SHORT ARTICLE

Maize Crop Price Prediction in Ghana Using Time Series Models

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Abstract:

The agribusiness has become very complex in recent years, and hence the importance of agricultural planning has increased. Crop producers can often base their decisions for crop production and selling on yield and price forecasts. Prediction of future crop selling prices is another important aspect in decision planning. In this research, the price of maize in Ghana was carefully studied. Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Triple Exponential Smoothing (TES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving-Average (SARIMA) modeling were done to find the best fit model to future predict the price of maize in Ghana. The results of this study indicate that the ARIMA model, with a Mean Absolute Error (MAE) score of 11.39, is the best fit model over other time series models considered in this paper. Using the ARIMA model, we predict a significant change in maize prices in the coming years, providing valuable insights for crop producers and decision-makers in the agribusiness sector.

Keywords: SES: Single Exponential Smoothing, DES: Double Exponential Smoothing, TES: Triple Exponential Smoothing, ARIMA: Autoregressive Integrated Moving Average, SARIMA: Seasonal Autoregressive Integrated Moving-Average

Introduction

Maize (Zea mays L.) is a member of the grass family (Gramineae) and originated from South and Central America. It was introduced to West Africa by the Portuguese in the 10th century (Oladejo & Adetunji, 2012). Maize is the most popular and extensively produced crop in Ghana. Its commercial and domestic value in Ghana is unmatched. In Ghana, the Obatanpa variety continues to be the most cultivated maize due to its relatively higher yield compared to other varieties (3.2 tons/ha versus 1.7 tons/ha) (Okai et al., 2015). Crop yield, in Africa and many other countries, is defined as metric tons of production per hectare or area cropped (Askar & James, 2014).

In Ghana, maize is a staple food of great socio-economic importance. It is used in preparing local dishes and drinks. The consumption of maize sometimes exceeds production, posing a threat to the country's economy. When consumption surpasses production, the country needs to import maize to fill the gap, which results in high prices and an increase in the inflation rate (Suleman & Sarpong, 2012). Therefore, it is crucial to forecast the price of maize.

In this study, price forecasts were conducted using five time series models: Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Triple Exponential Smoothing (TES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving-Average (SARIMA). These models have been extensively used for forecasting economic time series, inventory, and sales (Suleman & Sarpong, 2012). Askar & James (2014) applied some of these models in crop yield prediction using time series analysis. McHugh et al. (2019) also employed them in forecasting day-ahead electricity prices using a SARIMAX model. These models have been widely used in research to analyze and create time series models for pricing, sales, and inventory data. In this study, we modeled and forecasted the price of maize in Ghana using all five models to find the best fit model for predicting the price of maize per 100kg bag in the upcoming years.

Related works

The field of maize price forecasting has seen various approaches and methodologies, each contributing to the understanding and improvement of prediction models. Accurate prediction of agricultural commodity prices is crucial for effective planning and decision-making in the agribusiness sector. The complexity of agricultural markets necessitates robust forecasting models to aid stakeholders in making informed decisions. Various studies have employed different time series models to forecast crop prices, each highlighting the strengths and weaknesses of their chosen methodologies.

McHugh et al. (2019) focused on modeling and forecasting the consumption and production of corn in Ghana using the Autoregressive Integrated Moving Average (ARIMA) methodology. The goal was to predict future values of consumption and production based on data from 1960 to 2010, sourced from Index Mundi (2011). The authors employed the Box-Jenkins approach to model and forecast corn consumption and production, revealing an increasing trend. Despite this increase, they stressed the need for government investment in corn production, farmer motivation, and improved land policies to ensure production consistently exceeds consumption, preventing the need for imports and controlling inflation rates.

Askar and James (2014) aimed to estimate crop yield in five districts in northern Ghana using time series models to predict crop production losses. The research applied various forecasting methods, including Simple Exponential Smoothing, Double Exponential Smoothing, Damped-Trend Linear Exponential Smoothing, and the Autoregressive Model (AR). The study's significant contributions include evidence of crop yield cycles in time series data for most districts and the impact of unobserved external factors on crop yield cycles. These results highlight the region-specific performance of prediction models and the necessity for different models for districts with varying yield spreads.

Zelingher and Makowski (2022) analyzed the quality of six regression algorithms in forecasting the monthly price of maize in its primary international trading market, using publicly available data of agricultural production at a regional scale. The forecasting process was done between one and twelve months ahead, using six different forecasting techniques. This study provides insights into the effectiveness of various machine learning techniques in maize price forecasting.

Mayabi (2019) developed an Artificial Neural Network (ANN) model to predict retail maize prices in Kenya. The study utilized historical price data to train the ANN model, demonstrating its potential in accurately forecasting maize prices. This research highlights the application of advanced machine learning techniques in agricultural price forecasting.

