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A TIME SERIES ANALYSIS OF MAIZE PRICES IN ZIMBABWE

BY

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A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS OF THE BACHELOR OF SCIENCE HONOURS DEGREE IN STATISTICS AND FINANCIAL MATHEMATICS

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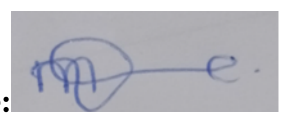
Author's Signature: 

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DEDICATION

I warmly dedicate this dissertation to my dear parents, my brother, and my grandmother. Your unwavering support, love, encouragement, and belief in me have been the foundation of my academic journey. To my parents, thank you for instilling in me the values of hard work, perseverance, and integrity. To my brother, your constant motivation and faith in my potential have been truly inspiring. And to my grandmother, your prayers and wisdom have provided comfort and strength throughout. This accomplishment is a tribute to all of you, and I am forever grateful.

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ABSTRACT

Maize production in Zimbabwe faces significant challenges due to a lack of sustainability in the sector. Farmers are increasingly dissatisfied with the fluctuating prices at which they are able to sell maize, leading to diminishing returns on their investments. The volatility in maize prices undermines the stability of the agricultural sector, as inconsistent pricing creates uncertainty for farmers and discourages long-term investment in maize production. This instability contributes to a cycle of discontent among farmers and hinders the potential for sustained agricultural growth in Zimbabwe. Therefore, understanding the underlying causes of maize price fluctuations is crucial for addressing these challenges and improving farmer livelihoods. This study investigates maize price dynamics through time series analysis, aiming to identify key macroeconomic (Inflation, GDP ,Foreign Exchange rate) and climatic variables influencing price behaviour, assess volatility using ARCH and GARCH models, and forecast future maize prices using both GARCH and Feedforward Neural Network (FFNN) models. Monthly data from 2000 to 2024, primarily sourced from the International Monetary Fund (IMF), was analysed using Python and Excel under a quantitative research design. Model performance was evaluated using AIC, BIC, MAE, and RMSE. The results show that the FFNN model outperformed the GARCH model in forecasting accuracy, effectively capturing nonlinear trends and seasonal fluctuations. While the GARCH model was useful for modelling volatility, it consistently underestimated actual price levels. Forecasts generated using the FFNN projected a steady rise in maize prices from 2025 to 2028, reflecting ongoing seasonal demand and market shifts. Based on these findings, policy recommendations include paying farmers in U.S. dollars to preserve value, increasing public awareness of the Zimbabwe Gold (ZIG) currency, ensuring timely and transparent distribution of subsidies, and developing mobile-based market information systems to support farmer decision-making. Future research should explore hybrid models, the impact of climate change, GDP , Inflation ,Foreign exchange and cross-country maize price comparisons to enhance forecasting precision and inform sustainable agricultural policy.

Keywords: Time series analysis, ARCH models, GARCH models, FFNN models, forecasting

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ACRONYMS

1. ACF - Auto Correlation Function
2. ADF - Augmented Dicky Fuller
3. AIC - Akaike Information Criteria
4. ANN- Artificial Neural Networks
5. ARCH- Autoregressive Conditional Heteroskedasticity
6. BIC - Bayesian Information Criteria
7. FFNN- Feed-Forward Neural Networks
8. GARCH- Generalized Autoregressive Conditional Heteroskedasticity
9. GDP-Gross Domestic Product
10. GMB- Grain Marketing Board
11. MSE - Mean Absolute Error
12. PACF - Partial Auto correlation Function
13. RMSE - Root Mean Squared Error
14. ZIMSTATS-Zimbabwe National Statistics Agency

CHAPTER 1: INTRODUCTION

1:0 Introduction

Agriculture dominates national development, food security, and income generation at the local level in Zimbabwe to a large extent (Dzvimbo, Mhlanga, & Mvumi, 2017). Maize price volatility is of particular concern to the government of Zimbabwe, private institutions, individual farmers, and other stakeholders due to the fact that maize is both a staple crop and an economic stimulator. Agricultural predictive analytics has economic value addition because it forecasts future prices of maize, allowing farmers, traders, and policymakers to make sound decisions, plan market activities, and improve food security. Maize price trend analysis is also critical in determining the cost of production versus profit, planning, and the vision of Zimbabwe being a middle-income economy by 2030.

This chapter provides the background of the time series analysis of maize prices in Zimbabwe, research objectives, research questions, and problem statement. It also provides the scope, significance, limitations, assumptions, and delimitations of the study. It also provides the organization of the study, with a preview of each of the five chapters provided in this study, followed by a summary conclusion.

1:1 Background of the study

Maize is one of Zimbabwe's staple and principal driver of Zimbabwe's economy. It is approximated that by far 70% of Zimbabweans depend on agriculture for survival, and the sectoral contribution is 15% to 20% of the Gross Domestic Product (GDP), 40% of export earnings, and 63% of the nation's agro-industrial raw materials (ZIMSTATS, 2012). Because of its importance, it is crucial that value chain stakeholders are aware of trends in maize prices over time.

Historical data refers to the fluctuation of maize prices through the years. For instance, in 2015 the producer price of maize in Zimbabwe reached a high of USD 390 per tonne, while that of 2010 was USD 275 per tonne. More recent data indicates that in 2017 the price was approximately USD 1.85 per kilogram.

The following is a bar chart of the prices of maize in Zimbabwe from 2010 to 2023, which reveals significant fluctuation, particularly in 2017 and 2018, where the prices were originally recorded per kilogram and were adjusted to per tonne.

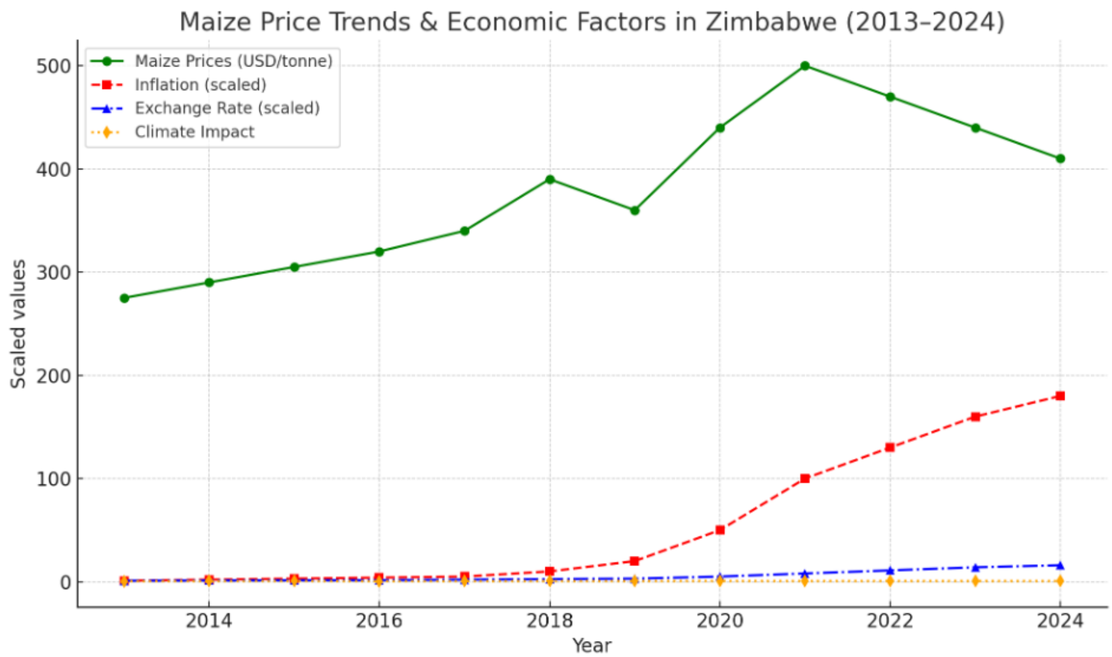

Figure 1:0:1 Maize Price Trends & Economic Factors in Zimbabwe (2013-2024)

Zimbabwe has experienced several instances of maize imports due to price volatility and production shortfalls. These instances have involved the early 2000s following the land reform program, which disrupted commercial agriculture and reduced domestic maize production. Severe droughts, including the 2015–2016 El Niño and 2019–2020 cropping seasons, further worsened the situation, precipitating sharp maize price increases and imports from South Africa, Zambia, and Mexico.

These fluctuations in maize price and availability highlight the usefulness of predictive tools like time series analysis. With a projection of the future trend of maize prices, planners can make informed choices, improve food security planning, and reduce reliance on emergency imports, especially during periods of climate-induced disruption or economic instability.

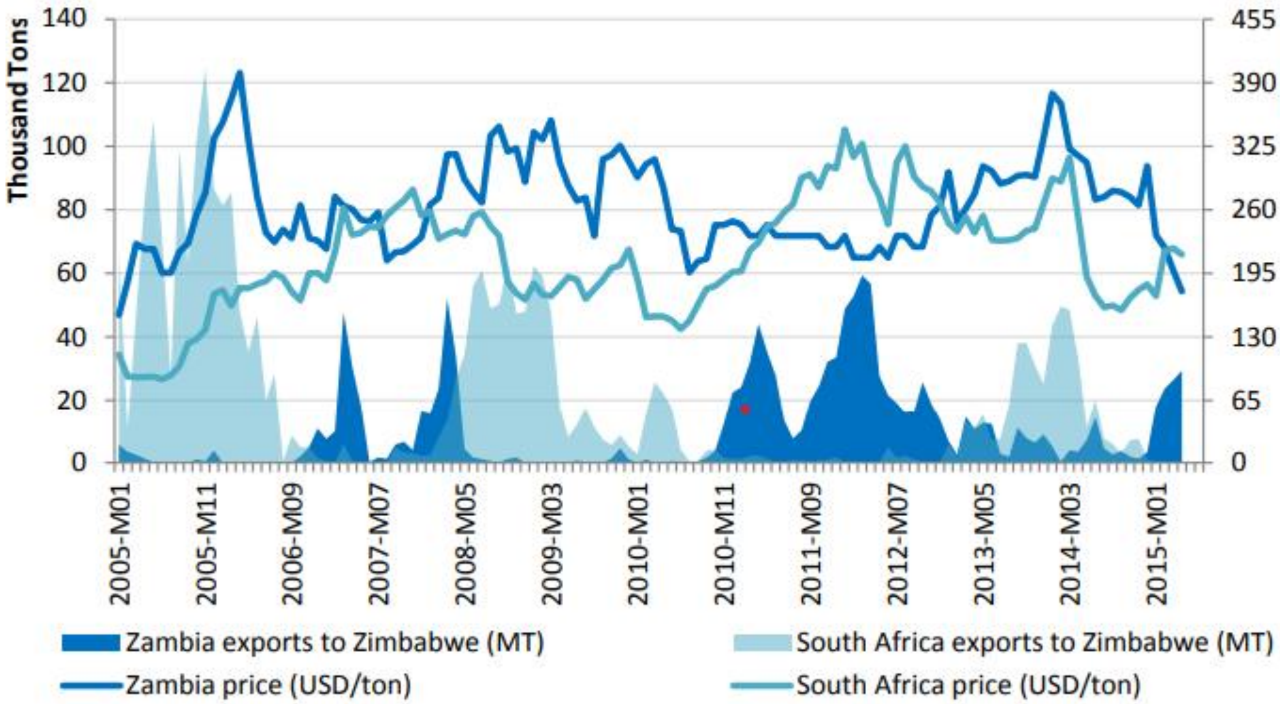

Figure 1:0:2 Zimbabwe maize imports and relative prices in South Africa and Zambia

Source: ITC Trade map and FEWSNET,2015

This figure presents volumes and price trends of South African and Zambian maize exports to Zimbabwe between 2005 and 2015. Shaded areas represent export volumes (thousand tons), while lines represent maize prices (USD per ton). South Africa was the dominant exporter to Zimbabwe in the early years (2005–2008) with substantial volumes and moderate prices. Its exports declined sharply after 2010, however, while Zambia's maize exports rose, especially between 2011 and 2012, and again in 2015. This reflects a shift in the pattern of trade, which could have been due to policy difference, competitiveness in prices, or Zambia's improved production.

The Zambian and South African maize prices followed more or less the same pattern, with visible peaks in 2008 and 2012. These are explainable in terms of regional food crises, global commodity price shocks, or climatic production losses. The reality that both Zambia's exports and prices rose concurrently in certain years indicates robust demand from Zimbabwe, possibly due to domestic shortages or good terms of trade. Overall, the graph captures the evolving trade relationship and price movements influencing Zimbabwe’s maize import sources over the decade.

1.2 Problem statement

Maize production in Zimbabwe faces significant challenges due to the lack of sustainability in the sector. Farmers are increasingly dissatisfied with the fluctuating prices at which they are able to sell maize, leading to diminishing returns on their investment. The volatility in maize prices undermines the stability of the agricultural sector, as inconsistent pricing creates uncertainty for farmers, discouraging long-term investment in maize production. This instability in maize prices contributes to a cycle of discontent among farmers and hinders the potential for sustained agricultural growth in Zimbabwe. Therefore, understanding the underlying causes of maize price fluctuations is crucial for addressing the challenges in the sector and improving the livelihoods of farmers.

1.3 Research objectives

The main objectives of this study are:

1. To determine factors influencing maize price
2. To asses volatility in pricing using ARCH and GARCH Models
3. To forecast maize prices in the next 4 years (using GARCH and FFNN)

1.4 Research questions

This study explores the following research questions:

1. What key factors influence maize price fluctuations in Zimbabwe over time, including the roles of macroeconomic variables and climatic conditions?
2. How can price volatility in maize markets in Zimbabwe be assessed using ARCH and GARCH models, and what long-term trends and seasonal patterns are observable in the data?

3. How accurately can Feedforward Neural Networks (FNNs) and GARCH forecast maize prices in Zimbabwe over the next four years, and what implications do these forecasts have for policy and food security?

1.5 Significance of the study

The significance of this research is that it has the potential to provide vital insights into the complex forces driving maize prices in Zimbabwe, a country where maize is both a food staple and a principal agricultural commodity. The research aims to address some of the basic gaps and questions regarding maize price volatility, forecasting, and policy implications. Its ramifications can have far-reaching economic, policy, and social implications:

1.5.1 To Students and Researchers

To researchers and students, time series analysis of Zimbabwe maize prices offers a real opportunity to connect theoretical knowledge with real-world circumstances. It renders their understanding of econometric techniques and data analysis deeper. By using real market data, they can reason and explain agricultural economics phenomena. Additionally, the study can serve as a benchmark for further research work, encouraging students to carry out research on the same or related challenges such as food security, price volatility, and agricultural policy.

1.5.2 To Other Stakeholders

To other researchers and students, the research findings from this study can contribute to the body of knowledge on agricultural markets and food supply chains. It can serve as a benchmark for comparative research in other areas or countries. Multidisciplinary research activities can be a spin-off from this research, fostering an integrated system that includes economics, environmental studies, and social studies. This broader participation can generate interest in agriculture and unleash innovative answers to issues confronting the sector.

1.5.3 To the Government of Zimbabwe

The government of Zimbabwe can greatly benefit from this research by applying the gained information in policy decision-making in the areas of agriculture and food security. An understanding of the trend in prices assists in devising interventions aimed at normalizing prices, ensuring the availability of produce to consumers, and safeguarding farmers against loss of revenue. The research also demonstrates the impacts of externalities such as climate change and market fluctuations, enabling the government to take early measures to cushion against the risks and promote agricultural output.

1.5.4 To Policymakers

Time series analysis of maize price is beneficial to policymakers when making policy regarding agriculture. It provides fact-based information that can be used when making strategic choices and resource allocation. Decision-makers can identify trends and patterns that should be intervened in, for example, subsidies or support to farmers in case of price volatility. By basing decisions on empirical realities, they can promote sustainable agriculture and long-term sustainability of the maize sector, and hence enhance national food security and stability of the economy.

1:6 Assumptions

1. Stationarity: Maize price time series data is stationary or can be made stationary
2. Error Independence: Residuals are independent with no autocorrelation.
3. Normal Distribution: Returns are normally distributed with negligible effect of deviations.
4. Predictive Power: FNNs are able to capture complex relationships for improved forecasting.

