Modeling Autoregressive Integrated Moving Average (ARIMAX) in Quarterly Agricultural GDP and Key Subsectors of Agriculture in Nigeria

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ABSTRACT

Agriculture remains a critical driver of economic growth, employment generation, and food security in Nigeria, yet the sector continues to experience structural volatility and productivity challenges. Accurate modelling and forecasting of Agricultural Gross Domestic Product (GDP) are therefore essential for effective economic planning and policy formulation. This study examines the dynamic behaviour of Nigeria's Agricultural GDP and evaluates the contributions of its major sub-sectors - crop production, livestock, forestry, and fishing - using the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) modelling framework. Annual time series data on Agricultural GDP and its sub-sectoral components were analyzed using modern time series econometric techniques. Preliminary statistical diagnostics, including descriptive analysis and unit root tests, were conducted to determine the stochastic properties and stationarity of the variables. Following differencing to achieve stationarity, alternative ARIMAX model specifications were estimated and evaluated using standard model selection criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The empirical results identified the ARIMAX(0,1,1) model as the most parsimonious and statistically adequate specification for modelling Agricultural GDP. The findings indicate that variations in Agricultural GDP are significantly influenced by short-run shocks and by the structural contributions of the agricultural sub-sectors, with crop production emerging as the dominant driver of sectoral output. Forecast results further reveal a sustained but moderate growth trajectory for Nigeria's Agricultural GDP within the forecast horizon, suggesting continued sectoral resilience despite macroeconomic uncertainties. The study concludes that integrating sectoral sub-components as exogenous variables improves forecasting performance and provides deeper insight into the structural dynamics of agricultural output. Consequently, the study recommends strengthened investment in crop production systems, improved livestock productivity, and enhanced data-driven agricultural policy frameworks to support sustainable sectoral growth and national economic diversification.

Key Words: Autoregressive Integrated Moving Average (ARIMAX), Agricultural GDP, subsectors of Agriculture ; Crop production, Livestock, Fishery and Forestry.

INTRODUCTION

Background to the Study

Agriculture remains a fundamental pillar of Nigeria's economy, contributing significantly to employment generation, poverty reduction, food security, and rural transformation. Historically, prior to the oil boom era, agriculture accounted for more than 60% of Nigeria's GDP and export earnings. Although the discovery of crude oil in commercial quantities in 1956 triggered a structural shift toward petroleum dependence, the agricultural sector has continued to maintain substantial macroeconomic relevance. Recent national accounts statistics indicate that agriculture contributes between 24% and 28% of Nigeria's real Gross Domestic Product (GDP), making it one of the largest non-oil sectors in the economy (National Bureau of Statistics [NBS], 2024; World Bank, 2023). This sustained contribution underscores the sector's resilience and structural importance in supporting economic stability, particularly during periods of oil price volatility and external shocks.

Beyond its GDP share, agriculture plays a critical role in employment generation and inclusive growth. The sector employs over one-third of Nigeria's total labor force and accounts for a significantly higher proportion of rural employment, where livelihood dependence on farming and related activities remains pronounced (Food and Agriculture Organization [FAO], 2022; International Labour Organization [ILO], 2023). Given that approximately 48% of Nigeria's population resides in rural areas, the sector's performance directly influences poverty dynamics, income distribution, and rural household welfare (World Bank, 2023). Empirical evidence suggests that agricultural growth has a stronger poverty-reducing effect compared to growth in non-agricultural sectors in developing economies, including Nigeria (FAO, 2022).

Furthermore, agriculture is central to national food security and inflation management. Rising food inflation in Nigeria has been closely linked to fluctuations in agricultural output, disruptions in value chains, climate variability, and insecurity in major farming zones (International Monetary Fund [IMF], 2023). Since food items constitute a large component of Nigeria's Consumer Price Index (CPI), instability in agricultural production transmits directly into broader macroeconomic instability. Consequently, agricultural performance has implications not only for GDP growth but also for price stability and monetary policy effectiveness.

Structurally, Nigeria's agricultural GDP is composed of four major sub-sectors: crop production, livestock, forestry, and fishing. Crop production consistently dominates sectoral output, often accounting for more than 60% of agricultural GDP, reflecting Nigeria's comparative advantage in staple crops such as cassava, rice, maize, yam, and sorghum (NBS, 2024). Livestock contributes moderately, supporting protein supply and rural income diversification, while forestry and fishing contribute smaller shares but remain vital for ecological sustainability and nutritional security (FAO, 2022). However, productivity across these sub-sectors remains below global averages due to technological gaps, limited mechanization, poor access to finance, post-harvest losses, and infrastructural deficiencies (World Bank, 2023).

In recent years, the sector has faced compounded challenges from climate change, insecurity, exchange rate instability, and input cost inflation. Climate-induced events such as flooding and desertification have disrupted cropping calendars and reduced yields, particularly in northern Nigeria (FAO, 2022). Additionally, farmer–herder conflicts and banditry have constrained farming activities, resulting in land abandonment and lower output growth (IMF, 2023). These structural vulnerabilities introduce volatility into agricultural GDP, making rigorous econometric modelling and forecasting essential for policy planning.

Given the strategic role of agriculture in Nigeria's economic diversification agenda, reliable modelling of agricultural GDP dynamics is crucial. Accurate forecasts enable policymakers to anticipate sectoral performance, allocate resources efficiently, and design targeted interventions to stabilize food supply and enhance productivity. Therefore, understanding both the aggregate performance of agricultural GDP and the relative contributions of its sub-sectors is central to evidence-based policy formulation and sustainable economic development.

Agricultural GDP dynamics are inherently time-dependent and influenced by both internal persistence mechanisms and exogenous structural drivers. As a macroeconomic aggregate, agricultural GDP reflects cumulative sectoral activities over time, making it subject to inertia, cyclical fluctuations, trend movements, and structural breaks. In time series econometrics, such behavior implies that current values of agricultural GDP are partly determined by their historical realizations, a phenomenon known as serial dependence or temporal persistence (Box *et al.*, 2015; Hyndman & Athanasopoulos, 2021). This persistence arises from production cycles, investment lags, policy implementation delays, climatic seasonality, and market adjustments within the agricultural sector.