These previous studies provide valuable insights into the application of time series models in agricultural forecasting. They highlight the importance of selecting appropriate models based on the specific characteristics of the data and the region under study. In our research, we modeled and forecasted the price of maize in Ghana using five time series models: Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Triple Exponential Smoothing (TES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving-Average (SARIMA). Our goal was to identify the best model for predicting maize prices per 100kg bag in the upcoming years, providing valuable insights for the agribusiness sector.

Data and research methodology

This study was carried out on the basis of corn sales per every 100kg bag in Ghana. The data begins in the period 1970 to 2017 and was collected from the Ghana open data project initiative website. The Ghana Open Data Initiative (GODI) started in 2012 after an Open data readiness assessment report indicated Ghana was ready for the open data initiative. Crops which are likely to be suitable for Area-Yield Index Insurance include rain-fed maize and rice, and possibly millet, sorghum and groundnuts.(Askar & James, 2014).This paper seeks to predict the price of one crop, maize. The models selected are among the best in terms of time series data and best fit this scenario. Since we are dealing with time series data sets, auto regression checks were done to test the autocorrelation between the lags of maize prices from the data and plotted in the chart below.

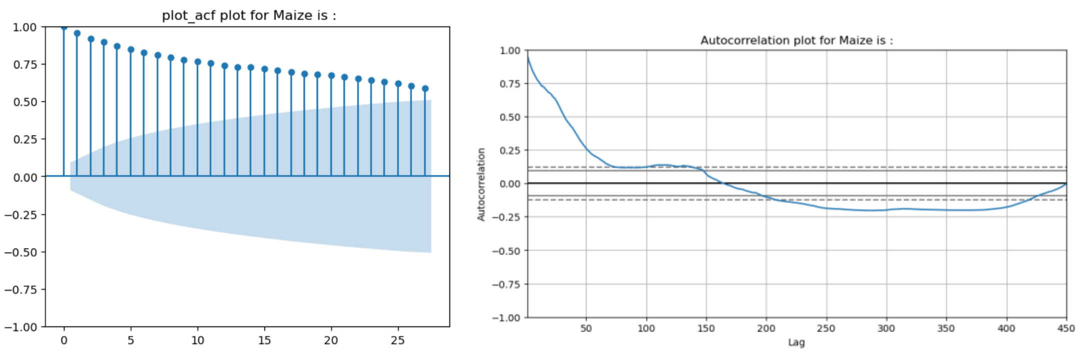

Figure 1. ACF charts of maize price Ghana from 1970 to 2017.

From Figure 1, the Autocorrelation Function (ACF) plot shows the correlation between maize prices at different time lags. Despite converting monthly data to yearly, the plot reveals significant autocorrelation, indicating a strong relationship between current and past prices. This suggests that historical maize prices can effectively predict future prices, which is crucial for reliable forecasting in the agribusiness sector.

The second graph, initially described as an autocorrelation plot for maize prices, shows a sharp decline from lag 0 to around 50, indicating a strong relationship between consecutive observations. However, the subsequent fluctuations around zero suggest that this relationship weakens over time. Given the yearly frequency of the data, this pattern might indicate a combination of factors, such as annual cycles or other periodic influences. However, the lack of significant peaks in the autocorrelation function suggests no dominant seasonal pattern or strong periodicity in the maize price data.

```
p-value for DATE
1970-05-01    -0.0000
1970-09-01    -0.0006
1971-08-01     0.0012
1972-02-01    -0.0001
1972-03-01    -0.0009
                ...
2017-08-01     9.1841
2017-09-01   -21.8933
2017-10-01     5.8253
2017-11-01    40.8859
2017-12-01   -65.0540
Name: PRICE, Length: 447, dtype: float64 after third order differencing: 1.4373355480014527e-16
---------------------------------------------
```

Figure 2. Results from performing Augmented Dickey-Fuller (ADF) test to check for stationarity.

Given the significant autocorrelation observed in the Autocorrelation Function (ACF) plot, it's crucial to test the stationarity of the time series. Stationarity implies that the statistical properties of the series, such as mean and variance, remain constant over time. Non-stationary data can lead to misleading statistical inferences, hence the necessity to transform the series if it is found to be non-stationary.

To determine the stationarity of our maize price data, we conducted the Augmented Dickey-Fuller (ADF) test. After applying third order differencing, the test results indicated a p-value of approximately 1.44e-16, confirming that the data is now stationary.

Furthermore, we analyzed the seasonality of the data to identify recurring patterns within specific intervals. This is essential because seasonal effects can significantly impact price trends. The seasonality test results indicated no significant seasonal patterns, consistent with the lack of dominant peaks in the ACF plot.