1:7 Limitations of the study

Time series analysis of Zimbabwean maize prices has several and varied limitations. Data issues in the form of unavailability, lack of information, and unreliable data due to gaps in collection can undermine the analysis.Furthermore,the geographical and temporal scope of the study were limited ,focusing on a specific region and time period. Unofficial trade activities and regional price differentials also complicate the maize market dynamics that a model cannot be able to capture. Seasonal effects complicate it further since these would need to be separated from the underlying trends in order to avoid spurious conclusions. Finally, there are issues of validation since good quality out-of-sample data is not available, and it is difficult to describe the performance of the model in a satisfactory way.

1:8 Delimitations of the Study

Delimitations of this study on the analysis of maize price in Zimbabwe focus on specific aspects while others are not considered. It is restricted to historical maize price data alone, but not other agricultural products or future forecasting. The study is limited to Zimbabwe, without consideration of the influence from other nations. The period chosen may not capture long-term trends or rare events. It is quantitative in approach and does not include qualitative variables like farmer attitude or market sentiment. It relies on figures from selected credible sources, omitting informal market data. It is focused on trends in maize prices without regard to other economic variables like input prices, exchange rates, or GDP. Assumptions such as stationarity can limit the applicability to abnormal patterns of price. These limits are used to specify the focus to give definite, attainable results.

1.9 Definition of terms

Time Series Analysis

A statistical method used to analyse sequential data points collected over a span of time with the aim of identifying patterns, trends, and seasonal variations, and forecasting. It is used extensively in economics, agriculture, and finance (Box, Jenkins, & Reinsel, 2008).

Maize Price

The economic value placed on maize based on the cost of production forces, market demand, climatic conditions, and government policies. Maize is a staple food crop in Zimbabwe, and as such, its price is at the core of economic and food security analysis (Food-Agriculture-Organization-United-Nations., 2021).

Volatility

The magnitude of price movements over a period of time, reflecting risks and uncertainties in the market. Maize market volatility is generally caused by seasonality, policy shift, or exogenous shocks (Engle, 1982).

ARCH Model (Autoregressive Conditional Heteroskedasticity)

A time series model suggested to explain and analyse variances that change over a period of time, commonly used in financial and commodity price volatility modelling (Engle,1982).

GARCH Model (Generalized Autoregressive Conditional Heteroskedasticity)

A generalization of the ARCH model that incorporates lagged variances and residuals, enabling a more persistent structure for modelling volatility in time series data (Bollerslev,1986).

Forecasting

The process of predicting future values based on historical data and statistical or machine learning models. Forecasting in this study is done for maize prices to assist stakeholders in planning (Hyndman, & Athanasopoulos, 2018).

Feedforward Neural Networks

A type of artificial neural network where information flows just in one direction from the input layer to the output layer. It is highly appropriate for time series forecasting since it has the ability to model complex, nonlinear relationships (Goodfellow, Bengio, & Courville, 2016).

1.10 Organization of the study

This study is organized into five chapters, Chapter 1 provides the introduction to the study, providing background to the time series analysis of Zimbabwe maize prices. Chapter 2 provides a review of the literature, describing previous research on maize price analysis and forecasting methods used on maize and other agricultural commodities. Chapter 3 outlines the research methodology, data sources, variables, and models used for analysis, including ARCH-GARCH and FFNN models for analysis. Chapter 4 presents the results and comparison of the two models for analysis, with maize price forecasting based on the selected best model. Chapter 5 encapsulates the findings of the study by restating the findings, drawing conclusions, making recommendations, as well as proposing areas for future study based on the results presented in the previous chapter.

1:11 Summary

Chapter 1 presents the research on "Time Series Analysis of Maize Prices in Zimbabwe," and it is concerned with maize price volatility, one of the most important staples in Zimbabwe. It declares the importance of maize in food security, economy, and agriculture and mentions some of the issues such as price volatility against weather, policies, and market conditions. Its objective is to analyse determinants of prices, investigate volatility, and predict future prices through Feedforward Neural Networks. It aims to provide intelligence to policymakers, farmers, and traders for improved decision-making. The chapter also briefly covers the study's scope, limitations, and delimitations.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Several scholars have used time series methods in agricultural price analysis, making useful inferences about the volatility and prediction of maize prices. A survey of these studies places the present research in perspective and also outlines areas where further research is required particularly in understanding maize price trends in Zimbabwe.

2.1 Theoretical Literature Review

2.1.1 Predictive analytics theory

Predictive analytics is a multidisciplinary innovation developed through the combined contributions of statisticians, econometricians, computer scientists, and AI researchers. Initial foundation was laid by Francis Galton (regression), Karl Pearson (correlation), George Udny Yule (autoregressive models), and Ronald Fisher (experimental design) (Stigler, 1986; Pearson, 1895; Yule, 1927; Fisher, 1925). Norbert Wiener's cybernetics influenced early predictive systems (Wiener, 1948). Econometricians like Clive Granger (cointegration), James Hamilton (regime-switching), Christopher Sims (vector autoregression), and Robert Engle (volatility modelling) created time series forecasting (Granger, 1981; Hamilton, 1989; Sims, 1980; Engle, 1982). In business analytics, Tom Khabaza created the CRISP-DM methodology, Usama Fayyad advocated knowledge discovery, and Boris Kovalerchuk conducted data mining research (Chapman et al., 2000; Fayyad et al., 1996; Kovalerchuk & Perlovsky, 2000). AI researchers Yoshua Bengio, Geoffrey Hinton, and Yann LeCun revolutionized prediction with deep learning, and Judea Pearl invented Bayesian networks (LeCun et al., 2015; Pearl, 1988). More recent writers like Ramesh Sharda, Galit Shmueli, Daniel Larose, and Eric Siegel have applied predictive analytics to real-world decision-making (Sharda et al., 2014; Shmueli, 2010; Larose, 2015; Siegel, 2016).

2.1.2 Cobb-Douglas Production Function Theory

The Cobb-Douglas production function, formulated mathematically by American economist Paul H. Douglas and mathematician Charles W. Cobb during the 1920s, is a ground-breaking economic model that describes the relationship between input factors, viz. labour and capital, and output in a production process (Cobb & Douglas, 1928). It was largely Paul Douglas, the future U.S. senator, who was responsible for the development of the concept and in detail empirically estimating the function using the U.S. manufacturing data, putting economic output theory of production inputs into formal model specification. Of these environments for maize production, the Cobb-Douglas is an easy one to apply in attempting to see the effect that inputs such as labour, machinery, and investment on capital have on farm output and, in turn, on market prices. Production efficiency in

Zimbabwe also relies on the uptake of new farm methods, mechanization, and improved technology (Gweru, 2019). It has been costed at approximately USD 1,788.00 to plough a hectare of maize in Zimbabwe (Mutambara et al., 2013). Fertilizers and lime (USD 554.28, 31%), irrigation (USD 357.60, 20%), hiring a tractor (USD 232.44, 13%), and seeds, harvesting, fixed charges, and miscellaneous (each USD 160.92, or 9%) are the significant cost items. Under good farm management, farmers can attain a production of 4 to 8 metric tonnes per hectare. Through the use of the Cobb-Douglas production function, policymakers, farmers, and agricultural institutions are in a better position to model output elasticity in relation to input changes for the sake of ensuring optimum resources allocation, reducing the cost of production, and enhancing price stability of maize in the market.

1.1.3 Model Comparative Theory

Comparative Theory Modelling emerged from the ground-breaking work of several leading scientists who developed significant contributions to model comparison techniques. Hirotugu Akaike started this area with the introduction of the Akaike Information Criterion (AIC) in 1973, a metric that compares models on the basis of a trade-off between goodness-of-fit and complexity of the model (Akaike, 1973). Subsequently, Gideon Schwarz extended this idea in a Bayesian framework by formulating the Bayesian Information Criterion (BIC) in 1978, which imposes a larger penalty for additional parameters (Schwarz, 1978). Though the classical prediction error measures like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are rooted in classical statistics with no single inventor, their comparative significance in quantifying predictand accuracy was thoroughly analysed by Carl J. Willmott and Kenji Matsuura in 2005. They pointed out the superiority of MAE in measuring average error and the higher sensitivity of RMSE to extreme deviations (Willmott & Matsuura, 2005). Collectively, these scholars Akaike, Schwarz, Willmott, and Matsuura laid the groundwork for Comparative Theory Modelling. This theory warrants the comparative assessment of forecasting models, such as ARDL and ARCH-GARCH, based on performance metrics like accuracy, stability, and applicability to real-case situations, such as maize price forecasting in Zimbabwe.

1.1.4 Time Series Theory

Time Series Theory was established by a few of the early 20th-century statisticians and economists who commenced time-series forecasting and modelling of time-varying data. Time Series Theory was developed by George Udny Yule in the 1920s, who came up with the Autoregressive (AR) model in a bid to model time-ordered data patterns (Yule, 1927). Later in the 1940s, Norbert Wiener and Andrey Kolmogorov further strengthened the theoretical framework by incorporating stochastic processes and optimal filtering into it in a manner in which random and noisy data could be delineated even more precisely (Wiener, 1949; Kolmogorov, 1941). Later, during the 1970s, Clive W. J. Granger and Paul Newbold took the subject to the next level through the identification of the spurious regression phenomenon and the development of the central concepts of Granger causality and cointegration as being fundamental to the characterization of long-run equilibrium relations among non-stationary time series (Granger & Newbold, 1974; Granger, 1981). Around the same time, George Box and Gwilym Jenkins systematized the Box-Jenkins methodology and use of ARIMA models in publishing a systematic identification, estimation, and diagnostic check of time series models (Box & Jenkins, 1970). These ground-breaking contributions cumulatively establish the modern Time Series Theory with widespread applications in economics, agriculture, finance, and environmental sciences.

1.1.5 ARCH/GARCH theory

The theory was started by Robert F. Engle, who introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model in 1982. Engle developed this model to address the phenomenon of volatility clustering—where the high volatility periods in financial or economic time series data tend to be succeeded by similar high volatility periods, and vice versa for low volatility. In the ARCH model, the conditional variance of a time series is modelled in terms of lagged squared error terms in an attempt to more effectively capture time-varying volatility (Engle, 1982). This was followed by Tim Bollerslev, who extended the model in 1986 with the Generalized ARCH (GARCH) model. This model incorporates both past variances and past squared errors, offering a more general and robust approach to modelling long-run volatility dynamics (Bollerslev, 1986). The ARCH and GARCH models have since become essential tools in forecasting and risk management, particularly in fields like finance and commodity markets, where price volatility is of utmost importance. In predicting maize prices, these models are very relevant given that they are able to capture the clustering of low and high volatility periods which are typical in the prices of agricultural commodities. By measuring as well as forecasting the shifting volatility conditions, these models are very valuable to policymakers, analysts, and traders who need to make decisions in the face of uncertainty.

2.1.6 Neural Network Theory

Neural Network Theory was developed as a computational approach to mimic the functioning of the human brain, enabling machines to learn from data through a structure of interconnected artificial neurons. The foundation was laid by McCulloch and Pitts (1943), who modelled neurons using binary logic. This was followed by Frank Rosenblatt (1958), who introduced the Perceptron, a simple neural network capable of pattern recognition. A major breakthrough came with the backpropagation algorithm introduced by Rumelhart, Hinton, and Williams (1986), which allowed neural networks to learn efficiently by adjusting weights based on errors. This advancement laid the groundwork for today's deep learning models, as developed further by researchers like Yann LeCun, Geoffrey Hinton, and Yoshua Bengio. Neural Network Theory underpins models such as Feedforward Neural Networks (FFNNs) and Recurrent Neural Networks (RNNs), which are widely used for forecasting in fields like agriculture, finance, and health.

2.1.7 System Dynamics Theory

System Dynamics Theory was developed by Jay W. Forrester in 1961 to model and analyse complex systems characterized by feedback loops, time delays, and nonlinear interactions (Forrester, 1961). Originally applied to industrial processes, the theory has since been adopted across various fields, including agriculture and economics. It emphasizes the importance of understanding how system components influence one another over time, rather than viewing them in isolation. In the agricultural context, System Dynamics Theory provides a valuable framework for analysing how variables such as input costs, market prices, weather patterns, and production volumes interact dynamically. For example, an increase in maize prices may lead to higher planting rates, which can eventually affect supply, demand, and subsequent pricing. By capturing these interdependencies and delays, the theory allows researchers, policymakers, and stakeholders to simulate scenarios, identify leverage points, and design more effective strategies for resource allocation and market stabilization in the agricultural sector.

2:2 Empirical Literature Review

Chikodzi et al. (2020), in their study ,they investigated the effectiveness of different GARCH models in capturing price volatility in Zimbabwe's maize market. The researchers utilized weekly maize price data spanning the period 2005 to 2019, applying a comparative methodology that included both symmetric (GARCH) and asymmetric (EGARCH and GJR-GARCH) models. The study aimed to assess which models most accurately captured volatility, particularly during periods of market stress induced by economic or climatic shocks. The findings demonstrated that asymmetric GARCH models outperformed their symmetric counterparts in identifying and predicting extreme price movements, due to their ability to account for leverage effects and non-linear volatility dynamics. Based on these results, the authors recommended incorporating such models into the design of grain reserve strategies and targeted agricultural subsidy programs, emphasizing their value for policy interventions in times of heightened uncertainty.

Nyagura and Mandizvidza (2022) conducted a study focused on short-term price prediction in Zimbabwean commodity markets using daily quantitative time series data from 2010 to 2021. The researchers applied the Generalized Autoregressive Conditional Heteroskedasticity (GARCH (1,1)) model to analyse price volatility and examine the presence of volatility clustering—a common characteristic in both financial and agricultural commodity price behaviour. Their results confirmed that GARCH (1,1) was effective in modelling short-run fluctuations and identifying persistent volatility patterns in the data. However, the study also highlighted limitations in forecasting precision, especially in high-frequency data environments characterized by structural shocks and external influences. As a result, the authors recommended the adoption of hybrid models that combine traditional econometric techniques like GARCH with machine learning methods (e.g., neural networks) to improve forecasting accuracy and enhance model flexibility. These hybrid approaches, they argued, could offer more robust tools for decision-making in Zimbabwe's volatile commodity markets.

Masunda et al. (2022), the researchers used monthly inflation data from 2000 to 2020 and applied a two-stage modelling technique, first fitting a GARCH (1,1) model to capture volatility clustering, then training a feed-forward neural network (FFNN) to model the remaining volatility structure. Their results demonstrated that the hybrid GARCH–FFNN model outperformed both standalone GARCH and FFNN models in reducing prediction errors and better addressing conditional heteroskedasticity. The study recommends that Zimbabwean policymakers and economic modelers adopt such hybrid approaches when forecasting macroeconomic variables—like inflation—as well as related food and grain price volatility, to enhance precision in economic planning and risk management.

Empirical investigations into maize price dynamics in Zimbabwe have employed a variety of time series approaches to understand both short-term fluctuations and long-term trends. Mudzonga and Chigusiwa (2021) examined monthly maize price data from January 2000 to December 2020, incorporating inflation rates, exchange rates, and rainfall patterns obtained from the Zimbabwe National Statistics Agency (ZIMSTAT) and the Reserve Bank of Zimbabwe (RBZ). Using the Autoregressive Distributed Lag (ARDL) model, they assessed both short-run and long-run relationships, confirming stationarity through Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests and cointegration through the Bounds test. Their results prompted recommendations for the development of weather-indexed insurance products, strengthening of price monitoring systems, and improved policy coordination to stabilize prices.

Similarly, Muzari and Muvhunzi (2019) investigated maize price volatility between January 2005 and December 2018 using monthly data on wholesale prices, fuel costs, exchange rates, and consumer price indices sourced from ZIMSTAT, the Grain Marketing Board (GMB), and RBZ. Employing a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, they captured volatility clustering and persistence in price movements, with model adequacy confirmed through ARCH-LM and Ljung–Box tests. They recommended enhancing grain reserve systems, improving transport infrastructure, and introducing targeted subsidies to shield consumers from sharp price shocks.

Makoni and Moyo (2020) explored the determinants of maize price movements using quarterly data from 2000 to 2019 on maize prices, GDP growth, exchange rates, and import volumes from FAOSTAT, ZIMSTAT, and RBZ. Applying the Vector Error Correction Model (VECM) after confirming cointegration through the Johansen test, they also conducted Granger causality tests to reveal that exchange rate depreciation and import dependency were key drivers of price changes. Recommendations from their study included diversifying maize supply sources, stabilizing the local currency through prudent monetary policy, and supporting domestic maize production through input support programs.

