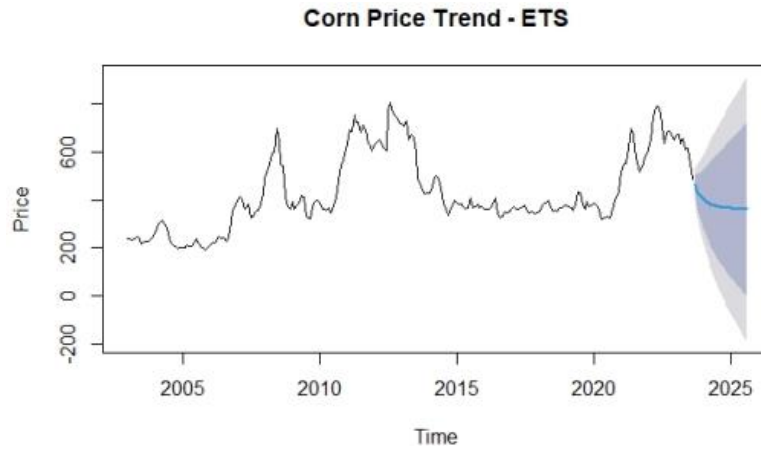


Figure 9. Price trend forecast for Corn by ETS model

Wheat's prediction under the ETS model is similar to that of soybeans, with a straight line and a price of around 600 shown as figure 10.

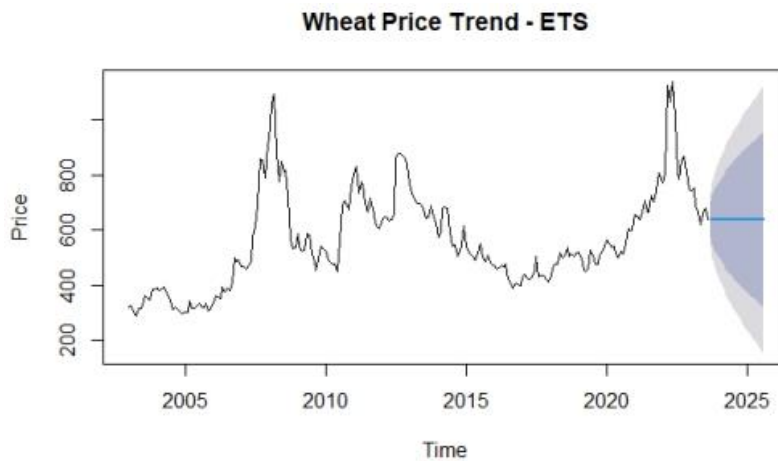


Figure 10. Price trend forecast for Wheat by ETS model

Similar to the previous, the price forecast for soybean meal turned out to be a curve with a very slight slope, fluctuating around 500 shown as figure 11.

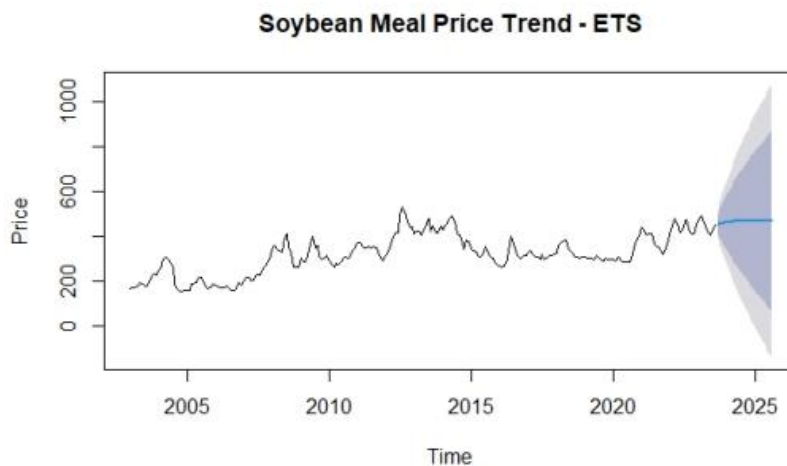


Figure 11. Price trend forecast for Soybean Meal by ETS model

4.2. Limitations of the ETS Model

After analyzing the prediction results of the four variables, one can see the irrationality. Following the residual test, it becomes evident that three p-values exceed 0.01 shown as table 1 below, which represents overall significant at 10% level, and one surpasses 0.001, indicating the model's validity.