Based on these tests, we selected the appropriate time series modeling methods. Given the stationary nature of the data and the absence of significant seasonality, methods such as Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES) were initially considered. However, the Autoregressive Integrated Moving Average (ARIMA) model emerged as the best fit, with a Mean Absolute Error (MAE) score of 11.39, demonstrating its robustness in capturing the patterns and trends in maize price data.

For deeper understanding of our data we further performed a seasonal decomposing check on our data after smoothing it. This is shown in the chart below.

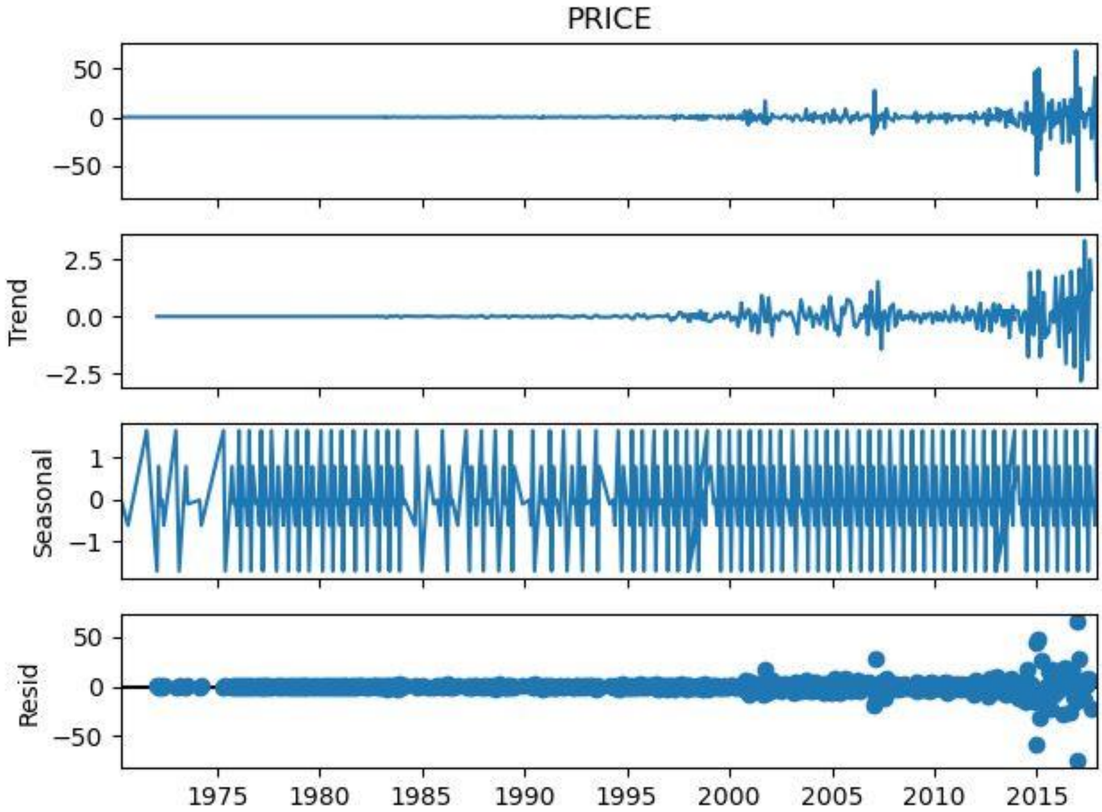

Figure 3. This shows the seasonal decomposing chart

Time series decomposition is a powerful tool to understand and visually analyze complex time-dependent data. A decomposition typically involves the following components: a trend component, seasonal components, and a residual component. These components show relationships in the data and reveal underlying patterns. Seasonal-trend decomposition based on loess (STL) is a powerful tool to explore time series data visually.(Krake et al., 2024).This chart is a time series decomposition of maize prices, breaking down the data into four key components: observed, trend, seasonal, and residual components.

- Observed Data: The first part shows the raw maize price data over time, from around 1970 to 2017. Initially, prices are relatively stable, but after 2000, there's noticeable fluctuation and volatility. This suggests that external factors such as economic changes, weather conditions, and policy shifts could have influenced the price variations (McHugh et al., 2019).
- Trend: This section illustrates the long-term progression of maize prices. The trend remains relatively flat until around 2000 when it begins to rise significantly, indicating an overall increase in maize prices over time. This long-term increase is crucial for understanding the broader economic and agricultural trends, reflecting increased demand or reduced supply over the years (Askar & James, 2014).
- Seasonal: The seasonal component captures the short-term cycles that repeat over fixed periods. This part of the graph shows regular oscillations, suggesting consistent periodic fluctuations in maize prices. These cycles could be tied to planting and harvesting seasons, which are typical in agricultural commodities (Mayabi, 2019).
- Residual: The residual component represents the random noise or irregularities in the data after removing the trend and seasonal components. Until around 2000, the residuals are small and stable, but they become more variable in recent years. This indicates an increase in unpredictable factors affecting maize prices, such as climate change impacts, market disruptions, or new agricultural technologies (Zelingher & Makowski, 2022).