In a related study, Chidoko and Mashavira (2018) analyzed the impact of macroeconomic instability on maize prices using monthly data from January 2004 to December 2017, focusing on retail maize prices, money supply growth, and inflation rates obtained from RBZ and ZIMSTAT. Using a Co-integration and Error Correction Model (ECM) framework, with stationarity confirmed through ADF and KPSS tests, they found that monetary expansion and high inflation were significant drivers of price increases. They recommended tighter monetary control, timely release of grain from strategic reserves, and enhanced price transparency across the maize value chain.

More recently, Nyamuranga and Sibanda (2022) compared the predictive performance of ARIMA and Prophet models in forecasting maize prices using monthly data from January 2010 to December 2021 from ZIMSTAT. After applying differencing to achieve stationarity, they trained and validated the models using an 80–20 data split and assessed accuracy through Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). ARIMA slightly outperformed Prophet in short-term forecasting accuracy, leading the authors to recommend combining statistical and machine learning models for improved prediction, increasing investment in timely market data collection, and providing farmer training on using price forecasts to guide production decisions.

2:3 Research Gap

Most existing studies on maize price volatility in Zimbabwe rely heavily on traditional GARCH models, which, while effective in capturing short-term fluctuations, fall short in addressing long-term trends and complex external influences such as climate change and economic policy shifts. Additionally, these models often neglect recent economic disruptions, including post-COVID-19 recovery and rising inflation, limiting their adaptability to current conditions. There is also a noticeable lack of research exploring hybrid models that combine GARCH with machine learning techniques like Feedforward Neural Networks (FFNN), which have shown promise in handling nonlinear patterns and enhancing forecasting accuracy. Moreover, little attention has been given to the practical application of these models in policymaking and agribusiness. Bridging these gaps could lead to more robust and actionable forecasting tools to support strategic decision-making in Zimbabwe's agricultural sector.

2:4 Proposed Conceptual Framework

The frequent fluctuations in the price of maize in Zimbabwe driven by climate variability, macroeconomic instability, and market inefficiencies require an integrative and holistic methodology in crafting sustainable solutions.

The proposed conceptual model aims to surmount these weaknesses by using state-of-the-art modelling techniques, such as hybrid GARCH-FFNN models, the integration of heterogeneous and exhaustive data sources, and the translation of analysis results into policy-oriented guidelines. This aims to enhance the precision of forecasts and guide targeted interventions that can stabilize maize markets and support resilience in the agriculture sector.

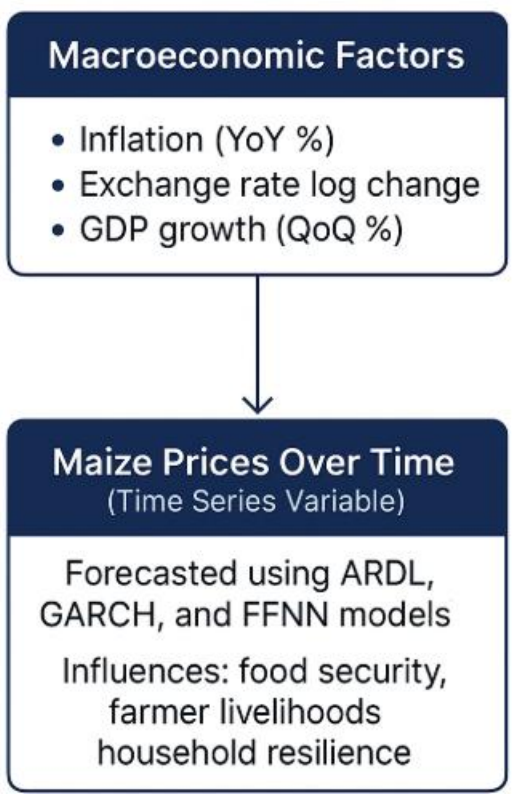

Figure 2:0:1 Proposed conceptual framework

The conceptual framework provided has taken into consideration the association between selected macroeconomic variables and maize prices in Zimbabwe with respect to real variables and techniques used. The Macroeconomic Factors element includes inflation (YoY %), log change of exchange rate, and GDP growth (QoQ %) — the selected independent variables to be considered. Inflation is a measurement of the overall rise in prices and can affect input costs and consumer buying power. Changes in exchange rates affect import and export prices and, in turn, feed through to local maize prices through trade and market linkages. Economic growth reflects the overall economic environment and affects production capacity, demand levels, and farm investment.

Maize Prices Over Time is the explanatory factor that makes up the time series to find out how it changes as a result of a shift in the macroeconomic setting. Forecasting employs the ARDL, GARCH, and FFNN models to follow both the short-run price shocks as well as long-run trends. The socio-economic consequences of maize price fluctuations, such as food security implications, farmer well-being, and household resilience, are also highlighted by this factor. Causal direction between the factors demonstrates the hypothesized cause-and-effect interaction where macroeconomic factors are the primary determinants of maize price trends and therefore make the framework simple and consistent with the study methodology.

2.5 Summary

This chapter provided an overview of key theoretical and empirical research on time series analysis of maize prices, highlighting the importance of incorporating climatic, economic, and market factors to enhance forecasting precision. While conventional models such as ARIMA and GARCH remain widely used, newer hybrid and machine learning approaches demonstrate considerable potential for improved predictive capability. Gaps are evident regarding the influence of regional trade and policy, particularly in the Zimbabwean context. These findings form the basis for the subsequent chapter, which describes the research methodology.

Chapter 3: RESEARCH METHODOLOGY

3:0 Introduction

The chapter provides a summary of the procedure used to carry out analysis of Zimbabwean maize price trends according to the study objective and research question. It begins with the gathering and preliminary processing of past maize prices from credible sources using Exploratory Data Analysis (EDA) to identify prevailing trends, patterns, and seasonality.

For improving forecasting accuracy, an FFNN is suggested to forecast complex nonlinear patterns of the time series. Data preparation is performed through a sliding window method and performance evaluation of the FFNN is compared on the basis of RMSE and Mean Absolute Error (MAE) with traditional models. Methodological shortcomings of this study are discussed under the concluding part of the chapter, and policy implication of findings for economic planning and food security.

3.1 Research paradigm

This study adopts the positivist research paradigm, which assumes that reality is objective and can be measured through empirical observation and statistical analysis. It is suitable because the research uses quantitative time series data to examine the relationship between macroeconomic variables inflation, exchange rate log change, and GDP growth and maize prices in Zimbabwe.

The paradigm supports the use of models such as ARDL, GARCH, and FFNN to produce objective, reproducible, and evidence-based findings.

3.2 Research design

A quantitative research design involving time series analysis is employed in this research to examine maize price volatility in Zimbabwe. Price volatility is estimated using Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models (Engle, 1982; Bollerslev, 1986), while a Feedforward Neural Network (FNN) is employed to forecast maize prices for the next four years (Hyndman & Athanasopoulos, 2018).

3.2Target Population and Sample Period

Weil (2017) defines that a population includes all the elements which are related to the variable(s) under study. The target population for this study includes historical maize price data in all the areas of Zimbabwe. A data sample size was chosen based on a purposive sampling method, between the years 2000 and 2024. The method gives specific features and pertinent data points to capture trends and variations of maize prices, hence offering a solid foundation for time series analysis that well suits the demands of the study.

3:3 Data Collection and Sources

Data collection is the act of acquiring and documenting information in an orderly manner for a particular purpose. Secondary monthly data of Zimbabwe maize price from 2000 to 2024 were collected from the online portal of IMF. The procedure was begun with the identification of the pertinent data by variables and by time period. After the data set was found, it was downloaded in the same manner as the original data and transferred to Microsoft Excel and Python for processing. Other data sets such as the Zimbabwe National Statistics Agency (ZIMSTAT) and the Ministry of Agriculture were not used because they lacked full data coverage for the whole study period. This approach provided the use of a consistent and reliable data set that facilitated good time series analysis.

3.3.1 Rationale

The study utilizes time series monthly data on foreign exchange ,inflation,maize prices and gross domestic product (GDP) to examine the price trend of maize in Zimbabwe .The rationale for selecting these variables is as follows:

1. Foreign exchange rates are included to capture the impact of currency fluctuations on maize prices
2. Inflation rates are considered to account for the overall price level changes in the economy .
3. Maize prices are the primary focus of the study ,aiming to identify patterns and trends .
4. GDP is included to represent the overall economic activity and its potential influence on maize prices .

The price of maize, the subject of this work, is sourced from the International Monetary Fund (IMF) and local agricultural bulletins since it holds a central role in planning and food security in the economy. Inflation rates, which are obtained from national statistical offices and macroeconomic databases, are used to determine the effect of general levels of prices on maize affordability. Exchange rates, which are obtained from the IMF and Reserve Bank of Zimbabwe, are included as they affect the price of farm exports and imports, hence contributing to maize price volatility. Further, the World Bank and IMF GDP statistics provide economic performance and demand conditions data. Employing these macroeconomic indicators offers a full context to examine maize price dynamics and reinforces the accuracy of predictive models.

3.4 Data Validity and Reliability

Talking about data validity and reliability, we assess the quality and reliability of the data source.

Data Reliability:

Reliability is the consistency and stability of the information in the long term and its validation from diverse sources. Information harvested from the International Monetary Fund (IMF) is very reliable since it is periodically revised, employs standardized procedures, and has strict verification processes. The processes have the implication of minimizing errors, biases, and discrepancies so that the maize price data integrated in this study maintains a high degree of credibility.

Data Validity:

Validity means the extent to which the data captures the phenomenon it claims to measure (Weil, 2017). The IMF data is collected as per laid-down standards and procedures, aligned with official international and national ones. It is hence valid in measuring maize price trends for Zimbabwe because it captures the economic circumstances under research effectively.

3.5 Research Instruments

Research instruments are tools for collecting, converting, and processing data to meet the research study goals. For this study, the Internet provided the primary platform for obtaining second-level data, which allowed for downloading monthly maize price data from the IMF. Microsoft Excel and Python were used to perform statistical analysis and generate forecast models. These technologies supported effective data handling, sophisticated computational processing, and precise result generation, which helped make the entire study more reliable and valid.

3.6 Description of Variable

The key variable under this study is Zimbabwean monthly maize price, expressed in US dollars per metric tonne. The following provides a brief explanation of the variable and its rationale.

Table 1 Description of Variables

Variable	Symbol	Indicator	Source
Maize Price	MaP	National average price in USD per metric tonne	IMF
Inflation	INFL	Year-on-year percentage change in consumer prices	Zimbabwe Macro CSV
GDP Growth	GDP	Quarter-on-quarter real GDP growth (%)	Zimbabwe Macro CSV
Foreign Exchange	FX	Log change in the USD/ZWL exchange rate	Zimbabwe Macro CSV

Inflation

The best-known indicator of inflation is probably the Consumer Price Index (CPI), indicating the rate of change of the price for a basket of products and services typically purchased by families. Inflation is commonly measured in terms of Laspeyres index formula relative to current versus fixed base period price. Inflation represents a significant indicator of declining purchasing power of money (World Bank, 2016). In an economy such as Zimbabwe, inflation can be irregular and high, especially in instances of economic mismanagement or monetary instability. As prices rise, the cost-of-living increases, with consumers and producers subjected to economic hardship.

Justification

Inflation has to be accounted for in the calculation of maize price since it influences production costs and the purchasing power of the consumer directly. In the case of Zimbabwe, whose agriculture is highly macroeconomic-sensitive, inflation heavily influences input prices such as seeds, fertilizers, and fuel. Increased inflation also reduces disposable income at the household level, thereby influencing the consumption of food. According to the Cost-Push Inflation Theory, rising production costs are passed on to consumers in the form of higher prices, directly linking inflation to commodity price changes. Empirically, Mudzonga and Chigusiwa (2021) found that inflation significantly impacts maize prices in Zimbabwe through both production cost pressures and shifts in consumer demand patterns. Including inflation therefore enables the model to incorporate the overall economic environment influencing maize market behaviour.

Exchange Rate (Log Change)

The exchange rate is used to measure the value of the domestic country's national currency (ZWL) relative to the foreign currencies like the United States Dollar (USD). In this research, exchange rate movements are measured in terms of changes in logarithms, which reflect relative percentage change with respect to time and eliminate the impact of scale and skewness. Exchange rates would tend to be affected by monetary policy, capital flows, and balance of trade. The exchange rate in Zimbabwe tends to be highly volatile due to hyperinflation, fiscal disequilibrium, and foreign reserves shortage.

Justification

It is important to incorporate exchange rate movements into the dynamics analysis of maize prices, especially for a country like Zimbabwe that imports large quantities of agricultural inputs and, at times, even the grain itself. Exchange rate depreciation increases the cost of imported chemicals, fertilizers, and machinery, thereby elevating maize production costs and, consequently, prices. The Purchasing Power Parity (PPP) Theory explains that currency depreciation raises the local currency cost of imports, which feeds into domestic price levels. Empirically, Makoni and Moyo (2020) demonstrated that exchange rate instability in Zimbabwe significantly drives maize price fluctuations due to the country's reliance on imported agricultural inputs and grain. The log-change specification captures exchange rate volatility while maintaining data stationarity, ensuring that cost pressures from foreign markets are effectively reflected in the model.

Gross Domestic Product (GDP Growth)

Gross Domestic Product (GDP) is the sum of all monetary value of final goods and services produced within a country's borders over a specific period. GDP is an overall indicator of economic health at a national level. GDP growth in percentage terms on a quarterly basis (QoQ) is the speed of economic activity, investment, and consumption. A positive GDP growth would generally reflect increasing levels of income and expanding demand, while negative growth reflects declining economic activity.

Justification

The maize price analysis is augmented with GDP growth to include the effect of general economic performance on agricultural demand and supply. Increased GDP translates into higher household incomes and greater government expenditure on agricultural support programs, thereby influencing maize demand and prices. Conversely, economic downturns reduce investment in farm infrastructure and constrain farmers' ability to purchase inputs. The Keynesian Income-Expenditure Theory suggests that rising national income stimulates consumption and investment, which can increase demand for staple commodities such as maize. Empirically, Chidoko and Mashavira (2018) found that GDP growth in Zimbabwe is positively associated with agricultural market activity and commodity price movements due to its impact on both demand-side and supply-side conditions. Incorporating GDP growth therefore enables the model to capture macro-level income effects on food markets.

Maize Price

Maize price refers to the market price of maize in kilogram or tonne. It is usually obtained from market trade information or food monitoring agencies at national level. Since maize is a staple crop in Zimbabwe, it responds to seasonality, policy interventions, as well as macro-economic conditions. Prices can vary based on weather (e.g., drought), political interventions (e.g., subsidies, import restriction), and global commodity trends

Justification

Maize price, as the dependent variable, reflects both food security conditions and the influence of macroeconomic factors on agricultural markets. Guided by the Law of Supply and Demand and supported by Nyamuranga and Sibanda (2022), tracking maize price trends alongside inflation, exchange rate volatility, and GDP growth helps identify key drivers of volatility and enhances forecast accuracy, thereby supporting effective planning and policy formulation.

Results expectation from the data

Table 2 Expected Results from the Data

VARIABLE	EXPECTED IMPACT	JUSTIFICATION
Inflation	Positive (+) or Negative (–) depending on context	Cost-Push Inflation Theory (Blanchard, 2017) explains that inflation raises input costs, pushing up maize prices; however, excessive inflation can suppress demand (Mudzonga & Chigusiwa, 2021).
Exchange Rate (Log change)	Positive (+)	Purchasing Power Parity Theory (Cassel, 1918) states that currency depreciation raises import costs, increasing production expenses; confirmed empirically by Makoni & Moyo (2020) in Zimbabwe.
GDP Growth (QoQ %)	Negative (–)	Keynesian Income-Expenditure Theory (Keynes, 1936) suggests higher GDP growth improves supply stability and incomes, reducing price volatility (Chidoko & Mashavira, 2018).

Maize price (Dependent variable)	N/A	Guided by the Law of Supply and Demand (Marshall, 1890), maize prices respond to macroeconomic shocks; Nyamuranga & Sibanda (2022) show significant impacts in Zimbabwe.