Table 1. Residual Test and Accuracy Function Results for the ETS Model

	Soybeans	Corn	Wheat	Soybean Meal
P-value	0.0109*	0.0231*	0.0311*	0.0017**
RMSE	63.3764	32.8346	50.6098	22.5710
MAPE	4.3754	5.0851	5.2342	5.0910
MASE	0.2340	0.2311	0.2407	0.2913

Notes: t-statistics, *** represents the significance at the 1% level, ** represents the significance at the 5% level, * represents the significance at the 10% level.

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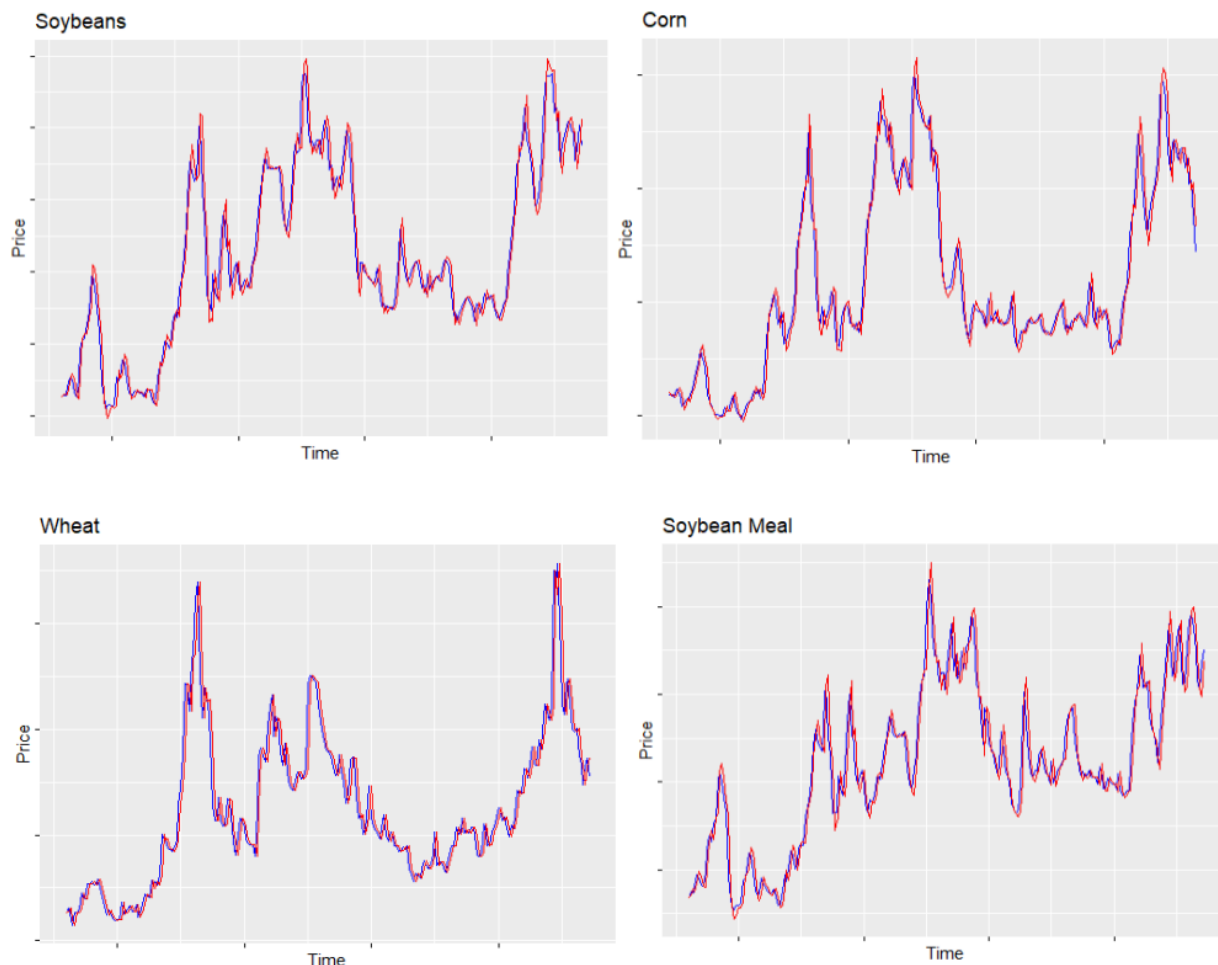


Figure 12. Degree of fit of the ETS model

5. Forecasting Price Trends with SARIMA Model

5.1. SARIMA Model Forecast Results

In light of the limitations associated with ETS model predictions, a quest for a more reliable forecasting model is imperative. Having identified the seasonal trend previously, the SARIMA model was employed for price trend predictions. Subsequently, assessments of model fit were conducted for each outcome shown as figure 17 below.