Understanding these components helps in identifying underlying patterns and behaviors in the price data, making it easier to forecast future prices and make informed decisions. The trend component is particularly useful for long-term planning, while the seasonal component aids in short-term decision-making. The residuals highlight the unpredictability and potential risks associated with maize prices.

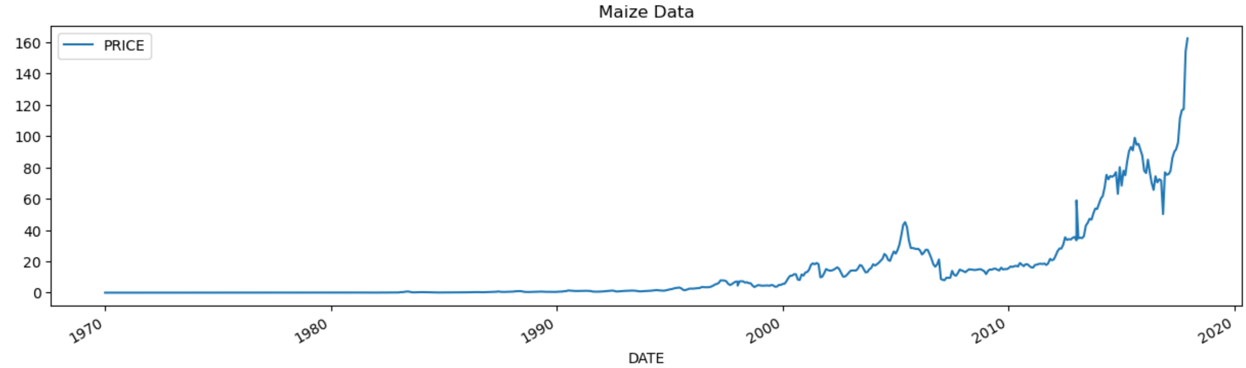

Figure 4. This shows the general overview of the data using line chart.

The above chart illustrates the comprehensive dataset after the cleaning process, spanning from 1970 to 2017. This visualization is essential as it provides a complete view of the historical maize price trends, forming the foundation for developing predictive models. We subsequently applied and evaluated five different models to identify the most suitable one for future price predictions. The following sections display the models alongside their respective charts, which include the training data, test data, predicted data, and the mean absolute error (MAE) score for each model, thereby facilitating an assessment of their accuracy and reliability.

Simple Exponential Smoothing (SES)

The idea of exponential smoothing is to smooth the original series the way the moving average does and to use the smoothed series in forecasting future values of the variable of interest. This forecasting method is most widely used of all forecasting techniques. It requires little computation. This method is used when data pattern is approximately horizontal (i.e., there is no neither cyclic variation nor pronounced trend in the historical data). (Ostertagová & Ostertag, 2011). The simple exponential smoothing equation is expressed as, $L\ t = \alpha\ y\ t + (1 - \alpha)\ L\ t - 1$, where Lt the smoothed value for year t becomes the forecasted value for year t+1(Askar & James, 2014). The figure below shows the results of the SES model after training and prediction. After the prediction the MAE score was 11.43.

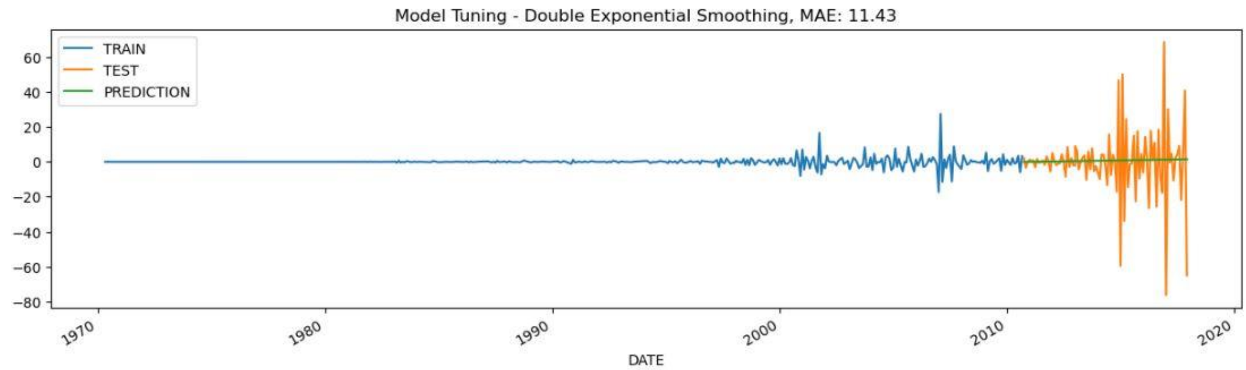

Figure 5. The chart shows the MAE score, Train, Test and predicted value for the SES model.