Empirically, agricultural time series often exhibit non-stationary characteristics, including stochastic trends and structural shifts. Non-stationarity implies that the statistical properties of the series—mean, variance, and autocovariance-change over time. Such properties are frequently observed in macroeconomic aggregates due to inflationary pressures, technological change, institutional reforms, and external shocks (Gujarati & Porter, 2021). In Nigeria, agricultural GDP has been influenced by policy reforms, insecurity in farming regions, exchange rate volatility, and climate variability (International Monetary Fund [IMF], 2023; World Bank, 2023). These factors may introduce structural breaks and evolving trend components, thereby necessitating rigorous pre-estimation diagnostics such as unit root testing and structural stability analysis.

Traditional time series modelling often begins with the Autoregressive Integrated Moving Average (ARIMA) framework, which captures the stochastic properties of a single variable by modeling its own past values and past error terms. The general ARIMA specification is expressed as: $ARIMA(p,d,q)$ where p denotes the autoregressive (AR) order, d represents the degree of differencing required to achieve stationarity, and q indicates the moving average (MA) order. The autoregressive component captures the influence of past values of the dependent variable, the integrated component accounts for non-stationarity through differencing, and the moving average component models the effect of past shocks or innovations (Box *et al*., 2015).

ARIMA models have been extensively applied in macroeconomic forecasting due to their flexibility in capturing dynamic structures and short-run dependencies (Hyndman & Athanasopoulos, 2021). In agricultural economics, ARIMA has been used to forecast crop output, food prices, and aggregate production indices. However, despite their usefulness, ARIMA models are fundamentally univariate, meaning that they rely solely on the historical path of the dependent variable. This assumption may be restrictive when the variable of interest is structurally determined by identifiable and measurable components.

In the context of Nigeria's agricultural GDP, aggregate output is not merely a stochastic process evolving independently; rather, it is structurally composed of sub-sectoral outputs—crop production, livestock, forestry, and fishing. These sub-sectors are not external random influences but integral determinants of the aggregate series. Ignoring their contributions in a univariate ARIMA framework may result in omitted variable bias and reduced forecasting precision (Gujarati & Porter, 2021). Moreover, agricultural GDP is susceptible to exogenous influences such as climate shocks, security conditions, and technological adoption, which further justify the inclusion of external regressors.

To address these limitations, the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model extends the ARIMA framework by incorporating external explanatory variables into the dynamic process. The general ARIMAX specification can be expressed as: $ARIMAX(p,d,q)\ with\ exogenoues\ variables\ X_t$. The inclusion of X_t, representing exogenous regressors, enables the dependent variable to respond not only to its past values and shocks but also to contemporaneous or lagged values of external structural drivers. In this study, the exogenous variables include outputs from crop production, livestock, forestry, and fishing sub-sectors. By explicitly modelling these components, ARIMAX captures both internal persistence and structural interdependence within the agricultural sector.

Recent empirical evidence supports the superiority of ARIMAX over pure ARIMA models in macroeconomic forecasting contexts where exogenous factors play a significant role. Hyndman and Athanasopoulos (2021) demonstrate that incorporating explanatory variables improves predictive accuracy when structural drivers influence the dependent variable. Similarly, Zhang et al. (2022) show that ARIMAX models outperform ARIMA in forecasting macroeconomic aggregates in emerging economies due to their ability to integrate external information. In the Nigerian context, studies on sectoral GDP modelling indicate that multivariate time series frameworks yield better out-of-sample forecasting performance compared to univariate approaches (Adebayo & Ojo, 2021).

Beyond methodological advantages, the use of ARIMAX aligns with Nigeria's broader economic transformation agenda. National development strategies emphasize agricultural diversification, value chain development, and productivity enhancement as mechanisms for reducing oil dependency and improving macroeconomic resilience (IMF, 2023; World Bank, 2023). Reliable modelling tools are therefore essential for quantifying sub-sectoral contributions, forecasting sectoral performance, and informing evidence-based agricultural policy.

From a theoretical standpoint, ARIMAX also aligns with structural decomposition principles in national income accounting, where aggregate sectoral output is understood as the summation of its constituent components. Incorporating sub-sectoral outputs into the dynamic modelling framework ensures coherence between econometric specification and economic theory. This approach strengthens interpretability, enhances policy relevance, and improves forecasting reliability. Therefore, modelling and forecasting Nigeria's Agricultural GDP using an ARIMAX framework provides substantial theoretical, methodological, and policy relevance. It enables a dynamic assessment of the magnitude and significance of sub-sectoral contributions while improving predictive accuracy. In a context characterized by volatility, structural shifts, and policy reform, such an approach provides a robust empirical foundation for strategic planning, resource allocation, and macroeconomic stabilization within Nigeria's agricultural sector.

Statement of the Problem

Despite the strategic importance of agriculture in Nigeria's economic development, there remains limited comprehensive empirical modelling that jointly examines the dynamic contribution of its sub-sectors to total Agricultural GDP using advanced multivariate time series techniques. Many existing studies either employ descriptive statistical methods or rely on simple regression frameworks that fail to adequately capture temporal dependencies and stochastic trends inherent in macroeconomic data.

Furthermore, agricultural output in Nigeria exhibits volatility arising from climate change, policy shifts, insecurity in farming regions, fluctuating input costs, and structural transformation within rural economies. These characteristics often induce non-stationarity, structural breaks, and serial correlation in the time series data. Traditional modelling approaches that ignore these properties may produce biased parameter estimates and unreliable forecasts. Another critical gap lies in forecasting. While projections of overall GDP are common, sector-specific and sub-sectoral dynamic forecasting models that integrate endogenous and exogenous effects remain underdeveloped in the Nigerian context. Without a robust ARIMAX framework, the relative contribution of Crop Production, Livestock, Forestry, and Fishing to total Agricultural GDP cannot be dynamically assessed over time.

Consequently, there is a need for a comprehensive econometric investigation that models and forecasts Nigeria's Agricultural GDP while explicitly incorporating its major sub-sectors as exogenous drivers within an ARIMAX structure. This study seeks to address this gap by providing a statistically rigorous modelling framework capable of generating reliable short- and medium-term forecasts.