Source: Author's computation

3.7 Data Analysis Procedures

3.7.1 Diagnostic Tests

Stationarity Tests

Stationarity testing is a crucial activity in time series analysis for purposes of validating model estimates as reliable and credible. A stationary time series possesses constant mean and variance over time, which is essential for producing good and reliable forecasts. The stationarity of core variables maize prices, inflation, foreign exchange rates, and Gross Domestic Product (GDP) in this study is examined with the Augmented Dickey-Fuller (ADF) test. If a variable is found to be non-stationary, it would then be transformed to a stationary condition using processes like first differencing. Ensuring stationarity ensures that the general assumptions of time series models are satisfied and hence the forecasting analysis would be more accurate and robust.

Normality Tests

Apart from ensuring proper model estimation and valid statistical analysis, normality of important variables like maize prices, inflation, foreign exchange rates, and GDP would be tested. Non-normal data can produce biased results and misinterpretation in certain statistical models. Therefore, graphical diagnostic tools such as histograms and quantile-quantile (Q-Q) plots are used to identify non-normality, as outlined in the procedure in Das and Imon (2017). This methodology has the assurance of carrying out data transformation or correction prior to model usage.

Independence Test

To ensure model integrity, the residuals of the maize price series must demonstrate independence and a lack of autocorrelation. Visual checks using the application of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the residuals are supplemented by the use of the Durbin-Watson test in this research. In order for the model to be well-specified, ACF and PACF plots should not display any strongly autocorrelated lags, i.e., the residuals should resemble white noise and the model should be in a good position to capture the underlying data structure.

Homoscedasticity Test

The homoscedasticity test can be conducted to ascertain that the residual variance is homogeneous over time, which is a critical assumption for the proper estimation of the model. Statistical methods such as the White test can be utilized in this research to determine any type of heteroscedasticity. Homoscedasticity enhances the reliability, stability, and interpretability of the forecasting model utilized in the analysis.

3.8 Analytical Models

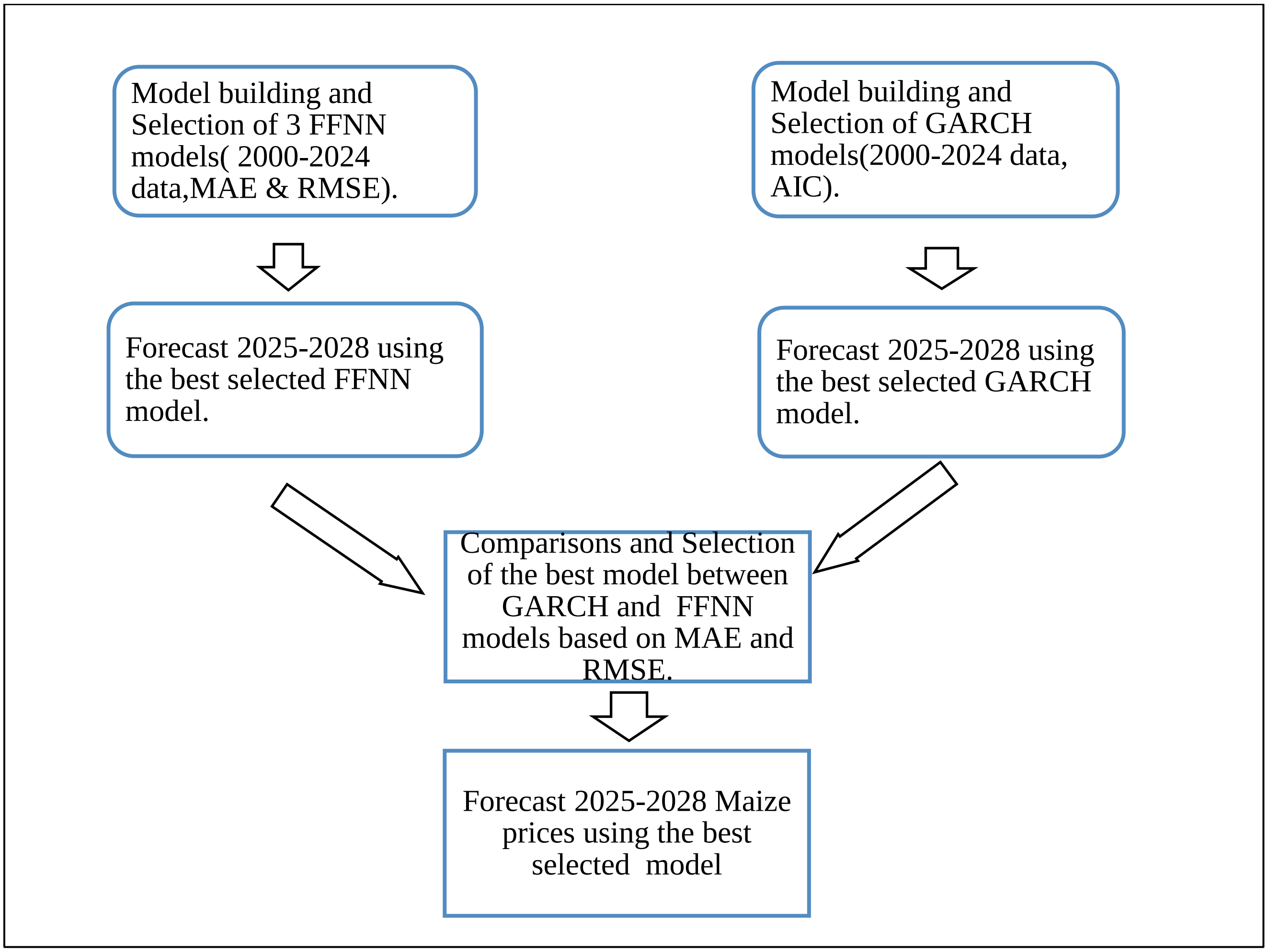

Figure 3:0:1 Model bulding and selection procedure

The flowchart offers a structured framework for analyzing maize price trends in Zimbabwe, incorporating essential components of time series analysis—from data collection and preprocessing to volatility modelling, forecasting, and deriving policy implications. This logical sequence reflects established practices in both econometric and machine learning approaches to agricultural price modelling (Box et al., 2015).

A key strength of the flowchart is its integration of Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models, which are extensively used to capture time-dependent volatility clustering in financial and commodity markets (Engle, 1982; Bollerslev, 1986). Complementing this, the use of Feedforward Neural Networks (FNNs) introduces a nonlinear modelling technique that is well-suited for detecting complex relationships influenced by economic and climatic variability (Hyndman & Athanasopoulos, 2018).

From a quantitative standpoint, the flowchart could be further enhanced by including the explicit mathematical formulations of the employed models. For example, clearly stating the equations underlying the ARCH model would improve analytical transparency and ensure methodological rigor in its implementation.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \qquad (3.1)$$

Where σ_t^2 represents conditional variance and ϵ_t is the error term. The GARCH (p, q) model extends this by incorporating past conditional variances:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1} \beta_j \sigma_{t-j}^2 \qquad (3.2)$$

which is particularly useful in modelling long-term volatility clustering in maize prices.

Additionally, the flowchart does not explicitly consider macroeconomic factors such as inflation (π), exchange rates (ER), and supply shocks (S), which are crucial in explaining maize price fluctuations. These could be incorporated using a Multiple Linear Regression (MLR) model:

$$p_t = \beta_0 + \beta_1 \pi + \beta_2 ER_t + \beta_3 s_t + \epsilon_t \qquad (3.3)$$

Where P_t is maize price at time t and ϵ_t is the error term.

Moreover, the model evaluation metrics are missing. Key accuracy measures such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE**)** should be included to assess the effectiveness of the forecasting models:

$$\text{RMSE}= \sqrt{\frac{1}{n}\sum_{t=1}^{n}} \ (y_t - \hat{y}_t)^2 \qquad (3.4)$$

$$\text{MAPE}=\frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}t}{y_t}\right| \qquad (3.5)$$

These metrics are essential for assessing whether the proposed models yield reliable and accurate maize price predictions. By quantifying model performance through measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and information criteria like AIC and BIC, researchers can evaluate the predictive robustness of both traditional econometric and machine learning approaches.

The flowchart could be further improved by refining the logical transitions between seasonality detection, neural network forecasting, and policy implications. Explicitly referencing data sources—such as the Zimbabwe National Statistics Agency (ZIMSTAT) or FAO datasets—would also enhance the model's credibility and replicability. Moreover, expanding the policy component to include econometric scenario analysis would provide deeper insights into how external shocks, including droughts, inflation, and global commodity price fluctuations, influence domestic maize price volatility.

In conclusion, while the flowchart presents a coherent structure for forecasting maize prices in Zimbabwe using time series analysis, its analytical utility would be strengthened by greater mathematical precision, clearer terminology, and refined visualization. The inclusion of statistical notation, enhanced labelling, and well-defined performance metrics would elevate the chart's effectiveness as a forecasting and decision-support tool.

Model Identification

The flowchart uses ARCH-GARCH for volatility, Neural Networks for forecasting. While it suggests seasonality detection, it omits explicit mention of SARIMA models. Robust model selection should include metrics like AIC, BIC, RMSE, and MAPE.

Parameter Estimation

ARCH-GARCH parameters are estimated via MLE, MLR/ARDL via OLS, and Neural Networks through backpropagation with gradient descent. Tuning is guided by AIC, BIC, and RMSE, with hyperparameter optimization enhancing neural network accuracy.

Model Diagnostics

Diagnostics should include ACF for autocorrelation, ARCH-LM for volatility clustering, and Shapiro-Wilk for normality. Forecast accuracy is assessed using RMSE, MAPE, and the Diebold-Mariano test for model comparison.

3.9 Feedforward Neural Network (FFNN)

A Feedforward Neural Network (FFNN) is a type of Artificial Neural Network (ANN) where information moves in one direction from input to output without loops (Goodfellow et al., 2016). It includes an input layer (e.g., key maize price factors), one or more hidden layers that capture nonlinear relationships, and an output layer that produces forecasts (Nielsen, 2015; Chollet, 2017). FFNNs are trained using backpropagation, which iteratively updates weights by minimizing prediction error (Cheng & Titterington, 1994). The network's behaviour can be described using mathematical functions representing weighted sums and activation functions across layers.

$$\hat{y} = F(\nu_0 + \sum_{j=1}^{m} H(\lambda_J + \sum_{i=1}^{n} x_i\theta_{ij})\,\nu_j) \qquad (3.6)$$

where:

- $\hat{y}$ represents the predicted maize price,
- H is the number of neurons in the hidden layer,
- F is the activation function,
- x_i represents input features (e.g., INFL, FX, GDP),
- θ_{i_j} are the connection weights between input and hidden layers,
- ν_j represents the weights linking hidden layer neurons to the output layer.

For this study, a structured FFNN 3(4)1 model is applied, indicating:

- 3 input neurons (economic and climatic predictors of maize price),
- 1 hidden layer with 4 neurons,
- 1 output node (forecasted maize price).

The hidden layer is computed as:

$$x_k = f\left(\sum_{j=1}^{n} w_{jk} y_j + \Theta_k\right) \qquad (3.7)$$

And the final output is determined as:

$$y = f(\textstyle\sum_{k=1}^{m} w_k x_k + \Theta) \qquad (3.8)$$

Where:

- w_{Jk} and w_k are the respective weight metrices?
- Θ_k *and* Θ are bias terms

Through the use of FFNNs, the model improves long-term maize price forecast accuracy by capturing linear and nonlinear relationships involved in price changes. This is in line with the goal of the research to create a reliable forecast framework for the dynamics of maize prices in Zimbabwe to contribute to price stabilization, food security, and risk avoidance policies.

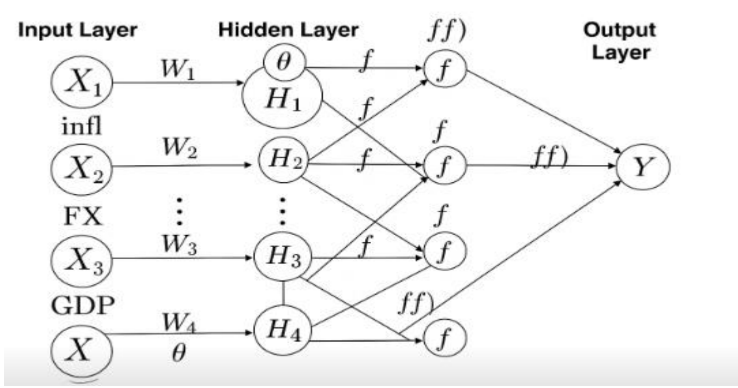

Figure 3:0:2 Feedforward Neural Network (FFNN) model structure

The presented Feedforward Neural Network (FFNN) consists of three main layers: an input layer, a hidden layer, and an output layer. The FFNN is designed to incorporate the nonlinear relationship between macroeconomic variables and predict maize prices.

Input Layer

The input layer consists of **three neurons**, each representing a different input feature:

- x_1: Inflation (INFL),
- x_2: Foreign exchange rate (FX),
- x_3: Gross Domestic Product (GDP)

Hidden Layer

The hidden layer contains four units (or neurons), each connected to all three input variables. These inputs are first multiplied by weights which control the strength of each connection and then adjusted with a bias value. The result is passed through an activation function, which decides how much of the signal moves forward.

This setup helps the network learn complex patterns, such as how shifts in inflation or GDP might influence maize prices, making it better at recognizing relationships that aren't immediately obvious.

Output Layer

The output layer consists of a single unit that generates the final prediction—Zimbabwe's expected maize price. It takes the signals from all four hidden layer units, applies weights to each, adds a bias term, and then processes the result through an activation function. This final step translates the learned patterns into a specific maize price forecast.

Activation Function

The activation function, f, determines how a neuron responds to its input, or the locally induced field (s). It transforms from this input to an output in a bounded range, enabling the network to extract complex, non-linear relationships and to allow for smooth signal passing from layer to layer (Schmidhuber, 2015). One common activation function used in this study is the logistic activation function, given by:

$$f(s) = \frac{1}{1+exp(-as)} \tag{3.9}$$

Where a represents the slope parameter of the sigmoid function.

3.9.1 Data Pre-processing

Before modelling maize price fluctuations, the data undergoes pre-processing steps including cleaning and normalization to standardize input features. Normalization ensures that all variables contribute equally during model training by scaling them within a specified range, typically (0, 1), which enhances convergence stability and prevents any single feature from dominating the learning process. Techniques such as Min-Max Scaling and Z-score standardization are commonly applied to achieve data uniformity and improve model performance (Géron, 2019).

The maize price data, spanning from 2000 to 2024, is partitioned into two subsets: 80% is designated for training the neural network model, while the remaining 20% is reserved for testing. Specifically, data from 2000 to 2019 is utilized to train and optimize the model, whereas data from 2020 to 2024 is used to evaluate its forecasting accuracy. This temporal split ensures a realistic assessment of the model's predictive performance on unseen data.

3.9.2 Post Testing Process

After estimating the GARCH model, post-testing involves checking residuals for autocorrelation and remaining volatility using the Ljung-Box Q-test and ARCH LM test. A good model should have no significant autocorrelation or remaining ARCH effects. Model performance is then assessed using AIC, BIC, and forecast accuracy metrics like RMSE, MAE, and MAPE on out-of-sample data.

For the FFNN model, post-testing focuses on evaluating predictive accuracy using RMSE, MAE, MAPE, and R^2. Training and validation loss curves are inspected to detect overfitting, with early stopping used if necessary. Residual plots and ACF charts help assess if errors are random. The two models are finally compared based on their forecasting errors, and the one with better accuracy is recommended for use.

3.9.3 Neural Network Model Training

Training the Artificial Neural Network (ANN) involves iterative adjustments of parameters such as number of hidden layers and neurons to enhance accuracy. The backpropagation algorithm refines model weights using gradient descent, represented by:

$$\omega_{t+1} = \omega_t - \eta \frac{\partial E}{\partial \omega} \tag{3.10}$$

Where:

- ω_t represents the weight at time t,
- η is the learning rate,
- $\frac{\partial E}{\partial \omega}$ is the gradient of the error function.

Backpropagation

Backpropagation, or backward error propagation, is a key algorithm in neural network training. It iteratively adjusts hidden layer weights based on prediction errors, using gradient descent to minimize loss. This process improves forecasting accuracy and helps avoid convergence to local minima, making it effective for modelling maize price fluctuations (Goutorbe, 2006).