Because of the inclusion of seasonal parameters, the SARIMA model is much more accurate than the ETS model in predicting Soybeans prices. Figure 13 shows that over the next 24 months, the price of Soybeans goes through two troughs and two peaks in turn, but the range of movement in the later

months is less extensive than in the earlier months. The model predicts price movements in the range of 1200-1500, but the error can be considerable due to other factors.

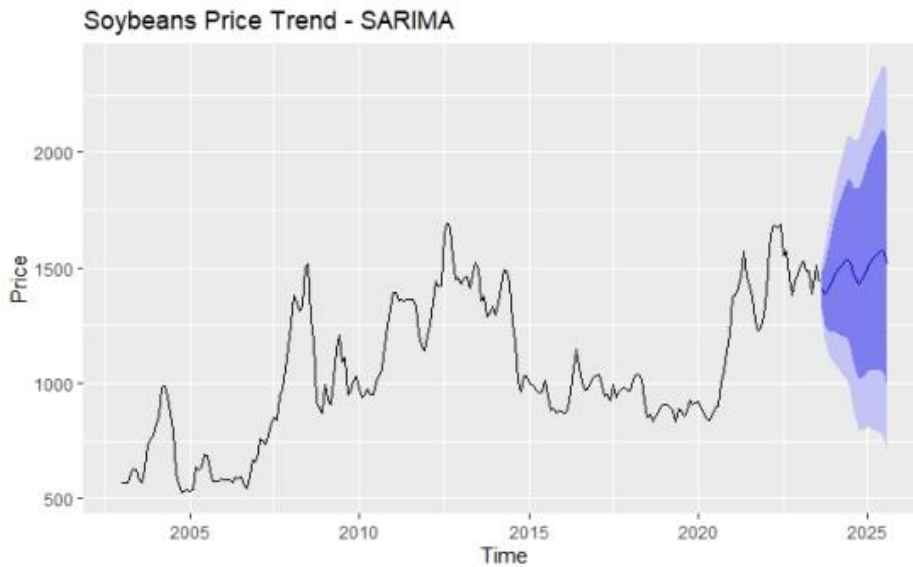


Figure 13. Price trend forecast for Soybeans by ETS model

The SARIMA model predicts a fluctuating downward trend for corn prices. The model predicts price movements in the range of 400-600 shown as figure 14.

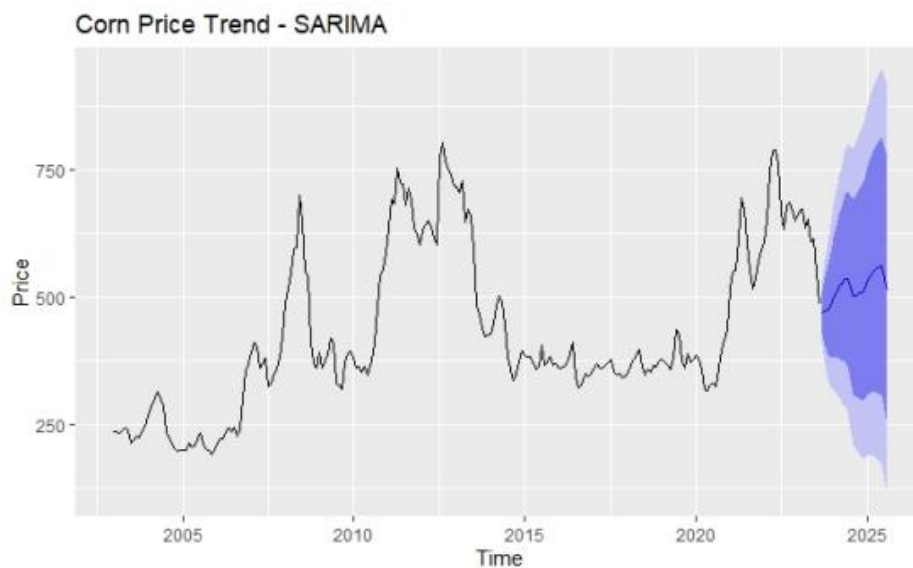


Figure 14. Price trend forecast for Corn by ETS model

According to the SARIMA model, wheat prices will reach the peak of this period in the next few months and then remain on a declining trend. The model also predicts price changes in the range of 500-800 shown as figure 15.