Aim and Objectives of the Study

The main aim of this study is to model and forecast Nigeria's Agricultural Gross Domestic Product (GDP) and to evaluate the dynamic contributions of its major sub-sectors - Crop Production, Livestock, Forestry, and Fishing - using the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) modelling framework. The specific objectives of the study are to:

i. Examine the statistical and stochastic properties of Nigeria's Agricultural GDP and its sub-sectoral components, including trend behavior, stationarity conditions, structural characteristics, and time series dependencies necessary for econometric modelling.

ii. Estimate an appropriate ARIMAX model for Agricultural GDP, incorporating Crop Production, Livestock, Forestry, and Fishing as exogenous variables, and determine the optimal model specification using standard model selection criteria.

iii. Assess the magnitude, direction, and statistical significance of the contributions of the agricultural sub-sectors to total Agricultural GDP, and evaluate the diagnostic adequacy and predictive performance of the estimated model.

iv. Generate short- and medium-term forecasts of Nigeria's Agricultural GDP and derive policy-relevant insights for agricultural planning, economic diversification, and macroeconomic stability.

Significance of the Study

This study is significant at the academic, methodological, policy, and strategic levels. From an academic standpoint, it contributes meaningfully to the growing body of literature on sectoral Gross Domestic Product (GDP) modelling by extending conventional univariate time series approaches to a multivariate framework using the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model. While many empirical studies on Nigeria's agricultural sector rely primarily on ARIMA specifications that capture only internal persistence, this study advances the discourse by explicitly incorporating sub-sectoral components - Crop Production, Livestock, Forestry, and Fishing - as exogenous determinants of Agricultural GDP. By doing so, it enriches empirical understanding of how structural dynamics within the agricultural sector influence aggregate performance. The study therefore bridges an important gap in macro-sectoral modelling literature by integrating endogenous time dependence with sector-specific structural drivers, thereby enhancing both explanatory depth and forecasting precision.

Methodologically, the study demonstrates the analytical strength of the ARIMAX framework in modelling macroeconomic time series characterized by persistence, structural shifts, and sectoral interdependence. The model specification captures autoregressive persistence, moving average dynamics, and the influence of exogenous regressors, thereby allowing the model to simultaneously account for historical inertia and contemporaneous structural effects. In the context of Nigeria's agricultural economy, this is particularly relevant because sectoral output is influenced not only by past performance patterns but also by structural contributions from its sub-components. The study therefore provides a replicable modelling framework for researchers engaged in macroeconomic forecasting, applied econometrics, and sectoral growth analysis. Additionally, by incorporating diagnostic testing, model selection criteria, and forecast evaluation metrics, the research strengthens methodological rigor and demonstrates how ARIMAX models can outperform purely univariate approaches in complex economic environments.

From a policy perspective, the study provides evidence-based insights critical for agricultural planning and macroeconomic management in Nigeria. Understanding the relative contribution and dynamic impact of Crop Production, Livestock, Forestry, and Fishing on aggregate Agricultural GDP enables policymakers to prioritize investment allocation, subsidy reforms, and targeted intervention strategies. Accurate forecasts generated from a multivariate framework can support medium- and long-term agricultural development planning, food security programs, rural employment strategies, and inflation management policies. Institutions such as the National Bureau of Statistics (NBS), the Federal Ministry of Agriculture and Food Security, and other economic planning agencies can utilize the findings to improve data-driven decision-making and performance monitoring. In an era marked by volatility in global commodity markets and domestic economic fluctuations, improved forecasting capacity enhances strategic preparedness and resource optimization.

Strategically, the study is highly relevant to Nigeria's broader economic diversification agenda aimed at reducing overdependence on crude oil exports. Agriculture remains one of the most viable non-oil growth drivers capable of generating employment, stabilizing rural incomes, and improving external sector resilience. By providing empirical validation of the structural determinants of Agricultural GDP and offering reliable forward-looking projections, this research supports national development objectives centered on sustainable growth and economic transformation. Consequently, the study does not only contribute to scholarly discourse but also offers practical tools for strengthening agriculture as a cornerstone of Nigeria's long-term economic stability and inclusive development trajectory.

Scope and Limitations of the Study

This study examines the modelling and forecasting of Nigeria's Agricultural Gross Domestic Product (GDP) using time series data obtained from the specified dataset. The analytical focus is restricted to the four major agricultural sub-sectors—Crop Production, Livestock, Forestry, and Fishing—treated as exogenous determinants within an ARIMAX modelling framework. The study applies a multivariate time series approach that integrates autoregressive and moving average dynamics with external regressors to improve forecasting accuracy and structural interpretation. The temporal scope is limited to the period covered by the dataset, and forecasts are generated within a short- to medium-term horizon based on model adequacy, diagnostic stability, and predictive performance. By concentrating specifically on sectoral interrelationships within agriculture, the study provides a structured and data-driven assessment of how sub-sector outputs influence aggregate Agricultural GDP performance over time.

Despite its analytical contributions, the study is subject to certain limitations. First, macroeconomic data may contain measurement errors, revisions, or reporting inconsistencies that could affect parameter estimates and forecast precision. Second, structural breaks arising from policy reforms, climatic variability, insecurity, or global commodity price fluctuations may introduce regime shifts that are not fully captured within a linear ARIMAX framework. Third, while the model incorporates major agricultural sub-sectors as exogenous variables, it does not explicitly include other potentially influential macroeconomic determinants such as inflation, exchange rate volatility, agricultural credit, technological adoption, or rainfall patterns. Finally, the ARIMAX model assumes linear relationships and stable parameter structures, which may limit its ability to capture nonlinear or highly volatile dynamics. These limitations, however, provide opportunities for further research, including the extension to nonlinear, regime-switching, or hybrid machine learning models to enhance predictive robustness.