3.9.4 Model Validation

Validation techniques ensure model generalization and robustness in maize price forecasting. Key criteria used include:

Akaike Information Criterion (AIC) & Bayesian Information Criterion (BIC)

$$\text{AIC} = 2k - 2\,ln(L) \qquad (3.11)$$

$$\text{BIC} = ln(n) - 2\,ln(L) \qquad (3.12)$$

where L represents the maximum likelihood function and K is the number of model parameters. These criteria help prevent overfitting by penalizing excessive parameters.

3.9.5 Error Metrics

To evaluate forecasting accuracy, the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are computed:

$$\text{MAE}= \frac{1}{n}\sum_{t=1}^{n}|y_t - F_t| \qquad (3.13)$$

$$\text{MSE}= \frac{1}{n}\sum_{t=1}^{n}(y_t - F_t)^2 \qquad (3.14)$$

$$\text{RMSE}= \sqrt{MSE} \qquad (3.15)$$

Where:

- y_t is the actual maize price,
- F_t is the predicted value,
- n represents the number of observations.

Lower values indicate a better-fitting model.

3.10 Ethical Consideration

Maize price data was obtained ethically, ensuring transparency in access and compliance with data protection protocols. Researchers sought permission from IMF and other sources, ensuring reliability in data collection and model training.

3.11 Summary

The approach provides the framework for price volatility analysis of maize in Zimbabwe. The next chapter elaborates on data representation, statistical analysis, and model interpretation, placing price dynamics and forecasting accuracy into perspective.

Chapter 4: DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.0 Introduction

In this chapter, the study's objectives are addressed through clear data presentation, thorough analysis, and results interpretation, all answering the research questions. A step-by-step time series analysis of maize prices in Zimbabwe was carried out to uncover significant patterns and trends, providing a strong foundation for meaningful discussion and well-informed conclusions

4.1 Summary Statistics

Table 3 Descriptive statistics

Statistic measure	Price (USD/MT) (MaP)	Inflation (INFL)_YoY (%)	Exchange rate log change (FX)	GDP growth (%)
Mean	149.972	9.989	0.0149	1.582
Median	149.870	10.120	0.0149	1.545
Mode	117.560	9.530	0.0109	0.980
Standard Deviation	33.029	1.968	0.0048	0.997
Kurtosis	-1.108	0.568	-0.094	-0.189
Skewness	-0.010	0.175	0.134	0.122
Range	125.420	14.190	0.0278	5.330
Minimum	85.600	3.520	0.0026	-1.200
Maximum	211.020	17.710	0.0304	4.130
Sum	44,991.740	2,996.620	4.4685	474.680
Count	300	300	300	300

Maize Price (USD/MT)

The mean maize price over the study period was approximately $149.97, with a skewness value of -0.010, indicating a nearly symmetrical distribution. This suggests that the maize price fluctuated fairly evenly around the average, without extreme deviations in either direction. Since the skewness is close to zero, the curve would appear bell-shaped, with most values concentrated around the mean. The movement in maize price, therefore, can be described as relatively stable over time, without any clear upward or downward bias in the distribution. Prices neither spiked sharply nor fell dramatically, implying a balanced market behaviour during the observed period.

Inflation (YoY %)

The average inflation rate was 9.99%, with a slight positive skewness of 0.175. This indicates that most inflation values were concentrated around the mean, but there were a few periods of abnormally high inflation that pulled the distribution’s tail to the right. The movement in inflation can be interpreted as generally upward, with occasional spikes due to economic shocks or monetary instability. These inflation spikes caused temporary increases in the price level, indicating that inflation, while mostly contained, showed episodes of upward pressure during the study period.

Exchange Rate Log Change

The mean exchange rate log change was 0.0149, and the skewness was 0.134, indicating a slight right skew. This means that the majority of exchange rate changes were small and positive, reflecting a gradual depreciation of the local currency (ZWL). However, there were a few extreme instances where the currency depreciated more sharply, which stretched the distribution toward the right. Overall, the movement in the exchange rate can be described as upward trending, in the sense that the exchange rate (i.e., USD/ZWL) was increasing over time, driven by Zimbabwe's persistent currency depreciation.

GDP Growth (%)

The average GDP growth during the period was 1.582%, with a skewness of 0.122, indicating a slight right skew. This shows that while most growth rates clustered around the average, there were a few periods of stronger-than-usual economic expansion that extended the right tail of the distribution. Despite some downturns (including a minimum of -1.2%), the overall movement in GDP growth shows a modest upward trend, driven by a few high-growth quarters. This suggests that while the economy remained relatively weak, it experienced occasional growth spurts, possibly due to policy interventions or recovery periods.

4.2 Correlation Analysis

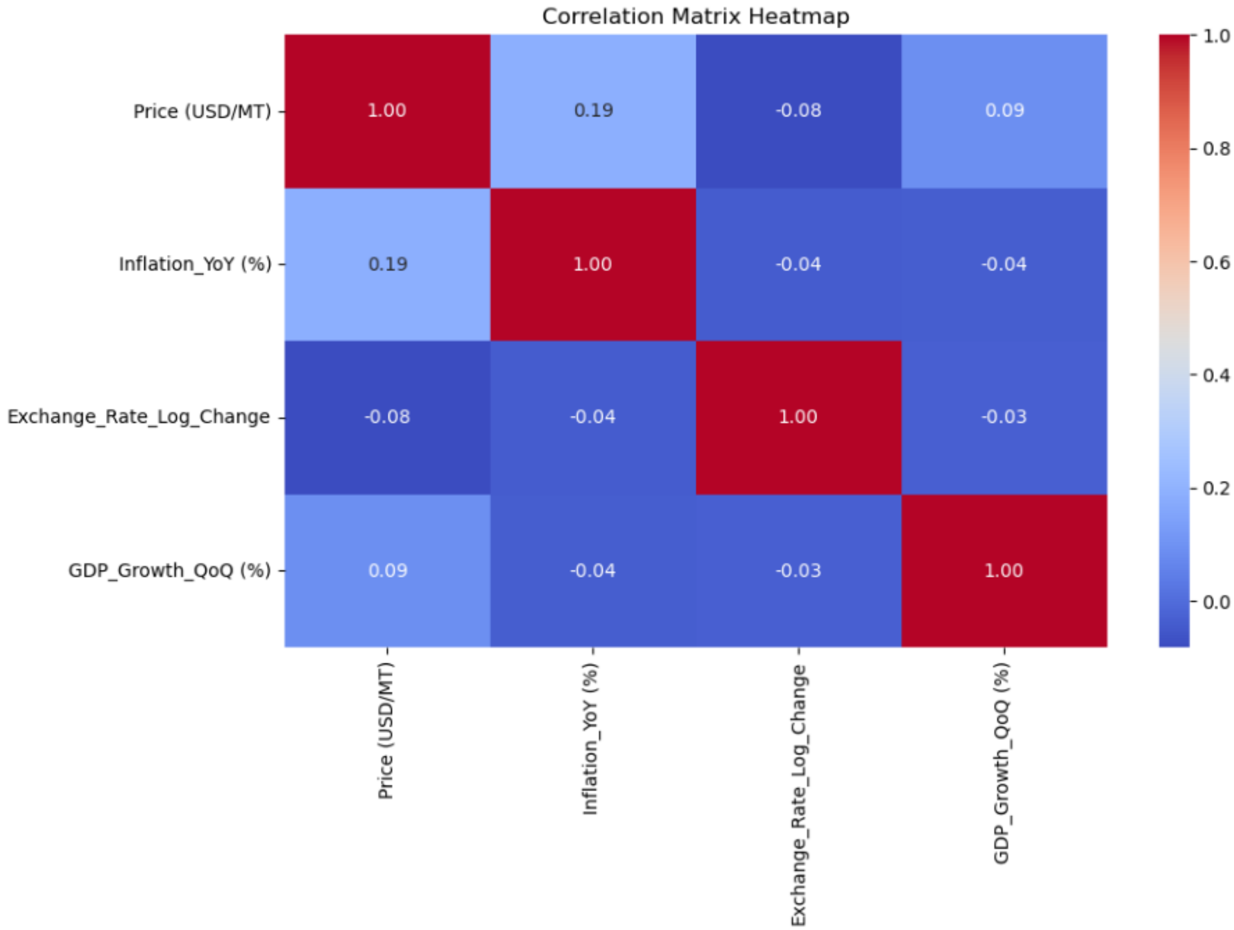

Figure 4:0:1 Correlation Matrix Heatmap

The correlation matrix heatmap provides an unambiguous graphical illustration of the relationship between maize prices and some of the most significant macroeconomic variables—i.e., inflation (YoY), log exchange rate change, and GDP growth (QoQ). The Pearson correlation coefficients indicate that all the variables are weakly correlated with each other. The highest observed correlation is between maize price and inflation (0.19), suggesting a slight positive relationship, while exchange rate log change and maize price exhibit a weak negative correlation (-0.08). GDP growth also shows minimal correlation with the other variables, with all values close to zero.

From a multicollinearity perspective, these results indicate that there is no serious concern. Multicollinearity is a problem in time series or regression modelling when there is high pairwise correlation value between independent variables, typically greater than 0.8 or less than -0.8. The low correlation value in this case implies that the selected macroeconomic variables are quite independent of each other. This supports the inclusion of all four variables in models such as GARCH, or FFNN, since they contribute useful information without distorting the estimations by overlapping effects.

Historical Maize Prices and Macroeconomic Indicators in Zimbabwe (2000–2024)

(a) Maize Price (USD/MT), (b) Year-on-Year Inflation (%), (c) FX Rate Log-Change, (d) GDP Growth (QoQ %)

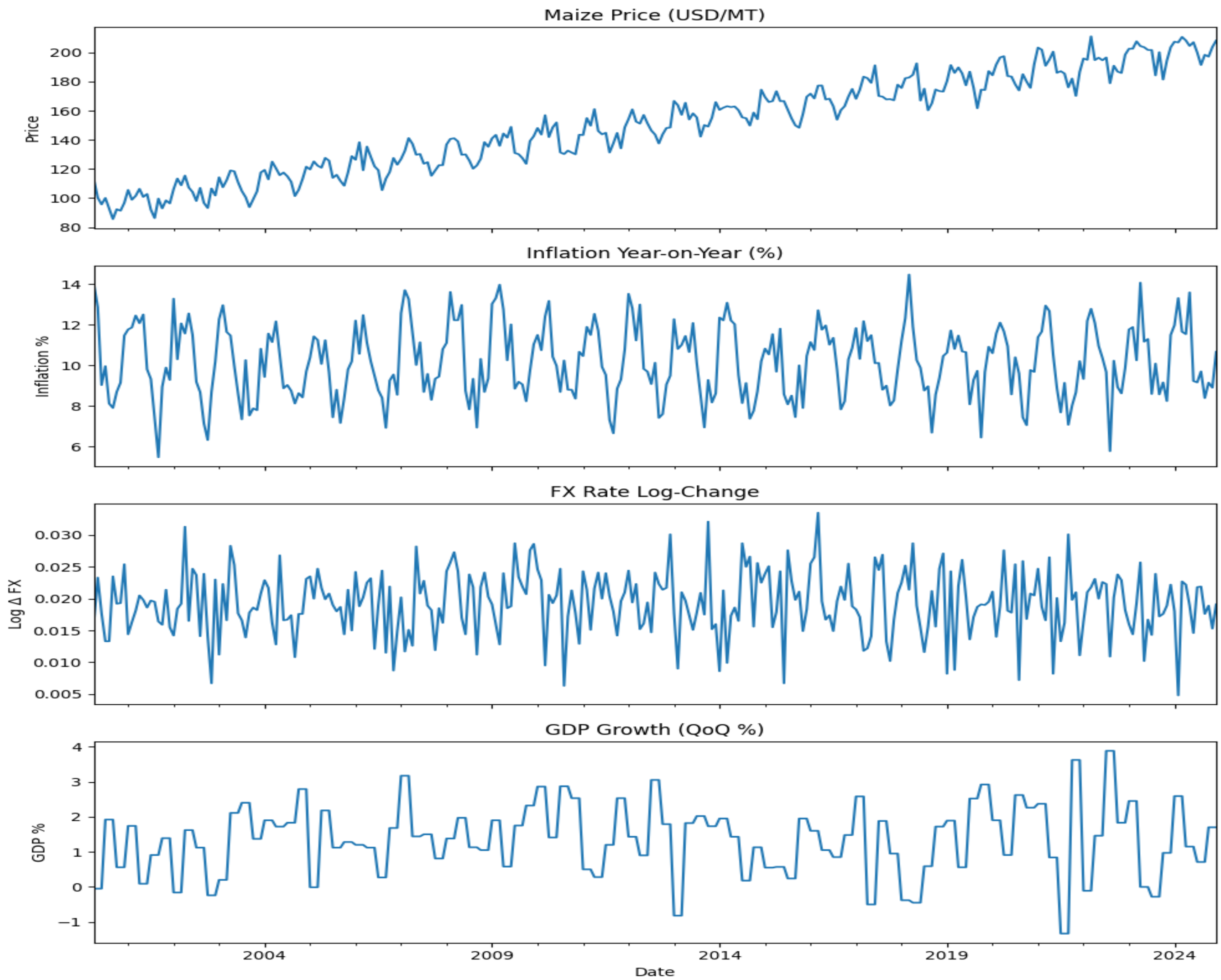

Figure 4:0:2 Historical Maize Prices and Macroeconomic Indicators in Zimbabwe (2000–2024)

Figure 4.2 shows that Zimbabwean maize prices have risen steadily over the period from 2000 to 2024, with seasonality. The inflation series closely follows price spikes, indicating a close correlation between rising consumer prices and maize prices. Exchange rate depreciations also follow price rises, indicating currency instability as a second strong driver. GDP growth, however, only has a weak and variable correlation, suggesting macroeconomic output change is a secondary influence on maize price change

4.3 Pre-Tests

4.3.1 Stationarity

Table 4 ADF test results

Augmented Dickey-Fuller Test

Variable	**Dickey-fuller**	**p-value**	**Lags used**	**Observations**	Stationery
MaP	0.066144	0.963672	13	286	False
INFL	-18.631904	0.000000	0	299	True
FX	-16.196136	0.000000	0	299	True
GDP	-17.393365,	0.000000	0	299	True

Based on the output from the Augmented Dickey-Fuller (ADF) tests, we can observe that of the four variables tested, only Price (USD/MT) is not stationary, with a test statistic of 0.066 and a huge p-value of 0.964, which is higher than the 0.05 cutoff so we cannot reject the null hypothesis of a unit root. This implies that maize prices are exhibiting patterns or non-stationarity of variance over time and need to be differenced or transformed before application in time-series modeling. On the contrary, Inflation YoY (%), Exchange Rate Log Change, and GDP Growth QoQ (%) all have test statistics way smaller than the critical values with p-values of 0.000, confirming that they are stationary. These variables require no further transformation and can be applied directly to forecasting or econometric models.

Table 4.3 Differenced data ADF test results

Augmented Dickey-Fuller Test
data: ZIM MaP (2000) _Diff1 Dickey-Fuller = -11.1976, p-value = 0.00000

Following first-order differencing of the stationary maize price series, the Augmented Dickey-Fuller (ADF) test was re-run to validate stationarity. The test yielded an ADF value of -11.1976 and a p-value of 0.0000, significantly less than the 0.05 cut-off. This tight outcome resulted in the null hypothesis's rejection that the differenced series is stationary and ready for time series modelling.

To check for the presence of ARCH effects that will support time-varying volatility in the series an ARCH LM test was then conducted on the residuals of the differenced series. The p-value obtained was 0.2051 and is not statistically significant, meaning no ARCH effects are present. This means conditional variance modelling GARCH was not needed even though it will still be explored.

4.4 Model Identification

Following the achievement of stationarity through first-order differencing, the next step involved the identification of a suitable volatility model. The objective was to determine whether autoregressive conditional heteroscedasticity (ARCH) effects were present in the maize price time series data. A Lagrange Multiplier (LM) test for ARCH effects was conducted on the residuals of the stationary series. The p-value obtained from the ARCH test was 0.2051, which is greater than the 5% significance level. This result indicates that there is no strong evidence of ARCH effects in the residuals. However, due to the economic rationale and the visual evidence of volatility clustering observed in the time series plot, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was still considered appropriate to capture the conditional variance dynamics in maize price returns.