Double exponential smoothing (DES)

Double Exponential Smoothing is an improvement of Simple Exponential Smoothing, also known as Exponential Moving Average, which does the exponential filter process twice. It's usually been used to predict the future data in time series analysis, where there is a trend in the data.(Hansun, 2016). The figure below shows the results of the DES model after training and prediction. After the prediction the MAE score was 11.43.

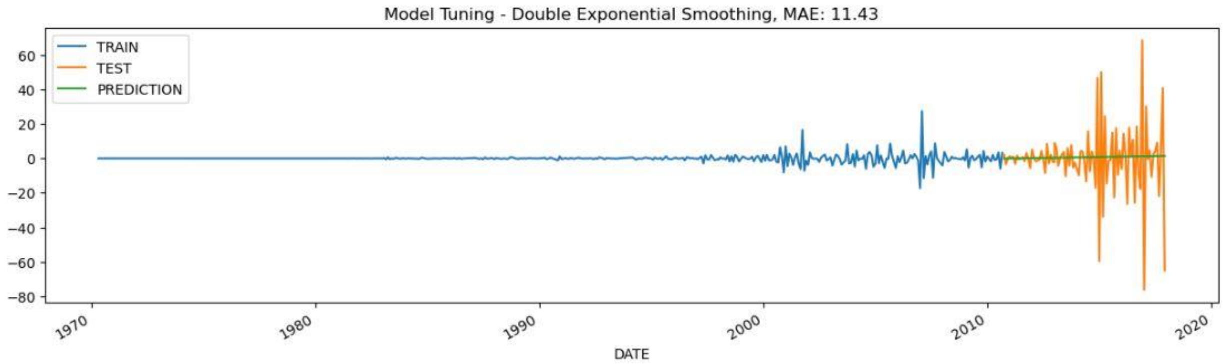

Figure 6. The chart shows the MAE score, Train, Test and predicted value for the DES model.

Triple exponential smoothing (TES)

In general, the exponential smoothing function is a straightforward method for smoothing time series data. It assigns exponentially decreasing weights over time. When dealing with high frequency signals, it is common to use a TES function. It can be used three times to smooth a three-signal time series and remove high frequencies encountered.(Dev et al., 2018). The figure below shows the results of the TES model after training and prediction. After the prediction the MAE score was 11.43.

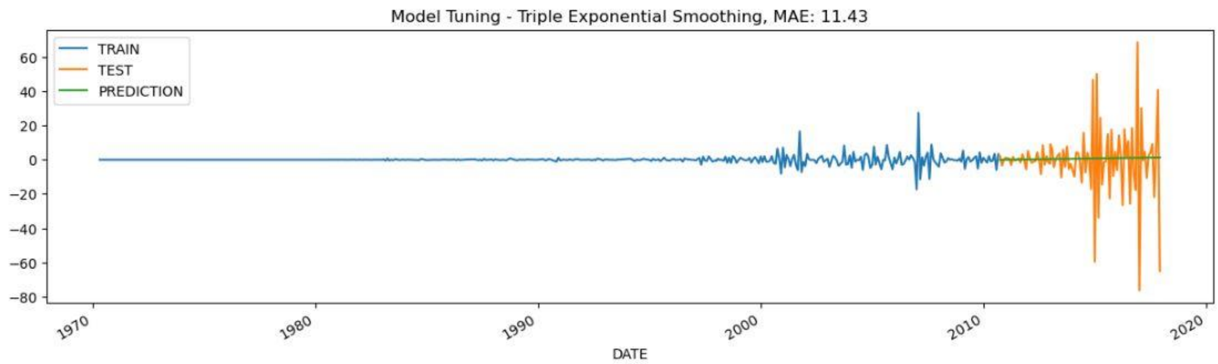

Figure 7. The chart shows the MAE score, Train, Test and predicted value for the DES model.

Autoregressive integrated moving average (ARIMA)

Auto Regressive Integrated Moving Average (ARIMA) explains the time series under consideration on the basis of its previous values, that is, its lags and the lagged prediction errors. It can be useful for the future forecast for a non-stationary time series exhibiting patterns and is not irregular white noise. The 3 characteristic terms of ARIMA model are the parameters (p, d, q) wherein, each of the terms are the orders of the AR term, the differencing needed to change the time series into a stationary one and the MA term respectively. The term AR in ARIMA signifies that it is a linear regression model that makes use of its lags in order to predict. Linear regression models give the finest results when there is no correlation between the predictors, and they are not dependent on each other.(Sirisha et al., 2022). The figure below shows the results of the ARIMA model after training and prediction. After the prediction the MAE score was 11.39.