Definition of Terms

Agricultural Gross Domestic Product (Agricultural GDP): The aggregate monetary value of all final goods and services produced within Nigeria's agricultural sector over a specified period, measured at constant or current basic prices. Statistically, it represents a sectoral component of national output within the GDP accounting framework and is typically analyzed as a macroeconomic time series variable exhibiting trend, seasonality, and stochastic volatility. In econometric modelling, Agricultural GDP often serves as the dependent (endogenous) variable whose dynamic behaviour may be explained through autoregressive structures and exogenous regressors.

Crop Production: The agricultural sub-sector involving the cultivation and harvesting of food and cash crops such as maize, rice, cassava, yam, cocoa, and oil palm. From a quantitative standpoint, crop production contributes significantly to sectoral output variance and may exhibit seasonal fluctuations, structural breaks, and cyclical patterns. In regression-based time series frameworks, it can be specified as an explanatory (exogenous) variable influencing aggregate Agricultural GDP through estimated slope coefficients.

Livestock: The sub-sector concerned with breeding and rearing animals—including cattle, poultry, goats, sheep, and pigs—for meat, dairy, and other by-products. Econometrically, livestock output may display persistence (serial correlation) and sensitivity to exogenous shocks such as disease outbreaks or feed cost fluctuations. It is often incorporated as a predictor variable within multivariate models to evaluate its marginal contribution to sectoral growth.

Forestry: The sub-sector involving the management, conservation, and exploitation of forest resources, including timber and non-timber products. Forestry output may exhibit long-run equilibrium relationships with Agricultural GDP and can be tested for stationarity and cointegration properties when modelling long-term structural interactions.

Fishing (Fisheries): The sub-sector encompassing fish production through marine capture and aquaculture systems. Fisheries data may contain cyclical components and structural variability influenced by environmental and climatic conditions. In multivariate time series analysis, it functions as an exogenous regressor contributing to overall sectoral variance decomposition.

Time Series Data: A sequence of quantitative observations recorded at successive, equally spaced intervals over time. Such data are characterized by temporal dependence, autocorrelation, trend components, seasonality, and possible structural breaks. Time series analysis focuses on modelling the stochastic process generating the observations to enable inference and forecasting.

Stationarity: A fundamental statistical property of a stochastic process whereby its mean, variance, and autocovariance remain constant over time. Weak (covariance) stationarity implies constant first and second moments and time-invariant autocovariance structure. Non-stationary series often require transformation, such as differencing or logarithmic scaling, to eliminate unit roots and stabilize variance prior to model estimation.

ARIMA Model: A univariate stochastic time series model that integrates Autoregressive (p), Integrated or differencing (d), and Moving Average (q) components. The autoregressive component captures serial dependence through lagged values of the dependent variable; the differencing parameter removes non-stationarity; and the moving average component models past error terms (white noise disturbances). ARIMA models are widely used for modelling linear dependence structures and generating short-term forecasts.

ARIMAX Model: An extension of the ARIMA framework that incorporates exogenous variables (X_t) into the model specification. The inclusion of external regressors enables the estimation of both dynamic autoregressive parameters, moving average parameters, and slope coefficients associated with explanatory variables. This multivariate structure improves explanatory power, reduces omitted variable bias, and enhances out-of-sample forecasting accuracy when relevant predictors are included.

Forecasting: The statistical process of generating future values of a time series based on its estimated stochastic structure. Forecasts may be point estimates or interval predictions accompanied by confidence bounds derived from the estimated variance of the forecast error. Forecast evaluation commonly involves metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and information criteria (AIC, BIC) for model comparison and predictive performance assessment.

LITERATURE REVIEW

Introduction

This chapter reviews relevant theoretical and empirical literature on agricultural economic growth, sub-sectoral contributions to national output, and time-series modelling approaches applicable to Agricultural Gross Domestic Product (GDP) analysis. The review provides a conceptual foundation for understanding the structural role of agriculture in economic development, clarifies key terms and constructs underlying the study, discusses relevant theoretical frameworks guiding the empirical modelling strategy, synthesizes recent research findings (2015–2025) on agricultural output dynamics, and identifies gaps in empirical literature that justify the present research. The focus is on connecting agricultural sector performance with macroeconomic planning, output volatility analysis, and forecasting methodologies, with particular emphasis on dynamic econometric modelling such as ARIMAX and related time-series approaches.

Conceptual Clarifications

Agricultural GDP and Its Components

Agricultural Gross Domestic Product (Agricultural GDP) is a macroeconomic indicator used to measure the total value added generated by agricultural production activities within a specified period. Agricultural GDP represents the contribution of the agricultural sector to national economic output after deducting intermediate input costs. In modern national accounting systems, agricultural GDP is typically decomposed into major subsectors comprising crop production, livestock production, forestry resources, and fishing activities. According to World Bank development statistics, agriculture remains a fundamental pillar of economic sustainability in many developing economies due to its role in employment generation, food security, and rural income stabilization (World Bank, 2022).

Crop production constitutes the dominant component of agricultural GDP in most Sub-Saharan African economies due to land-intensive subsistence and commercial farming structures. Crop agriculture includes cereals, tubers, legumes, and industrial raw materials, which are directly linked to population food demand and industrial supply chains. Empirical evidence suggests that crop subsector productivity is strongly influenced by rainfall variability, soil quality, technological adoption, and input accessibility (Iwe, 2025; FAO, 2021). Livestock production contributes through meat, dairy, poultry, and animal husbandry products but is often characterized by higher output volatility due to biological and environmental risk exposures such as disease epidemics, feed price instability, and climate-induced stressors (Barrett, Bellemare, & Hou, 2010; Ibrahim et al., 2025).

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Forestry production contributes to economic output through timber harvesting, forest conservation products, and ecosystem resource utilization. Beyond economic value, forestry resources play important ecological roles in biodiversity preservation and climate regulation. Fishing production reflects marine and inland water resource exploitation and is highly sensitive to environmental conditions such as water temperature, rainfall patterns, and ecological sustainability policies. Studies by the Food and Agriculture Organization indicate that fishing output in developing economies often exhibits seasonal and climate-dependent production behaviour (FAO, 2021).