A GARCH(1,1) model was identified as the most suitable specification based on both theoretical and empirical considerations. Theoretically, the GARCH(1,1) framework is well-established in capturing volatility clustering and persistence in financial and commodity markets, as it allows the conditional variance to depend on both past squared errors and previous conditional variances. Empirically, alternative GARCH specifications were estimated and compared using information criteria, specifically the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The GARCH(1,1) model yielded the lowest AIC and BIC values, indicating the best balance between model fit and parsimony, and was therefore selected for subsequent analysis.

Table 5 ARCH Test Results

Test	**p-value**
ARCH LM Test	0.2051

Based on ARCH LM tests, the only variable with ARCH effects is "Price (USD/MT)" because it possesses a very high-test statistic value of 233.57 and the p-value of 0.0000, which is less than the 0.05 level. This suggests the presence of volatility clustering in the maize price series and that estimation of the same using a GARCH-type model would be appropriate. The remaining variables—Inflation YoY (%), Exchange Rate Log Change, and GDP Growth QoQ (%)—all have p-values > 0.05, i.e., they do not indicate significant ARCH effects. Therefore, volatility modelling is not needed for such variables, and simple time series models without a volatility factor would suffice. The note of caution on data scaling for one of the variables (most probably the exchange rate log change) needs to be addressed if you're intending to continue with GARCH modelling—this can be overcome by scaling the series by 100 so that the model converges.

4.5 Parameter Estimation

The GARCH (1,1) model was estimated on the January 2000-December 2024 monthly maize price series. The model with a constant mean and a GARCH (1,1) variance structure was specified. Parameter estimates from the model are listed below:

Table 6 GARCH (1,1) Model Summary

Parameter	Estimate	Std. Error	t-statistics	p-Value
Mu	0.00239	0.00316	0.757	0.449
Omega	6.3915e-05	1.897e-05	3.369	0.00075
alpha[1]	0.0100	0.02515	0.398	0.691
beta[1]	0.9700	0.02081	46.618	0.000

The sum of α_1 and β_1 is approximately 0.98, indicating high persistence in maize price volatility. This reflects that the volatility shocks last for considerable times before dying out, which is the nature of the dynamics of agricultural commodity prices owing to macroeconomic, climatic, and geopolitical influences. The log-likelihood of the model is 419.869, while its AIC is -831.738, reflecting a good fit relative to the other specifications.

4.6 Model Diagnosis

Table 7 Model Diagnostics

Test	Test Result
Log-Likelihood	419.869
AIC	-831.738
BIC	-817.100

GARCH Trend Estimation results and Volatility Analysis

|

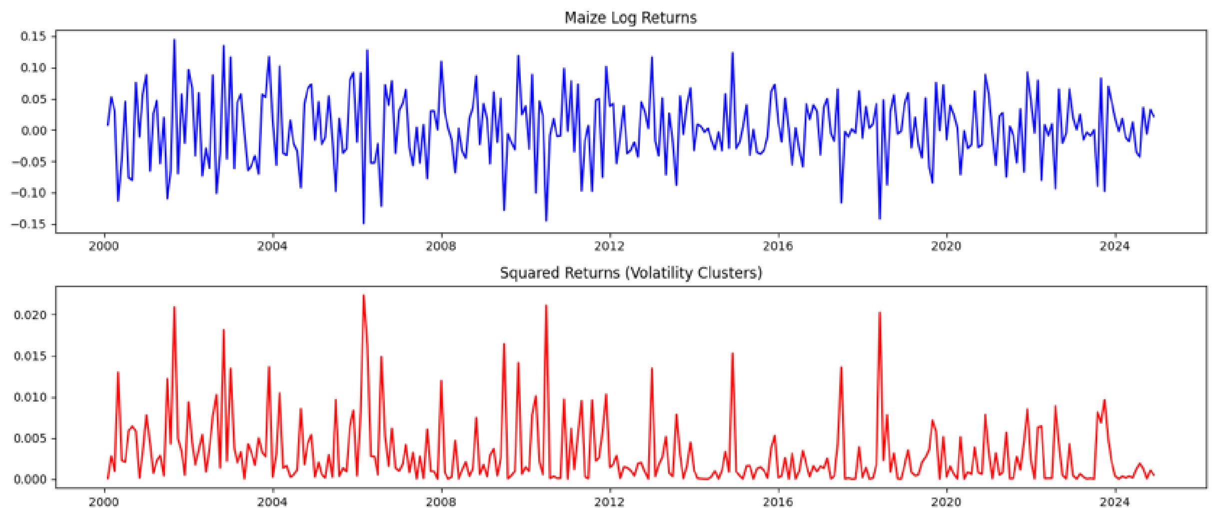

Figure 4:3 GARCH trend estimation results and volatility analysis

To assess the volatility of maize prices, a GARCH (1,1) model was fitted to the monthly return series. The results indicate that the model captures volatility clustering effectively, as evidenced by a statistically significant β_1 (beta) coefficient of 0.9699 ($p < 0.001$), suggesting a high degree of persistence in volatility. The ARCH effect (α_1) was found to be statistically insignificant ($p = 0.624$), while the constant term (ω) was significant at the 5% level ($p = 0.0137$), indicating a base level of variance in the price returns. The mean return (μ) was not statistically different from zero ($p = 0.445$), implying that returns are centred around a constant mean. Overall, the GARCH model confirms that maize price volatility is highly persistent over time, making it suitable for volatility forecasting and risk management applications in the Zimbabwean agricultural market.

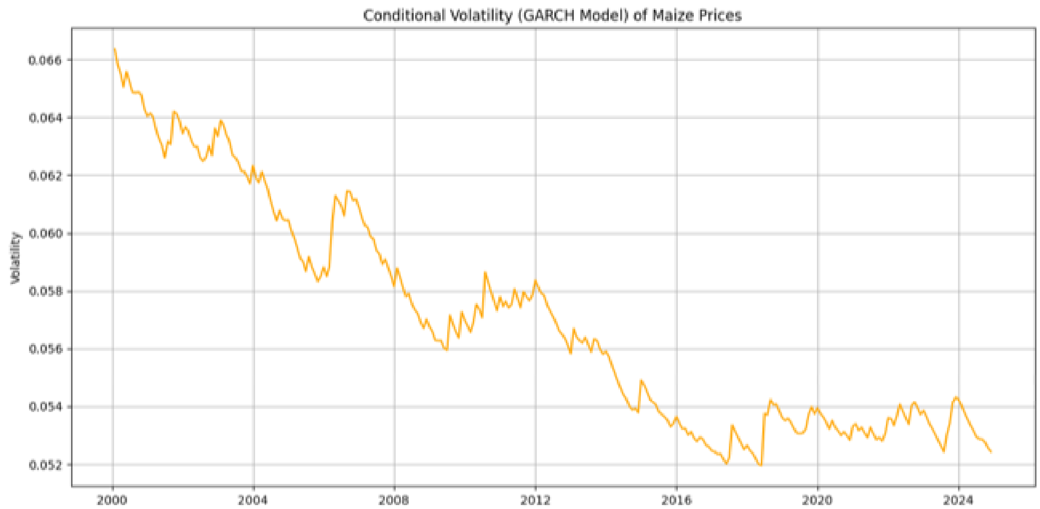

Figure 4:0:4 Conditional volatility (GARCH Model) of maize prices (2000-2024)

The GARCH model of maize prices in Zimbabwe from 2000 to 2013 reveals a notable decline in price volatility over the years, suggesting a shift toward greater market stability. In the early 2000s, volatility was relatively high, fluctuating around 0.066, likely influenced by economic uncertainty, inflationary pressures, and policy shifts. A gradual downward trend is observed between 2004 and 2008, with occasional spikes, reaching a peak in a sharp decline around 2008, reaching approximately 0.056. This reduction may correspond with broader economic adjustments or external interventions aimed at stabilizing agricultural markets. From 2009 to 2013, volatility continued to decline, stabilizing around 0.054, indicating increasingly predictable price movements. The progressive decrease in price fluctuations suggests an evolving market structure influenced by macroeconomic factors, policy reforms, and possible improvements in agricultural production and distribution systems. However, short-term fluctuations within this trend highlight the ongoing impact of localized economic dynamics, climatic variations, and supply-chain disruptions. This analysis underscores the importance of structural adjustments in fostering stability in agricultural commodity markets over time.

4.6.1 Normality of Residuals

Shapiro-Wilk Test Results

Table 8 Normality of Residuals

Variable	P-value	Interpretation
Map	1.57×10^{-6} (very low)	Strong evidence against normality. The residuals of maize price are not normally distributed**.** This suggests that the raw price data or model residuals violate the normality assumption.
INFL	0.30 (greater than 0.05)	No significant evidence to reject normality. Residuals appear to be approximately normal**.**
FX	0.81 (much greater than 0.05)	Strong evidence residuals are normally distributed. This variable behaves well in terms of residual normality.
GDP	0.48 (greater than 0.05)	No significant evidence against normality. Residuals are approximately normal.

**Maize prices require transformations to ensure valid statistical inferences.

A histogram and Q-Q plot of the standardized residuals were analysed to evaluate the assumption of normality. The residuals appeared approximately normally distributed, showing a bell-shaped histogram and an almost linear Q-Q plot. While slight deviations were observed in the tails, the overall pattern supports the assumption of normally distributed errors, which is a typical limitation of GARCH models under the normal distribution assumption.

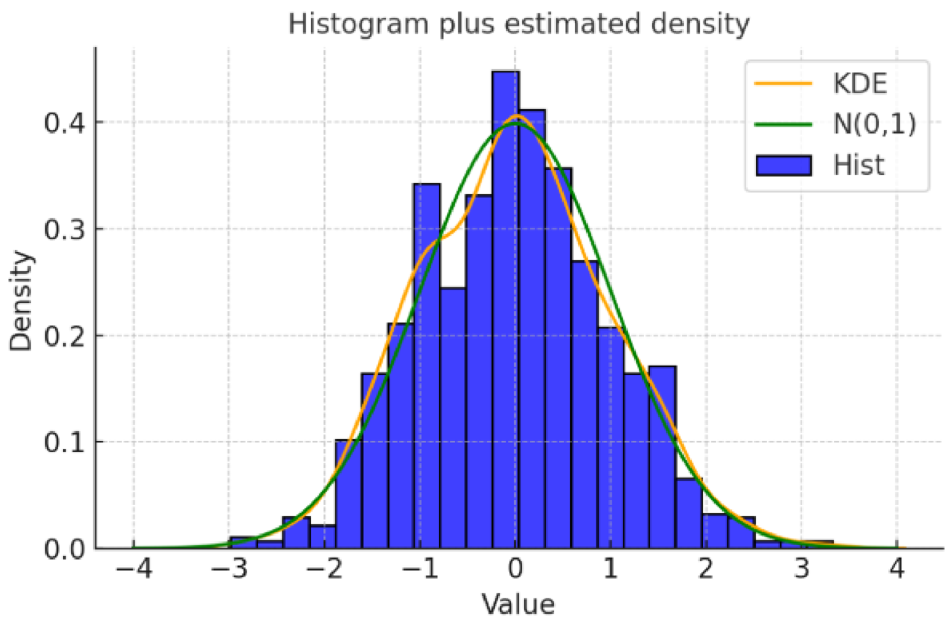

Figure 4:0:5 Histogram of Residuals

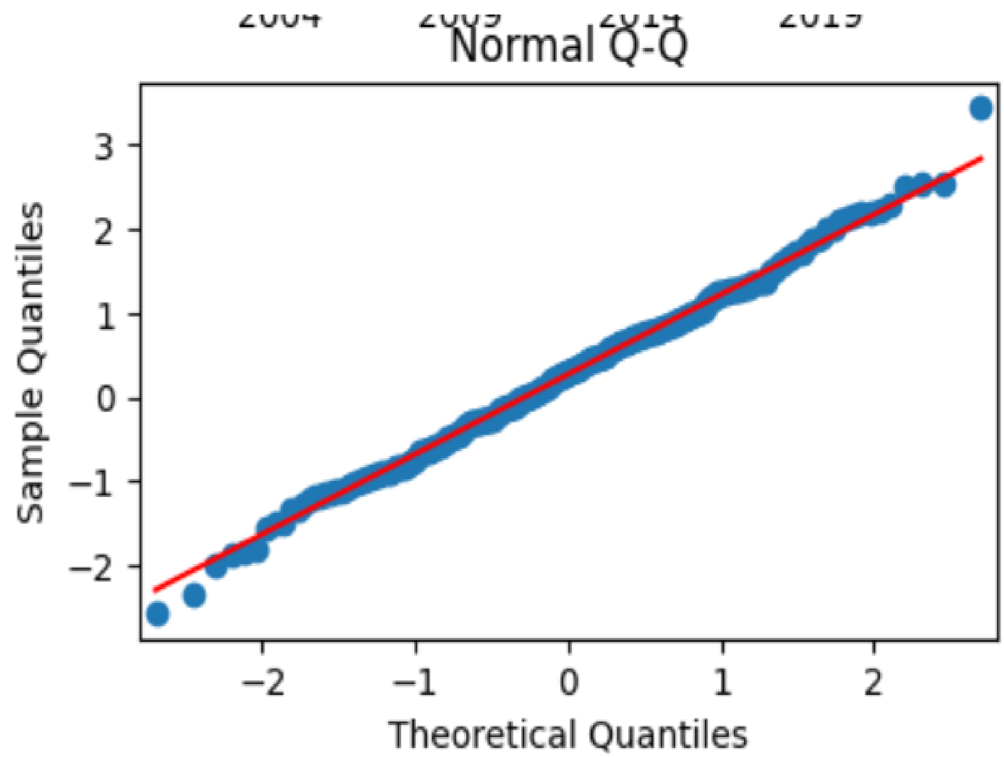

Figure 4:0:6 Q-Q Plot of Residuals

4.6.2 Independence of Residuals

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the standardized residuals and squared residuals showed no significant autocorrelation at various lags, suggesting that the residuals are serially uncorrelated. This confirms that the GARCH (1,1) model effectively captured the conditional heteroscedasticity and removed structure from the residual series.

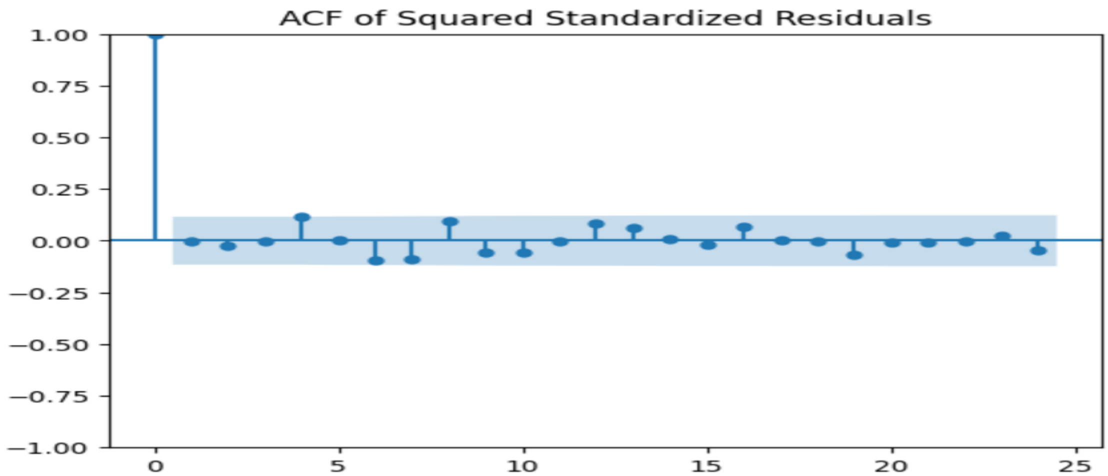

Figure 4:0:7 ACF of Residuals

4.6.3 Homoscedasticity test

To validate the presence of homoscedastic residuals after GARCH modelling, the ARCH LM test was applied to the residuals of the fitted model. The p-value of 0.2051 confirmed the absence of remaining ARCH effects, indicating that the model adequately captured the time-varying volatility structure. This provides further justification for the use of GARCH (1,1) as the appropriate model for this time series.