Figure 15. Price trend forecast for Wheat by SARIMA model

The SARIMA model has predicted the price of soybean meal to have an overall increasing trend over the next 24 months but with minor fluctuations in the middle. The soybean meal price is forecast to be the most stable compared to the previous ones, between 430-500 shown as figure 16.

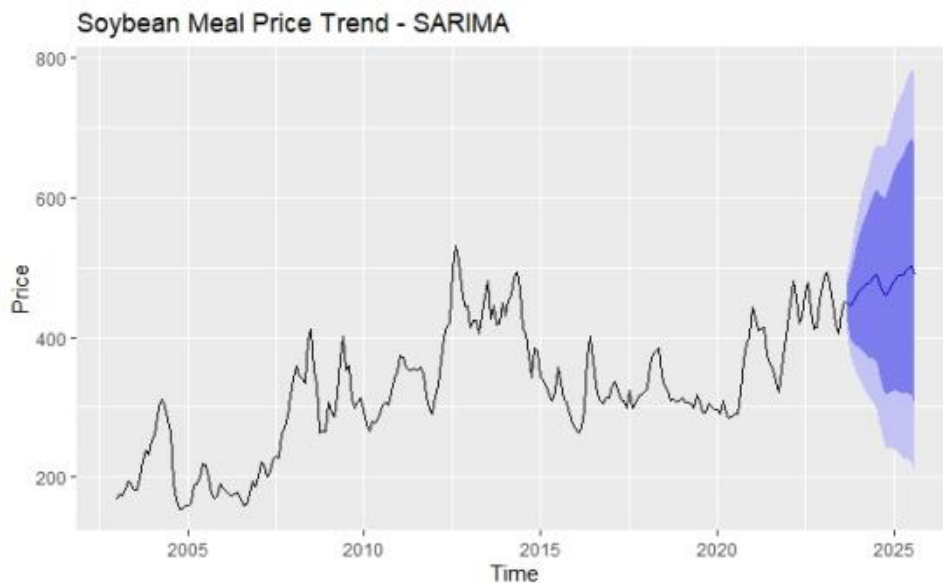


Figure 16. Price trend forecast for Soybean Meal by SARIMA model

5.2. Summary of the SARIMA Model

Examining the Ljung-box statistics provided by the residual test offers a clear insight into the accuracy of the SARIMA model in predicting the four datasets. Firstly, the p-values of the residual tests, which are all greater than 0.01, prove that the residuals are also less significant at the 10% level shown as table 2. It shows that the model explains the datasets to a high degree and is more suitable for predicting the four sets of data. Secondly, parameters such as RMSE, MAPE, and MASE are of higher quality. The suitability of this model for predicting the selected price trend is evident from the comparison between the fitted and actual values in the model's validity (figure 17).

Table 2. Residual Test and Accuracy Function Results for the SARIMA Model

	Soybeans	Corn	Wheat	Soybean Meal
P-value	0.0669	0.0490*	0.0294*	0.0227*
RMSE	58.2163	30.2053	49.1526	20.8060
MAPE	4.0185	4.5495	5.2250	4.7481
MASE	0.2142	0.2079	0.2388	0.2738

Notes: t-statistics, *** represents the significance at the 1% level, ** represents the significance at the 5% level, * represents the significance at the 10% level.

Despite following recommended procedures and using the "auto. arima" code to determine the optimal ARIMA order of "1,1,0" challenges emerged in automatically determining the optimal seasonal order through the same function. This prompted us to conduct a manual debugging process, drawing upon the methodological experience to identify the most effective seasonal order and achieve optimal forecasting results.