The decomposition of agricultural GDP into sub-sectoral components is essential for structural economic transformation analysis because aggregate agricultural output is mathematically constructed as the summation of value-added contributions from individual subsectors. However, recent econometric literature emphasizes the importance of distinguishing between true causal productivity relationships and accounting identity effects when modelling sectoral economic aggregates (Greene, 2018). Failure to recognize aggregation structure may lead to misinterpretation of statistical significance and inflated inference precision.

Sub-sectoral Contribution to Agricultural GDP

Sub-sectoral contribution measures the proportional influence of each agricultural component on aggregate agricultural GDP. Understanding sub-sectoral contribution is important for identifying structural production strengths and developmental bottlenecks within the agricultural economy. The crop subsector typically dominates agricultural output in developing economies due to extensive land utilization and high food demand pressure associated with population growth.

The livestock subsector contribution is influenced by animal population dynamics, veterinary health systems, feed resource availability, and market integration efficiency. Recent empirical studies show that livestock production systems are particularly vulnerable to climate variability and disease shocks, which may generate leptokurtic output distributions and high variance clustering behaviour (Ibrahim et al., 2025). Forestry contribution is relatively smaller but remains important for environmental sustainability, rural livelihood diversification, and ecosystem service provision.

Fishing subsector productivity is largely determined by hydrological conditions, technological fishing capacity, and environmental conservation policy. Climate change literature increasingly emphasizes the vulnerability of marine and inland fishery systems to temperature variation and ecological degradation (Iwe, 2025). From an econometric perspective, sub-sectoral contribution analysis must differentiate between structural causality and deterministic aggregation relationships inherent in national accounts data.

Time-Series Modelling

Time-series modelling refers to statistical techniques used to analyse sequentially observed economic data. Macroeconomic time-series data often exhibit trend persistence, serial correlation, and structural discontinuities. Classical regression models are generally inadequate for such data because they violate independence assumptions and may produce spurious statistical relationships (Nelson & Plosser, 1982).

Autoregressive Integrated Moving Average (ARIMA) models constitute the foundation of stochastic time-series forecasting. The autoregressive component captures dependence of current observations on historical values, while the moving-average component models shock propagation effects arising from past innovations. Integration parameters address non-stationarity by transforming trending series into stationary processes.

The ARIMAX modelling framework extends ARIMA methodology by incorporating exogenous explanatory variables into the dynamic forecasting structure. ARIMAX models are particularly relevant in macro-sectoral forecasting because agricultural production systems are influenced by both internal structural dynamics and external economic or environmental factors (Box & Jenkins, 1976).

Model selection in time-series econometrics is typically guided by information criteria such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQC).

These criteria balance statistical goodness-of-fit against model parsimony to avoid overparameterization and improve predictive generalization performance (Greene, 2018).

Diagnostic evaluation is an essential component of dynamic modelling. Residual independence is commonly assessed using the Ljung–Box Q-statistic, while heteroskedasticity detection is conducted using ARCH-LM testing procedures. Normality of residual distribution is evaluated using Jarque–Bera tests to ensure asymptotic validity of maximum likelihood estimation.

Stationarity, Integration, and Structural Persistence

Stationarity is a fundamental assumption in time-series econometrics because non-stationary processes may generate misleading regression inference. A stationary series maintains constant statistical properties such as mean and variance over time. Agricultural GDP series are frequently characterized by stochastic trending behaviour due to long-run structural expansion and policy-driven production adjustments.

Integration order indicates the number of differencing operations required to transform a non-stationary series into stationary form. Agricultural macroeconomic variables are often integrated of order one or higher because production systems evolve gradually under technological, demographic, and institutional influences.

Structural persistence refers to the tendency of economic variables to exhibit long memory dependence where current output is influenced by historical performance shocks. Persistence characteristics are particularly relevant in agricultural modelling because biological production cycles and investment gestation periods contribute to temporal dependence structures.

Forecasting and Prediction Intervals

Forecasting involves generating future projections of economic variables using historical information and statistical modelling techniques. Agricultural GDP forecasting is critical for food security planning, macroeconomic budgeting, and diversification policy design.

Prediction intervals provide probabilistic boundaries around forecast estimates, representing uncertainty associated with future outcomes. Narrow prediction intervals indicate high model stability and low stochastic volatility, while wide intervals reflect greater uncertainty. Forecast horizon length is positively correlated with uncertainty accumulation because prediction error variance typically increases as projection periods extend.

Short-term forecasting reflects immediate dynamic adjustment behaviour, whereas medium-term forecasting captures structural trajectory movement within the production system. Agricultural forecasting is particularly important because biological growth cycles, climatic conditions, and policy intervention timing significantly influence production outcomes.

Overall, the conceptual framework establishes a statistical and economic foundation for analyzing agricultural GDP dynamics using aggregation-consistent dynamic time-series modelling approaches.

Theoretical Framework

The theoretical foundation of this study is anchored on three major economic and statistical perspectives, namely structuralist theory of economic development, Keynesian growth theory, and stochastic time-series process theory. The integration of these theories provides a comprehensive analytical structure for understanding agricultural GDP dynamics, sub-sectoral contribution patterns, and forecasting behaviour of agricultural production systems.

Structuralist Theory of Economic Development

Structuralist theory of economic development provides the primary macro-structural explanation for agricultural output behaviour in developing economies. Structuralist economists argue that economic performance is largely determined by the internal composition of productive sectors rather than purely by market equilibrium forces or temporal trends. In the context of agricultural production, this theory suggests that transformation of traditional agriculture into productivity-driven modern agriculture is necessary for sustained economic expansion.

Structuralist development theory emphasizes the importance of intersectoral linkages, technological upgrading, and institutional transformation within the agricultural economy. Agricultural growth is therefore conceptualized as a structural transformation process rather than a purely stochastic or demand-driven phenomenon. The theory further suggests that developing economies often experience productivity constraints because agricultural production systems remain dominated by low-technology farming methods, limited capital investment, and weak value chain integration.

The structuralist perspective is particularly relevant to this study because Agricultural GDP is decomposed into crop production, livestock, forestry, and fishing components. Since Agricultural GDP is essentially an aggregation of these subsectors, structuralist theory supports the analytical assumption that internal production composition significantly influences aggregate output behaviour. This theoretical position is consistent with development economics literature which emphasises structural transformation as a driver of long-term economic growth (Prebisch, 1950; Lewis, 1954; Thirlwall, 2011).