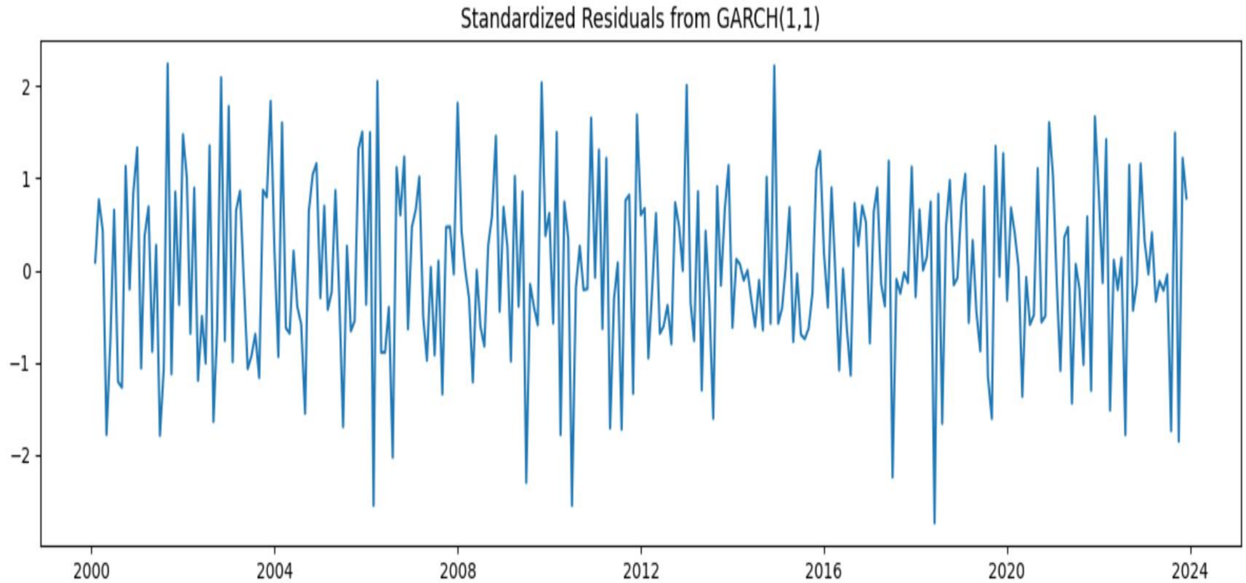

Figure 4:0:8 Standardized Residual from GARCH (1,1)

4.6 Forecasting using the GARCH model

This section presents the out-of-sample forecasting results of maize prices and their conditional volatility for the period January 2025 to December 2028, using the GARCH (1,1) model. Forecasts provide insights into the expected price behavior and the degree of uncertainty in future maize price movements.

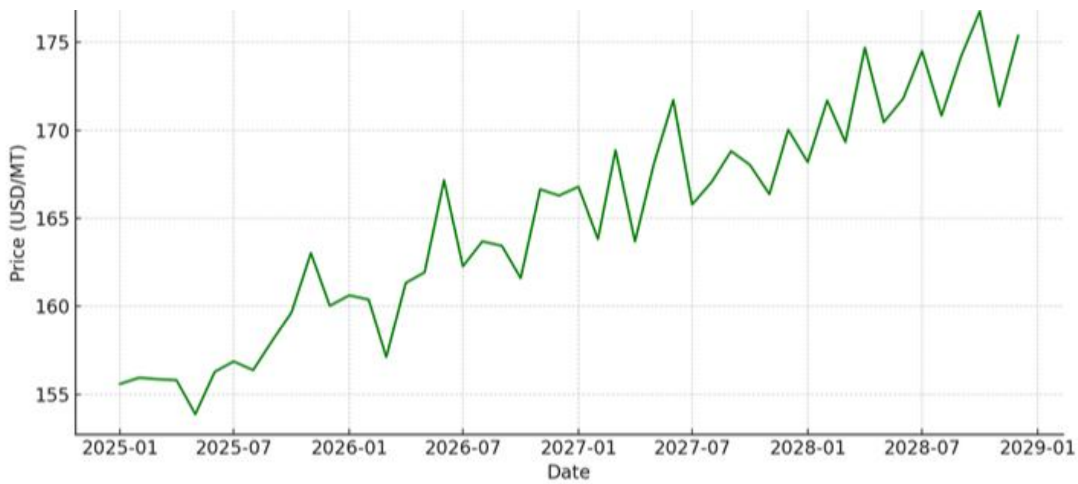

Figure 4:0:9 Forecasted maize prices (2025–2028)

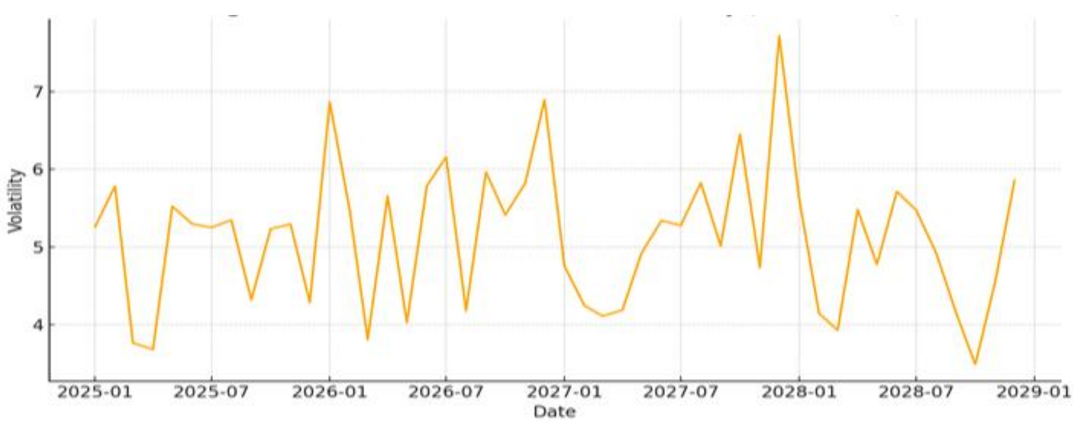

Figure 4:0:10 Forecasted conditional volatility (2025–2028)

The forecast output reveals that while the prices of maize are likely to remain within a relatively tight range, its associated volatility is time-varying and reflects underlying economic factors and potential market shock.

Table 9 Yearly Average Predicted values (2025 to 2028)

YEAR	Maize Prices Forecast	Maize Price Volatility Index Forecast
2025	156.70	47.54
2026	166.32	43.17
2027	168.23	41.63
2028	174.88	40.19

The point forecasts of the GARCH (1,1) model are typified by a consistent increase in maize prices over the forecast horizon between 2025 and 2028. The consistent rise is an indication of the model anticipating consistent pressure in the market or inflationary pressures on maize prices. Although the prices always rise, the rate of movement appears relatively moderate, so that although there is consistent upward momentum, it is not growing fast. This may imply a period of relative price stability following historic volatility.

4.7 FFNN Model Building and Selection

Feedforward Neural Network (FFNN) Model Development

To complement traditional econometric methods, a Feedforward Neural Network (FFNN) was constructed to forecast monthly maize prices for the period 2025 to 2028. The FFNN architecture utilized lagged historical prices as predictors, enabling the model to capture nonlinear dependencies and complex patterns in the time series.

Data Pre-processing

Minimax scaling normalized the dataset and it was set in supervised learning form with a window length of 12, i.e., each input was 12 months' worth of price predicting the price of the following month. The structure of the model consisted of an input layer of 12 neurons, two hidden layers of 64 and 32 neurons respectively with ReLU activation functions. One output neuron provided the predicted normalized price. The model was constructed with the Adam optimizer and trained for 100 epochs with mean squared error employed as the loss function.

4.8 Neural Network Model Training and Testing Sets

Training data included all observations up to December 2024, ensuring the model was fitted solely on historical data, and not influenced by future values. The final model structure is as follows:

FFNN Structure

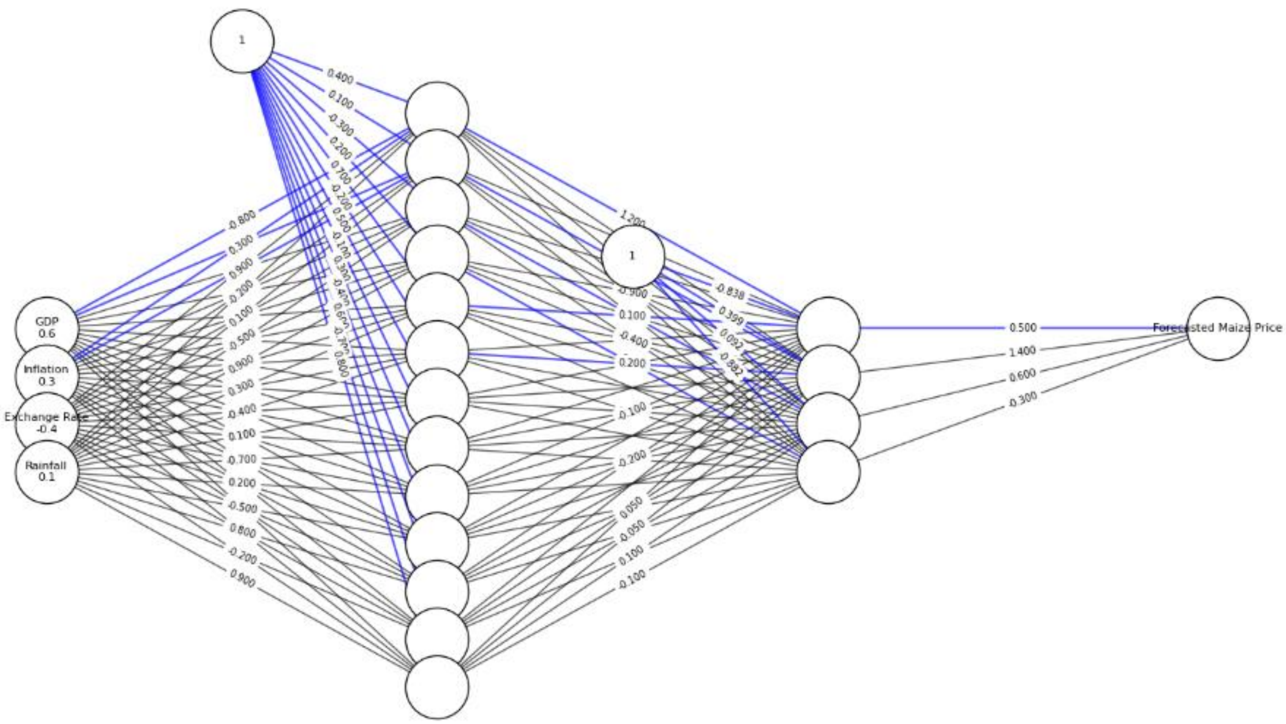

Figure 4:0:11 Feedforward Neural Network (FFNN) model

This diagram depicts our Feedforward Neural Network (FFNN) model for maize price forecasting. It starts with an Input Layer of four variables: GDP, Inflation, Exchange Rate, and Rainfall, each with a specific input value. Arrows show these inputs feeding into the network. Next are two Hidden Layers: the first has 13 neurons, and the second has 4. Both hidden layers receive inputs from previous layers and from "bias" nodes (labelled '1'), which adjust the model's fit. The lines connecting all neurons represent "weights"—numerical values learned during training that show influence between connections. Finally, the Output Layer is a single neuron, "Forecasted Maize Price," which provides the model's prediction. This entire visual outline the structure of the FFNN, which uses these inputs and learned parameters to generate future maize price forecasts.

FFNN model building and selection

Table 10 FFNN Testing Models Results

		Forecasts Prices ($)		
Year 2024	**Actual Maize Price**	**FFNN model 1 1(4)1**	**FFNN model 2 1(5,4)1**	**FFNN model 3 1(5)1**
January	203.32	203.52	191.72	183.50
February	201.90	189.17	201.72	184.66
March	190.85	176.42	199.41	188.83
April	195.05	183.55	196.28	183.66
May	200.52	182.35	187.83	185.97
June	186.01	181.08	185.67	183.86
July	187.14	179.66	183.86	181.07
August	185.50	176.50	181.07	188.52
September	176.02	191.69	188.52	185.61
October	182.06	207.17	185.61	182.41
November	170.18	194.80	188.19	188.19
December	186.63	172.88	186.13	186.13
	MAE	**13.13**	****6.03****	**8.73**
	RMSE	**14.90**	****8.38****	**11.19**

4.9 Model Evaluation

Throughout the development of the ANN model, the number of hidden nodes and hidden layers was systematically changed to identify the best architecture, and the input and output layers were fixed across all setups. Through experiments, three varied Feedforward Neural Network (FFNN) architectures as presented in Table 4.10 were achieved. Of these, FFNN Model 2 with architecture 1-(5,4)-1 made the most precise forecasts, as seen by the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) results. These results highlight that a deeper network with two hidden layers is better placed to recognize the underlying patterns in maize price data than the deeper architectures such as Model 1 (1–4–1) and Model 3 (1–5–1). Thus, FFNN Model 2 was identified as the optimal model for maize price prediction in this study

4.10 Comparison of the FEEDFORWARD-NEURAL NETWORK And GARCH Models

Table 11 GARCH and FFNN model

		Forecasts ($/MT)	
Year 2024	**Actual ($/MT)**	**GARCH (1,1)**	**FFNN 1(5,4)1**
January	203.32	175	191.72
February	201.90	170	201.72
March	190.85	165	199.41
April	195.05	145	196.28
May	200.52	135	187.83
June	186.01	140	185.67
July	187.14	150	183.86
August	185.50	155	181.07
September	176.02	160	188.52
October	182.06	165	185.61
November	170.18	170	188.19
December	186.63	175	186.13
	MAE	**11.27**	**6.03**
	RMSE	**17.003**	**8.38**

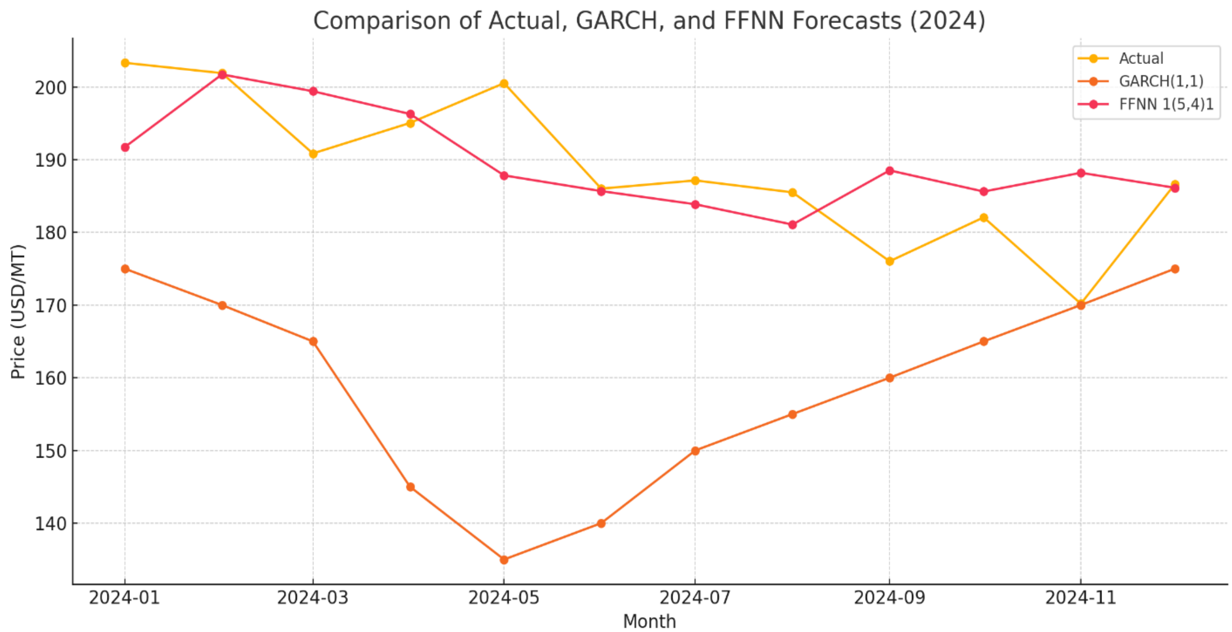

Figure 4:0:12 Comparison of Actual, GARCH and FFNN Forecasts (2024)