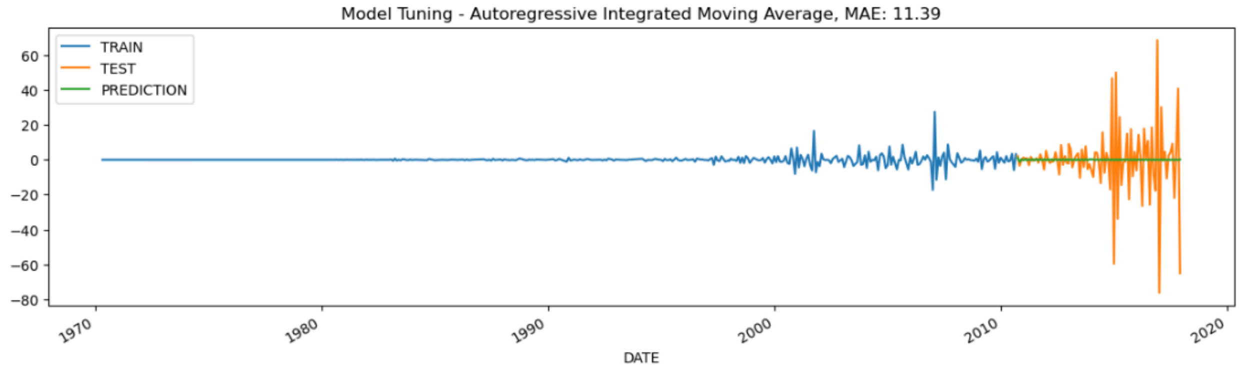

Figure 8. The chart shows the MAE score, Train, Test and predicted value for the ARIMA model

Seasonal autoregressive integrated moving average (SARIMA)

If a time series is univariate and contains trend and/or seasonal components, then Seasonal ARIMA (SARIMA) model is used. If an external predictor, known as, 'exogenous variable' is added to the SARIMA model then, it is known as the SARIMAX model.(Sirisha et al., 2022). The figure below shows the results of the SARIMA model after training and prediction. After the prediction the MAE score was 11.44.

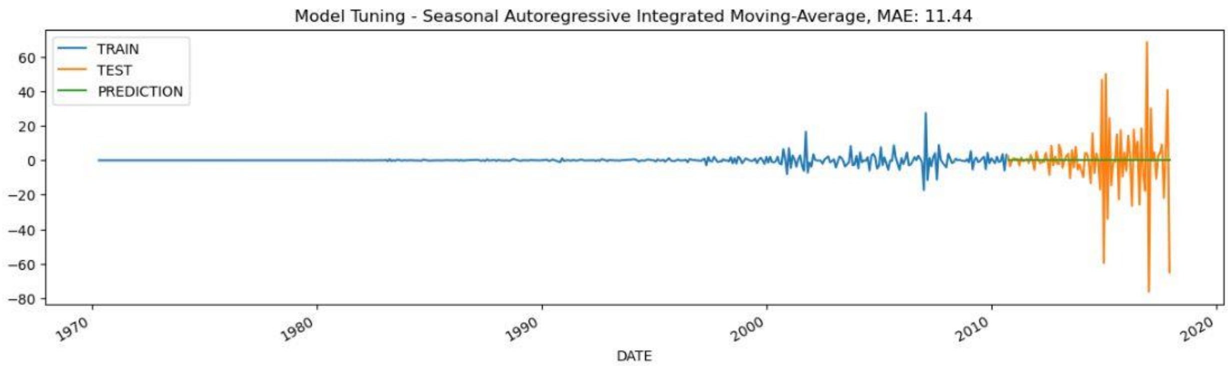

Figure 9. The chart shows the MAE score, Train, Test and predicted value for the SARIMA model.

Implementation

To ensure a robust analysis, we first cleaned and preprocessed the raw data to address any inconsistencies, missing values, and outliers. Following this, we applied this various time series models including Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Triple Exponential Smoothing (TES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving-Average (SARIMA) to the dataset. Each model was rigorously tuned to identify optimal parameters, enhancing their predictive accuracy. We then evaluated the models using Mean Absolute Error (MAE) as the primary metric, comparing their performance on both training and test datasets. The implementation involved training the models, forecasting, and visualizing the predictions to ensure they accurately captured the trends and patterns in maize prices. This comprehensive approach ensured that our forecasts were both reliable and relevant for decision-making in the agribusiness sector.