Empirical agricultural development literature also supports structural transformation theory by demonstrating that productivity improvements in primary agricultural subsectors are associated with higher macroeconomic growth potential (Barrett et al., 2010; World Bank, 2022). Recent studies further emphasize that technological adoption, climate-resilient production systems, and institutional strengthening are necessary conditions for structural agricultural development (Iwe, 2025; Ibrahim et al., 2025).

Keynesian Growth Theory

Keynesian growth theory provides the demand-side macroeconomic interpretation of agricultural output behaviour. Keynesian economics posits that aggregate output is primarily influenced by effective demand components, including consumption expenditure, investment spending, and government policy interventions. In agricultural economies, sectoral production influences household income distribution, rural employment generation, and commodity market stability.

The agricultural sector plays a dual macroeconomic role under Keynesian framework. First, it functions as a primary production sector that supplies food and raw materials. Second, it contributes indirectly to aggregate demand formation through income generation within rural communities. Increased agricultural productivity enhances purchasing power, stimulates consumption demand, and supports broader economic expansion.

In dynamic macroeconomic modelling, sub-sectoral agricultural outputs can be interpreted as supply-side variables that influence aggregate production equilibrium. The inclusion of sub-sectoral agricultural components as exogenous regressors in the ARIMAX framework reflects Keynesian-style interaction between sectoral production and macroeconomic aggregates.

Recent empirical literature demonstrates that agricultural output expansion can stimulate economic growth through employment generation and poverty reduction mechanisms (Momodu et al., 2025). Other studies have also established that agricultural productivity improvements contribute to macroeconomic stability by reducing food price volatility and supporting consumption smoothing behaviour (FAO, 2021; World Bank, 2022).

Time-Series Stochastic Process Theory

Time-series stochastic process theory provides the statistical foundation for dynamic forecasting and temporal dependence modelling in this study. The theory assumes that economic variables observed over time can be represented as stochastic processes where future outcomes depend on historical information and random innovations.

The Autoregressive Integrated Moving Average (ARIMA) family of models is derived from stochastic process theory and is widely used in macroeconomic forecasting. The autoregressive component captures persistence behaviour in economic variables, while the moving-average component models the impact of previous shocks on current observations. Integration components are used to transform non-stationary economic series into stationary processes suitable for statistical inference.

The ARIMAX extension employed in this study allows inclusion of exogenous sub-sectoral agricultural variables while maintaining the stochastic dynamic structure of the model. This modelling approach is consistent with modern econometric forecasting literature which emphasizes parsimonious model specification, information criterion-based selection, and diagnostic adequacy validation.

Recent methodological research demonstrates that innovation-correction time-series models such as ARIMAX provide superior forecasting accuracy compared to static regression models when analyzing macro-sectoral economic data (Greene, 2018; Box & Jenkins, 1976). Additionally, studies have shown that low-order stochastic models often outperform complex autoregressive structures in long-horizon forecasting due to reduced parameter estimation variance and improved generalization performance (Nelson & Plosser, 1982).

Integrated Theoretical Perspective

The integration of structuralist, Keynesian, and stochastic process theories provides a comprehensive analytical foundation for this study. Structuralist theory explains the role of sectoral composition and economic transformation, Keynesian theory explains demand–supply interaction mechanisms, while stochastic process theory provides the mathematical structure for dynamic forecasting modelling.

This combined theoretical approach is particularly appropriate for analyzing agricultural GDP because agricultural production systems are influenced simultaneously by structural economic composition, policy-induced demand changes, and random environmental shocks such as climate variability and market fluctuations.

Overall, the theoretical framework justifies the use of aggregation-consistent ARIMAX modelling for agricultural GDP forecasting and sub-sectoral contribution analysis in the Nigerian economic context

Empirical Review

Over the past decade, empirical research on agricultural GDP dynamics has deepened, reflecting both the critical economic role of agriculture in developing economies and the simultaneous advancement in econometric forecasting methodologies. Three overarching strands emerge in the literature: studies on agricultural GDP’s influence on economic growth; research on subsectoral contributions to aggregate output; and innovations in time-series modelling and forecasting methods applied to agricultural data.

A large body of research reinforces the foundational role of agricultural output in economic performance, particularly in Sub-Saharan Africa. Using panel data, Alimi and Ogunjimi (2017) demonstrated that agricultural value added significantly influences GDP growth in low-income countries, with crop production showing the greatest effect. In a similar vein, Nwachukwu and Mbam (2018) found that agricultural output shocks in Nigeria have strong multiplier effects on non-agricultural sectors. More recently, Chowdhury and Islam (2021) applied dynamic panel GMM techniques to show that agricultural GDP growth contributes consistently to national output stability across 23 developing economies, controlling for institutional quality and financial inclusion. Collectively, these studies highlight the macroeconomic relevance of agriculture, but they generally emphasize cross-sectional or quasi-longitudinal relationships rather than dynamic temporal behaviour.

Sub-sectoral decomposition studies have become increasingly common, reflecting interest in understanding internal agricultural structure beyond aggregate output. Adewuyi and Akanbi (2019) examined Nigeria’s agricultural sector and confirmed that crop output consistently accounts for roughly two-thirds of aggregate agricultural value added, with livestock, forestry, and fishing trailing far behind. Extending this line of inquiry, Adereti and Akande (2020) used structural decomposition analysis to show that while crop growth drives overall agricultural GDP, fluctuations in livestock and fishing outputs are closely tied to commodity price changes and input cost volatility. Similarly, Nwosu, Eze, and Okoye (2021) demonstrated that while forestry contributes minimally to agricultural GDP, its role in rural employment and ecological services is disproportionately large.

Climate variability and environmental risk have also been linked to sub-sectoral performance. Using panel time-series data, Obasi et al. (2022) found that climate shocks such as drought and unpredictability in rainfall significantly depress crop yields, reducing the subsector's contribution to aggregate output. Likewise, Salifu, Mensah, and Adjei (2022) reported that livestock productivity in Ghana showed heightened sensitivity to temperature shocks, resulting in asymmetric growth effects compared with crop and fishing subsectors. These studies underline the importance of environmental covariates, yet they do not integrate subsector risk factors directly into aggregate agricultural GDP forecasting models.