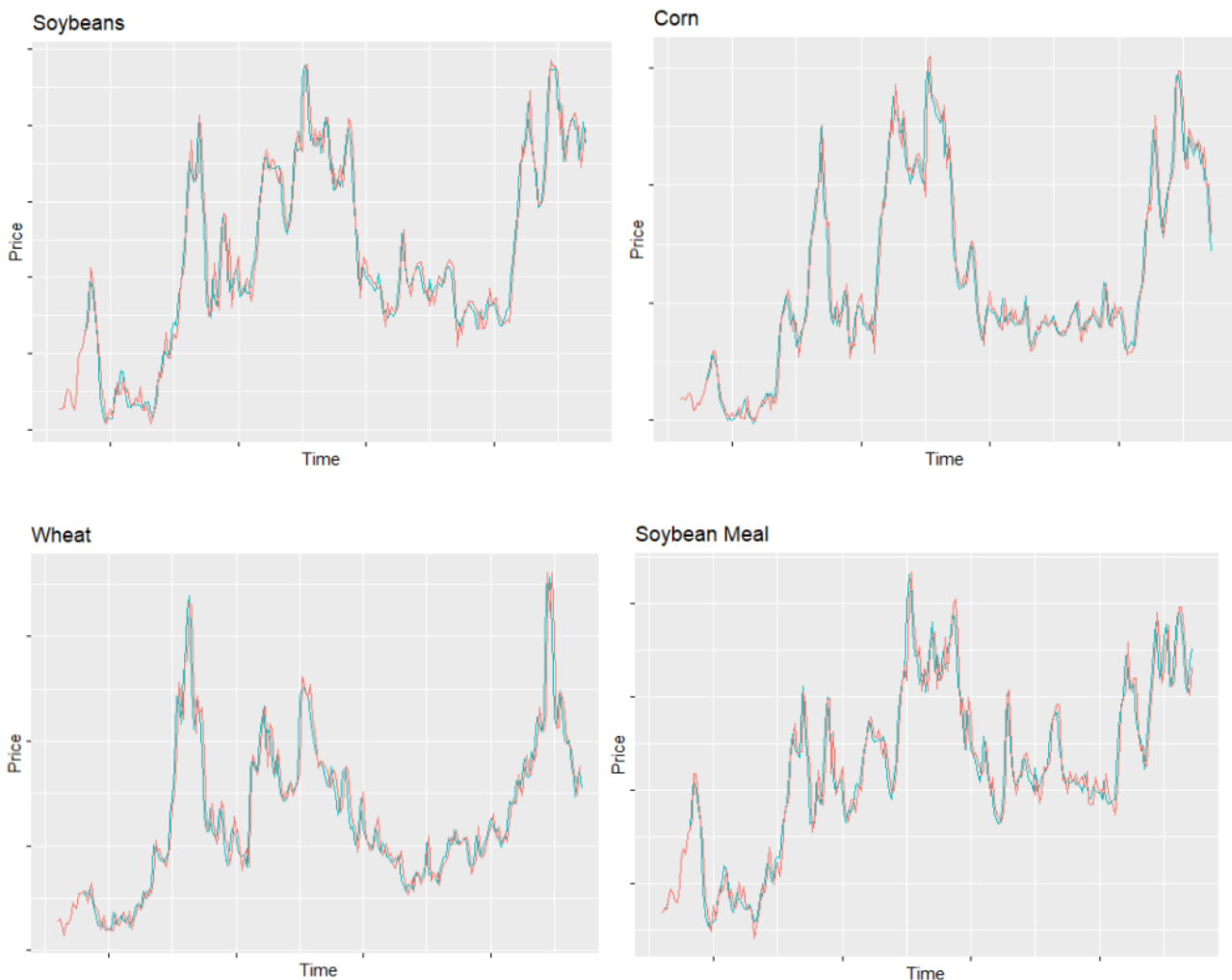


Figure 17. Degree of fit of the SARIMA model

6. Conclusion

This paper used two models to forecast price trends and found that the SARIMA model was much more accurate in predicting price trends than the ETS model predicted. This is because price trends for grains are inherently seasonal and cyclical.

Grains have different growth cycles and exhibit different seasonality; due to the different growth cycles, supply, demand, and storage also change, thus showing seasonal movements. In addition, the

speculative factor is also a factor that should not be ignored, and it is affected by the three factors mentioned above, thus affecting the whole market. Therefore, the SARIMA model, with the addition of seasonal order, better reflects the impact of seasonal variation on the accuracy of forecasting results.

Although this paper has improved the accuracy of the forecast, it should also pay attention to the problem of the scale of the vertical coordinate, that is, the magnitude of the price change. It can be noticed that soybeans have the most enormous magnitude of change compared to the other three grain commodities, and it need to pay more attention to external factors, such as geopolitics or changes in transport routes, when we need to study further the futures price trends of a high-priced commodity like soybeans. When studying futures price trends for soybean meal, a commodity with relatively concentrated price movements, it is also essential to be mindful of risk control and not to ignore small fluctuations in the forecast horizon.

Models should be chosen carefully when studying seasonal fluctuations. The SARIMA model performs better in commodity futures price forecasting but is unsuitable for all situations. It is crucial to choose a suitable model for each situation to improve the accuracy of the forecast

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