Results and Discussion

Results

Model performance analysis

To evaluate the effectiveness of various time series models for predicting maize prices, we employed Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Triple Exponential Smoothing (TES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving-Average (SARIMA). The performance of each model, assessed using Mean Absolute Error (MAE), is illustrated in the graphs below. Accurate price forecasting, as emphasized by Askar and James (2014) and McHugh et al. (2019), is crucial for economic planning in agriculture. The following sections detail the performance of each model through their respective graphs.

Single Exponential Smoothing (SES):

The SES model's performance is visualized in figure 5. The blue line represents the training data, the orange line represents the test data, and the green line represents the model's predictions. The Mean Absolute Error (MAE) for this model is 11.43, indicating that SES provided a moderate level of accuracy in capturing the underlying patterns in the maize price data.

Double Exponential Smoothing (DES):

In the DES model graph, we see a similar level of accuracy as SES with an MAE of 11.43. The DES model incorporated trend adjustment, which helped in better alignment between the predicted values and the actual test data. Also located in figure 6.

Triple Exponential Smoothing (TES):

The TES model includes both trend and seasonal adjustments. The MAE for TES is also 11.43, showing consistent performance with SES and DES. The model accounts for seasonal components, but the accuracy remains similar. Located in figure 7.

Autoregressive Integrated Moving Average (ARIMA):

In figure 8, the ARIMA model's performance, shown in the graph, highlights its effectiveness in capturing the nuances of maize price fluctuations. With an MAE of 11.39, ARIMA slightly outperforms the other models, demonstrating robust predictive capabilities and providing the most accurate predictions.

Seasonal Autoregressive Integrated Moving-Average (SARIMA):

The SARIMA model graph in figure 9 indicates an MAE of 11.44. Despite incorporating seasonal adjustments, SARIMA had a slightly higher MAE compared to ARIMA, suggesting that the non-seasonal characteristics of the data were better captured by ARIMA.

The table below show the MAE score for each of the five models after creation and predicting of each model against the trained and test data.

Table1. Show the MAE score for all five models.

Model	**MAE Score**
SES	11.43
DES	11.43
TES	11.43
ARIMA	11.39
SARIMA	11.44

From the table above the ARIMA model obtained the lowest score therefore making it the best fit model to use in forecasting the current and future sales of the maize crop at 100kg per bag in the Ghanaian market. This theory was further tested by using the model to predict the prize of the maize crop for each month of the following year then plotted against original data to visualize the data.