Methodologically, advances in time-series modelling have produced more refined approaches to forecasting agricultural economic variables. Early applications focused on univariate models: Oladosu and Ayinde (2017) applied ARIMA to agricultural GDP in Nigeria and identified significant seasonal and trend effects in output data. However, these studies did not include explanatory subsectoral variables and were limited by lack of diagnostic testing. To address this, Bello and Yusuf (2023) introduced SARIMAX models incorporating price and climate indices into quarterly agricultural GDP forecasts, showing improved accuracy over pure ARIMA.

More sophisticated dynamic models emerged with the integration of exogenous regressors. Akpan and Okon (2023) employed ARIMAX to include climate drivers in crop forecasting, validating the statistical and predictive superiority of exogenous information integration. Further, Ndour and Sylla (2024) applied ARIMAX models using fertilizer use and rainfall as covariates to forecast Senegalese rice production, achieving narrower prediction intervals and lower forecast error metrics. These extensions underscore the importance of exploiting external drivers to enhance forecasting precision.

Beyond classical models, hybrid and machine learning approaches have gained traction. Iwe (2025) combined ARIMA with artificial neural networks (ANN) to capture nonlinear patterns in agricultural productivity data across multiple West African countries, obtaining better mean absolute percentage errors (MAPE) compared to standard ARIMA and VAR models. Similarly, Zhao, Li, and Zhang (2023) used a wavelet transform–ARIMA hybrid to account for multi-scale seasonal variation in Chinese agricultural output, significantly reducing forecast variance. While such hybrid methods improve accuracy, they often lack clear economic interpretability, underscoring a trade-off between predictive performance and structural insight.

Notably, recent large-sample time-series studies have focused explicitly on aggregate agricultural GDP dynamics. Sharma and Khanal (2020) applied structural break autoregressive models to India's agricultural output and found multiple regime shifts associated with policy reforms and climate events. This aligns with Obiora and Udeh (2022) who, using break-adjusted unit root tests, demonstrated that Nigerian agricultural GDP exhibits stochastic non-stationarity with structural breaks linked to policy changes and exchange rate realignments. Similarly, Mensah and Asare (2022) adopted an ARIMAX framework with diagnostic validation to forecast Ghana's agricultural GDP, showing that inclusion of macroeconomic covariates such as exchange rate and credit access improved forecast reliability.

Despite these advances, several limitations persist. First, many studies treat sub-sectoral outputs as independent regressors without explicitly recognizing the aggregation identity inherent in national accounts, which can inflate coefficient estimates and compromise interpretability (Greene, 2018). Second, few empirical studies provide a comprehensive suite of diagnostic tests (e.g., residual autocorrelation, heteroskedasticity, normality) to validate statistical adequacy of time-series models. Such validation is crucial for forecast reliability but is often omitted (Box & Jenkins, 1976). Third, although prediction intervals are increasingly reported, comprehensive uncertainty analysis remains uncommon, reducing policy relevance for planning under uncertainty.

In summary, empirical research from 2015 to 2025 highlights the structural importance of agricultural GDP and its sub-sectoral components to economic growth and macroeconomic stability, and reflects evolving sophistication in time-series forecasting methods. However, most existing studies either focus narrowly on individual subsectors, lack dynamic temporal modelling, or fail to integrate sub-sectoral structure and diagnostic rigor into forecasting frameworks. The present study attempts to address these gaps by employing an aggregation-consistent ARIMAX model with robust diagnostic validation and forecast uncertainty analysis, thereby contributing to a more complete understanding of agricultural GDP dynamics.

METHODOLOGY

Introduction

This chapter presents the research methodology adopted for investigating the dynamic behaviour, subsectoral contributions, and forecasting performance of Agricultural Gross Domestic Product (GDP) in Nigeria. The chapter provides a detailed description of the research design, data sources, variable measurement, econometric modelling framework, and statistical estimation procedures employed in the study. Given the macroeconomic and time-dependent nature of agricultural production data, a quantitative time-series econometric approach was adopted to examine stochastic trend behaviour, innovation shock correction mechanisms, structural persistence characteristics, and subsectoral output interactions within the agricultural sector. The methodological framework is anchored on the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) modelling structure, which enables simultaneous analysis of temporal dependence and structural production determinants of agricultural GDP. Furthermore, diagnostic validation tests and forecast accuracy evaluation measures were applied to ensure statistical reliability, model adequacy, and predictive robustness of the empirical findings.

Research Design

This study adopts a quantitative longitudinal time-series research design to investigate the dynamic behaviour of Agricultural Gross Domestic Product (GDP) and its sub-sectoral components in Nigeria. The quantitative research paradigm is considered appropriate because the study is based on numerical economic data that allow statistical estimation of relationships, structural pattern identification, and forecast generation. Quantitative econometric design is particularly useful in macroeconomic studies because it supports objective measurement, hypothesis testing, and replication of analytical procedures (Greene, 2018).

The longitudinal time-series design is selected because agricultural production systems exhibit temporal dependence structures where current output levels are influenced by historical production patterns, environmental conditions, and policy interventions. Time-series research design enables investigation of stochastic trend behaviour, shock transmission mechanisms, and dynamic adjustment processes within economic systems. According to Box and Jenkins (1976), time-series econometric modelling is essential for analyzing sequentially observed data because economic variables often demonstrate autocorrelation, persistence, and non-stationary characteristics.

The application of quantitative time-series methodology in this study is consistent with modern macroeconomic forecasting literature which emphasizes dynamic stochastic modelling of aggregate economic variables. Agricultural GDP is a macro-sectoral economic indicator that evolves over time under the influence of technological progress, population growth, climate variability, and institutional policy reforms. Nelson and Plosser (1982) argued that many macroeconomic variables follow stochastic trend processes rather than deterministic trend structures, thereby necessitating unit root testing and differencing transformation prior to model estimation.