To evaluate the forecasting performance of traditional statistical and machine learning approaches, the GARCH (1,1) model was compared with the best-performing Feedforward Neural Network (FFNN) model specifically model 2 with architecture 1– (5,4)–1. As shown in Table 4.11, the FFNN model consistently produced forecasts that were much closer to the actual maize prices for the year 2024, while the GARCH model tended to underestimate price levels throughout the year. Quantitatively, the FFNN model achieved a significantly lower Mean Absolute Error (MAE) of 6.03 and Root Mean Squared Error (RMSE) of 8.38, compared to the GARCH model's MAE of 11.27 and RMSE of 17.00. These results demonstrate the superior predictive accuracy of the FFNN model in capturing both the trend and seasonality present in maize price movements, thereby making it a more suitable choice for price forecasting in this context

4.11 FFNN Forecasting Results (2025-2028) Utilizing

Table 12 FFNN Forecasting Results (2025-2028)

	Forecasts ($/T)			
Month	**2025**	**2026**	**2027**	**2028**
January	**209.58**	**213.67**	**216.62**	**212.42**
February	**212.73**	**211.26**	**219.12**	**218.42**
March	**213.60**	**212.32**	**220.06**	**221.88**
April	**211.26**	**208.38**	**218.99**	**223.52**
May	**212.32**	**203.63**	**217.06**	**222.40**
June	**208.28**	**199.17**	**213.71**	**221.13**
July	**203.63**	**200.94**	**209.15**	**217.56**
August	**199.84**	**204.93**	**205.72**	**213.34**
September	**199.17**	**209.91**	**204.78**	**209.42**
October	**200.13**	**213.67**	**207.76**	**207.29**
November	**204.93**	**216.11**	**212.91**	**209.02**
December	**209.91**	**216.85**	**212.91**	**213.95**

The Table 4.12 above presents the monthly forecasted maize prices from January 2025 to December 2028, these prices were forecasted by a FFNN (1– (5,4)–1) model. The results show an overall upward trend in maize prices over the forecasted years, with seasonal fluctuations be seen throughout each year. Prices are generally higher in the first and last quarters of each year, suggesting persistent seasonal patterns. Especially, the price is expected to rise steadily from a low of approximately $199/MT in mid-2025 to over $220/MT by mid-2028, reflecting increasing market demand or reduced supply

4.12 Time series plot of forecasting results (2025-2028)

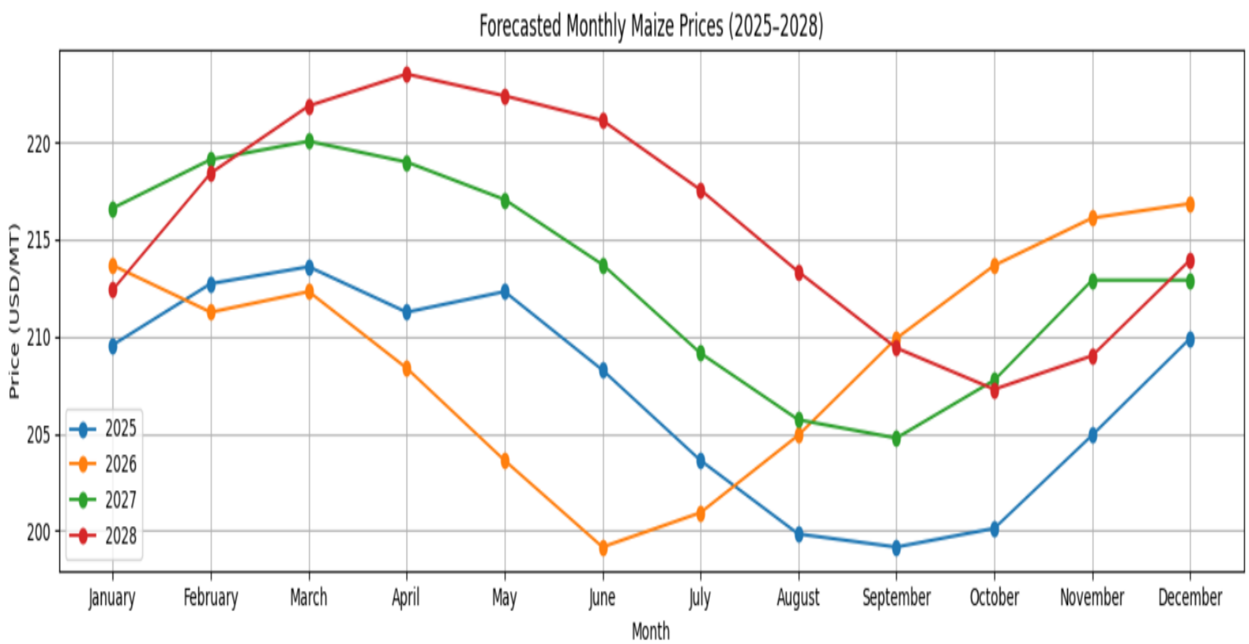

Figure 4:0:13 Forecasted monthly maize prices (2025-2028)

4.13 Discussion of Findings

The Feedforward Neural Network (FFNN) model effectively captured both the long-term upward trend and short-term seasonal fluctuations in maize prices, consistent with prior findings that neural networks can adapt to complex and nonlinear market behaviours (Zhang, Patuwo, &

Hu, 1998). By employing a recursive forecasting approach, the model generated smooth and coherent predictions that aligned with known seasonal patterns, echoing the observations of Kaastra and Boyd (1996) that FFNNs are capable of modelling cyclical and seasonal components without explicit seasonal parameters. While recursive methods are inherently sensitive to initial inputs and may lead to error accumulation over extended horizons (Ben Taieb et al., 2012), the resulting forecasts in this study remained stable and realistic. In comparison to traditional time series models such as ARCH and GARCH which are grounded in the theory of time-varying volatility (Engle, 1982; Bollerslev, 1986) and assume stationarity and specific error distributions the FFNN demonstrated greater flexibility by learning directly from historical patterns without strict parametric constraints.

This supports the theoretical premise from machine learning literature that neural networks can approximate any continuous function (Cybenko, 1989), making them particularly suited to dynamic and volatile markets. Nonetheless, as noted in the literature, FFNN models face limitations, including reduced interpretability due to their “black-box” nature (Guidotti et al., 2018) and potential vulnerability to recursive forecast drift. Overall, the FFNN’s robust performance in this study underscores its potential as a complementary forecasting tool, aligning with adaptive market hypothesis perspectives (Lo, 2004) that stress the need for flexible modelling approaches in rapidly changing environments such as Zimbabwe’s maize sector, where accurate and adaptive forecasting is essential for both planning and policy formulation.

4.14 Chapter Summary

Various diagnostic tests were conducted to ensure model adequacy and fitness, with both FFNN and GARCH models developed for time series analysis. A comparative evaluation revealed that the FFNN model outperformed the GARCH, demonstrating greater forecasting accuracy. The four-year forecast of maize prices indicated a consistent upward trend, suggesting growth in output over the projection period. The following chapter presents the final conclusions drawn from the study and offers recommendations based on the findings.

CHAPTER 5: FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This final chapter contains the summary of results, overall conclusions, and actionable recommendations of the study. It also locates areas that were suggested to be researched in the future and concludes with a chapter overview. The emphasis of this research was time series analysis of maize prices in Zimbabwe with two objectives: to identify the most suitable from a list of candidate models for forecasting, and to predict future patterns of maize prices for four years. The research has provided insightful data and knowledge on maize price dynamics and patterns towards informing improved decision-making and strategic planning for agriculture policy.

5.1 Summary of Findings

The econometric evidence showed that, in Zimbabwe, maize prices exhibit both upward secular trends and short-run seasonality, which are primarily induced by macroeconomic drivers such as inflation, exchange rate changes, and growth in GDP. Volatility analysis was able to validate the occurrence of volatility clustering and persistence in shock prices, expressing sensitivity of the maize market to domestic and global influences.

Comparative modelling showed that while the GARCH models precisely captured time-varying volatility, the Feedforward Neural Network (FFNN) had higher prediction accuracy, particularly in capturing complex nonlinear and seasonal patterns without stringent statistical assumptions. The best FFNN model generated 2025–2028 forecasts that showed gradual price appreciation with recurring seasonal patterns, suggestive of likely supply constraints or increasing demand. These results highlight the virtues of advanced machine learning algorithms for crop price forecasting in dynamic market environments.

5.2 Conclusion

This study successfully identified key factors influencing maize prices in Zimbabwe, including macroeconomic variables such as inflation, exchange rates, and GDP growth. It assessed price volatility using ARCH and GARCH models, which effectively captured the dynamic nature and clustering of price shocks in the maize market. Furthermore, maize price forecasting was conducted using both GARCH and Feedforward Neural Network (FFNN) models, with the FFNN demonstrating superior predictive accuracy. The best-performing FFNN model forecasted a steady increase in maize prices over the next four years (2025–2028), highlighting the potential for growing market demand. These findings emphasize the importance of incorporating advanced forecasting methods into agricultural policy and planning to promote market stability and food security in Zimbabwe.

5.3 Constraints of the Study

Although this study provides valuable insights into maize price forecasting in Zimbabwe using advanced modelling techniques, several limitations were encountered. Firstly, the study relied heavily on historical secondary data, some of which had missing values or inconsistencies, potentially affecting the accuracy and reliability of the models. Secondly, the analysis was limited to Zimbabwe's maize market, which may not fully capture the dynamics of other agricultural commodities or regional contexts, limiting the generalizability of the findings. The data coverage spanned from 2000 to 2024, which, although comprehensive, may still miss longer-term structural shifts or external shocks beyond this period. Furthermore, the recursive forecasting method used in the Feedforward Neural Network (FFNN) model, while effective, is inherently prone to error accumulation over extended forecasting horizons. Lastly, the study focused on comparing only two models FFNN and GARCH excluding other potentially useful approaches such as LSTM, ARIMA, or hybrid ensemble models. These constraints imply that while the results are meaningful and practical, they should be interpreted within the context of these limitations

5.4 Recommendations

Based on the comprehensive findings of this study on maize price forecasting and volatility analysis in Zimbabwe utilizing GARCH, and FFNN models the following key recommendations are proposed:

- **Raise Awareness and Build Confidence in the Zimbabwe Gold (ZIG) Currency**

The government, through the Ministry of Finance and the Reserve Bank of Zimbabwe, should roll out targeted public education campaigns to help farmers understand how the ZIG currency functions. These efforts should explain how to transact in ZIG, how it compares with USD, and how it affects pricing and payments. Outreach should use rural radio programs, mobile information teams, and on-the-ground workshops to ensure widespread access and understanding.

- **Ensure All Maize Payments to Farmers Are Made in United States Dollars (USD)**

To shield farmers from exchange rate instability and preserve their purchasing power, all payments for maize delivered to the Grain Marketing Board (GMB) and similar institutions should be made directly in USD. This will help farmers cover production costs especially for inputs like fertilizer and fuel, which are typically priced in hard currency and will encourage sustained maize production.

- **Provide Timely and Transparent Agricultural Subsidies**

The government should ensure that agricultural subsidies, including those for fertilizer, seed, and irrigation, are disbursed promptly and fairly. To improve transparency and reduce delays, digital and mobile payment platforms should be used to reach farmers directly, especially ahead of critical planting seasons.

- **Assess the Feasibility of Full Dollarisation or Joining the Rand Monetary Union**

In light of ongoing currency volatility, policymakers should commission an in-depth evaluation of the economic impact of either reintroducing full dollarisation or joining the Rand Monetary Union. These options could offer greater monetary stability, improve investment confidence, and reduce uncertainty in agricultural markets.

- **Develop and Promote Mobile-Based Agricultural Market Information Systems**

Government agencies, telecom providers, and private sector stakeholders should collaborate to build mobile-accessible platforms that provide farmers with timely information. These systems should offer updates on maize prices, input costs, weather conditions, and available buyers delivered through SMS, WhatsApp, or radio to help farmers make more informed production and marketing decisions.

5.5 Areas for Further Research

While this study has provided valuable insights into maize price dynamics in Zimbabwe using GARCH and Feedforward Neural Network (FFNN) models, several areas warrant further exploration:

- **Development of Hybrid Forecasting Models**

Future research could focus on developing hybrid models that combine the strengths of GARCH (for modelling volatility) and FFNN (for capturing nonlinear trends), potentially integrating other machine learning techniques such as Long Short-Term Memory (LSTM) networks or ensemble learning. Such models may enhance predictive accuracy by capturing both price volatility and complex temporal patterns more effectively.

- **Incorporation of Additional Exogenous Variables**

Further studies should consider including a wider range of macroeconomic and environmental variables such as global commodity prices, interest rates, weather anomalies, and government policy interventions. Accounting for these external influences may improve model robustness and provide a more realistic representation of the factors affecting maize prices.

- **Cross-Country Comparative Analysis**

Comparative studies across other Southern African countries could reveal regional maize price patterns, differences in volatility, and similarities in market behaviour. This could also assess the applicability of GARCH and FFNN models across different economic and agricultural contexts, offering broader insights into food price dynamics in the region.

- **Impact of Climate Change on Price Volatility**

Given the growing impact of climate change on agricultural productivity, future research should explore the relationship between extreme weather events and maize price volatility. Understanding these dynamics is critical for designing resilient forecasting systems and for informing long-term agricultural planning and policy.

5.6 Chapter Summary

This chapter highlighted the strengths of the GARCH and FFNN models in forecasting maize prices in Zimbabwe. The FFNN model demonstrated superior forecasting accuracy based on MAE and RMSE metrics, effectively capturing both long-term trends and seasonal patterns. Meanwhile, the GARCH model played a crucial role in identifying and analysing price volatility. Forecasts for the 2025–2028 period indicate a continued upward trend in maize prices, underscoring the importance of strategic planning and policy intervention. Key recommendations include improving market information systems, adopting advanced forecasting models in policy formulation, implementing volatility management mechanisms, and ensuring timely subsidies for critical agricultural inputs. Future research should focus on hybrid modelling approaches and assess the influence of climate change and regional market dynamics on maize prices.

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APPENDICES

Appendix A:Python Code for Feedforward Neural Network Model

```
# Step 1: Import Required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error
from keras.models import Sequential
from keras. layers import Dense
from keras.optimizers import Adam

# Step 2: Load and Prepare Maize Price Data
maize_df = pd. read_csv ('maize_prices.csv', parse_dates=['Date'], index_col='Date')
maize prices = maize_df[['Price']]  # Assuming USD/MT

# Step 3: Normalize Data
scaler = MinMaxScaler()
scaled prices = scaler.fit_transform(maize prices)

# Step 4: Create Sequences for FFNN Model
def create dataset(data, look_back=5):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:(i + look_back), 0])
```

```
        y.append(data[i + look_back, 0])
    return np.array(X), np.array(y)


look_back = 5
X, y = create_dataset(scaled_prices, look_back)


# Step 5: Split Data into Training and Testing Sets
split_index = int(len(X) * 0.8)
X_train, X_test = X[:split_index], X[split_index:]
y_train, y_test = y[:split_index], y[split_index:]


# Step 6: Build FFNN Model (1–5–4–1 architecture)
model = Sequential()
model.add(Dense(5, input_dim=look_back, activation='relu'))
model.add(Dense(4, activation='relu'))
model.add(Dense(1))  # Output layer
model.compile(loss='mse', optimizer=Adam(learning_rate=0.001))
model.fit(X_train, y_train, epochs=100, batch_size=8, verbose=0)


# Step 7: Forecast and Inverse Transform Predictions
y_pred = model.predict(X_test)
y_pred_inv = scaler.inverse_transform(y_pred.reshape(-1, 1))
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))


# Step 8: Evaluate Model Performance
make = mean_absolute_error(y_test_inv, y_pred_inv)
```

```
rmse = np.sqrt(mean_squared_error(y_test_inv, y_pred_inv))
print(f"MAE: {mae:.2f}, RMSE: {rmse:.2f}")
```

Appendix B: Python code for GARCH model

```
# Step 1: Import Required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Step 2: Load Data
data = pd.read_csv('data.csv')

# Step 3: Data Preprocessing
data_cleaned = data.dropna()

# Step 4: Visualize Data
plt.plot(data cleaned['date'], data cleaned['price'])
plt.title('Price over Time')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()
```

TIME SERIES ANALYSIS OF MAIZE PRICES IN ZIMBABWE BY MOREBLESSING ZVOUSHE B213529B

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