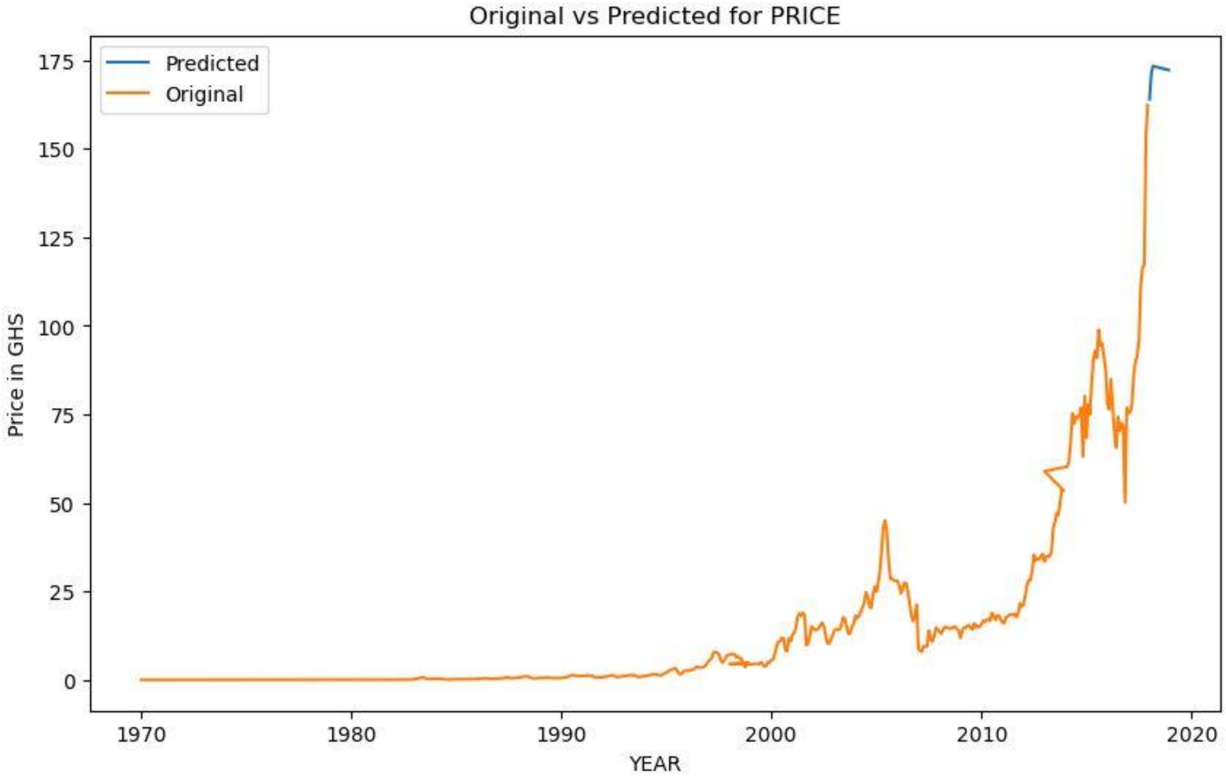

Figure 11. The chart shows the original and the new predicted price of maize

This graph illustrates the ARIMA model's forecast of maize prices over a 12-month period. The blue line represents the predicted prices, while the orange line shows the original observed data. The ARIMA model, with an MAE of 11.39, effectively captures the price trend, indicating minor fluctuations but overall stability in maize prices for the upcoming year.

From the chart,the ARIMA model forecast suggests relatively stable prices with minor fluctuations, as shown in the graph where the blue line represents the predicted prices, and the orange line represents the original data. This stability contrasts with the sharp price increases observed post-2010, attributed to adverse weather conditions like the 2015/2016 drought (Duncan et al., 2016), and policy changes such as the "Planting for Food and Jobs" initiative (Osei-Agyeman et al., 2018). These factors underscore the limitations of using historical price data alone for predictions. Future models should incorporate variables like climatic data, government policies, and global market conditions to improve accuracy and provide valuable insights for decision-making in the agribusiness sector.

Discussion

The results underscore the complexities involved in predicting maize prices, highlighting the limitations of models that rely solely on historical price data. Initially, the DES model appeared promising; however, ARIMA emerged as the most effective model with an MAE of 11.39. This underscores the importance of flexibility and thorough evaluation in time series forecasting.The sharp increase in maize prices post-2010 can be attributed to a combination of external shocks and policy changes that disrupted previous stability. Adverse weather conditions, such as droughts and floods, became more prevalent, significantly impacting maize yields. For instance, the 2015/2016 agricultural season experienced severe droughts, which drastically reduced yields (Duncan et al., 2016). Climate change has further increased the variability of weather patterns, making agricultural production more unpredictable and leading to supply shortages and higher prices (Mastrorillo et al., 2016; Hassan et al., 2019).Government interventions during this period also played a crucial role in shaping maize prices. Programs like the "Planting for Food and Jobs" initiative aimed at enhancing productivity faced initial implementation challenges, such as delays in the distribution of fertilizers and other inputs, which caused short-term supply issues and affected pricing (Osei-Agyeman et al., 2018; Zougmoré et al., 2018). Additionally, export bans and fluctuating import tariffs introduced price distortions, creating uncertainty in the supply chain (Nielsen et al., 2018).Global market dynamics, including rising international commodity prices and currency depreciation, exacerbated the situation, making it challenging for local producers to stabilize pricing (Abdulai & Huffman, 2014; Asante et al., 2019). These factors, coupled with fluctuating input costs due to inconsistent fertilizer subsidies and rising transport expenses, led to increased production costs and ultimately higher consumer prices (Diao et al., 2018).

The implications of these factors are critical for understanding the limitations of predictive models that fail to account for such shocks and policy changes. Without incorporating these variables, predictions may be significantly inaccurate, not reflecting the complexities of Ghana’s agricultural market (Kumah et al., 2020). To enhance the reliability of forecasts, it is essential to integrate a comprehensive set of variables, including climatic data, government policy changes, and global market conditions. Acknowledging these dynamics will improve our understanding of maize price fluctuations and aid policymakers and stakeholders in making informed decisions to stabilize the agricultural sector (Chamberlin et al., 2014; Dorward et al., 2015).

Future research

Future work should focus on incorporating these external factors into predictive models to develop a more accurate representation of the underlying drivers of maize prices. This will ultimately inform better policy decisions and agricultural strategies, supporting food security in Ghana.

Conclusion

This study has demonstrated the critical importance of accurate maize price forecasting in Ghana using time series models. Through the application and evaluation of Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Triple Exponential Smoothing (TES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving-Average (SARIMA), we identified the ARIMA model as the most effective, with an MAE of 11.39.

The analysis highlighted the need to consider external factors, such as adverse weather conditions, government policies, and global market dynamics, which significantly impact maize prices. The integration of these variables into predictive models is essential for improving the accuracy and reliability of forecasts.

By enhancing our predictive framework to account for these influential factors, we can provide better support for policymakers and stakeholders in making informed decisions. This will help stabilize the agricultural sector, ensure food security, and ultimately contribute to the economic stability of Ghana. Future research should continue to explore the impact of these external variables to further refine and improve predictive models for maize prices.

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