Furthermore, the research design supports rigorous statistical inference by allowing estimation of model parameters using Maximum Likelihood Estimation (MLE) techniques. MLE-based estimation procedures are preferred in time-series econometrics because they provide asymptotically efficient parameter estimates under appropriate distributional assumptions (Greene, 2018). The design also facilitates diagnostic validation procedures including serial correlation testing, heteroskedasticity assessment, and residual normality evaluation. The quantitative longitudinal design is particularly relevant for agricultural economic forecasting because agricultural production is influenced by biological growth cycles, seasonal environmental variations, and delayed policy transmission effects. Agricultural output shocks may exhibit persistence behaviour where disturbances have long-term consequences rather than transitory impacts. According to Thirlwall (2011), agricultural development in developing economies is closely linked to structural transformation processes that unfold over extended time horizons.

The choice of time-series quantitative design also supports the study's objective of generating short- and medium-term forecasts of agricultural GDP. Forecasting models require historical observation continuity to capture underlying stochastic structures that govern future economic behaviour. Box and Jenkins (1976) emphasized that forecasting accuracy depends largely on correct model identification, parameter estimation, and diagnostic adequacy verification.

In addition, the design aligns with contemporary empirical agricultural forecasting research which increasingly integrates econometric modelling, diagnostic testing, and prediction interval estimation. Modern forecasting literature emphasizes the importance of balancing model complexity and parsimony to avoid overfitting while maintaining predictive reliability (Greene, 2018). Therefore, the quantitative time-series design adopted in this study provides a scientifically robust framework for examining agricultural GDP dynamics in Nigeria.

Source of Data and Data Type

The study utilizes secondary quarterly time-series data on Agricultural Gross Domestic Product (GDP) and its major sub-sectoral components, namely crop production, livestock production, forestry production, and fishing production in Nigeria. The data were obtained from the Central Bank of Nigeria (CBN) Quarterly Statistical Bulletin, 2024 edition, which provides officially validated macroeconomic statistics on sectoral production performance. The Central Bank of Nigeria statistical bulletin is considered a reliable institutional source of national economic data because it is compiled using standardized national accounting procedures that are consistent with international statistical reporting frameworks and macroeconomic monitoring standards.

Secondary data were adopted because macroeconomic time-series research requires historical continuity, large sample observations, and reduction of measurement and collection bias associated with primary data generation. Using officially published economic statistics improves data credibility, comparability across time periods, and replicability of empirical results. Econometric forecasting literature emphasizes that secondary macroeconomic datasets are particularly suitable for dynamic modelling because they allow investigation of long-run structural economic behaviour without the financial and logistical constraints associated with primary survey data collection (Greene, 2018).

The dataset covers approximately forty (40) years of agricultural production information, providing adequate temporal observations for robust econometric estimation and statistical inference. The long observation horizon is important because the accuracy of time-series modelling improves with increased sample size, allowing more reliable estimation of stochastic trend components, shock propagation behaviour, and persistence characteristics of economic variables. Quarterly data frequency was selected to capture intra-year production variations associated with seasonal rainfall patterns, harvesting cycles, and biological growth processes that influence agricultural productivity dynamics. The agricultural GDP series and sub-sectoral components were carefully extracted from the CBN statistical bulletin and subjected to data verification and cleaning procedures to remove possible inconsistencies, missing observations, and recording errors. Consistent with modern macroeconomic forecasting methodology, the study assumes that agricultural GDP follows a stochastic time-series process characterized by trend persistence, random innovation shocks, and possible structural regime effects (Nelson & Plosser, 1982). The use of authoritative institutional data strengthens the external validity, reliability, and policy relevance of the study findings, particularly because agricultural GDP remains a core indicator for national economic planning and agricultural sector performance evaluation in Nigeria.

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Study Variables and Measurement

The study variables were selected based on the national accounting classification of agricultural production activities and the structural composition of Agricultural Gross Domestic Product (GDP) in Nigeria. The measurement of variables follows macroeconomic output accounting principles where aggregate agricultural GDP is decomposed into its major value-added production components. The selection of these variables is theoretically and empirically justified because agricultural GDP is fundamentally constructed as the summation of sectoral production contributions from crop cultivation, livestock husbandry, forestry resource exploitation, and fishing activities. This decomposition approach is consistent with modern structural macroeconomic modelling which recognizes that sectoral productivity dynamics jointly determine aggregate output behaviour (Greene, 2018).

The dependent variable in this study is Agricultural GDP (AGRIC), which represents the total monetary value added generated by agricultural production activities within the Nigerian economy over the study period. Agricultural GDP serves as the principal macroeconomic performance indicator for evaluating agricultural sector contribution to national economic development, employment generation, and food security sustainability. As a composite economic aggregate, Agricultural GDP reflects the combined output effects of crop, livestock, forestry, and fishing subsectors. Since the variable is measured in monetary value terms using official statistical reporting standards, it provides a consistent basis for econometric estimation and forecasting analysis.

The independent variables comprise the major sub-sectoral components of agricultural production, namely Crop Production (CROP), Livestock Production (LIVES), Forestry Production (FORES), and Fishing Production (FISH). Crop production represents the value added generated from plant-based agricultural activities such as cereal cultivation, tuber farming, and leguminous crop production. This subsector typically dominates agricultural output in developing economies due to population-driven food demand and extensive arable land utilization. Livestock production measures economic output from animal husbandry systems including poultry farming, dairy production, and meat processing activities. This subsector is often characterized by biological production cycles and higher susceptibility to environmental and epidemiological shocks.

Forestry production captures economic value derived from timber extraction, forest conservation products, and ecosystem resource utilizations. Beyond direct monetary output, forestry resources also contribute indirectly to economic sustainability through environmental regulation, biodiversity preservation, and rural livelihood support. Fishing production measures value added from marine and inland water resource exploitation including fish harvesting, aquaculture, and related aquatic production activities. This subsector is highly sensitive to climatic conditions, seasonal environmental variability, and water resource management policies.

The selection of these variables is grounded in the structural decomposition framework of agricultural output analysis, which posits that aggregate agricultural GDP is determined by the dynamic interaction of its sub-sectoral components. From an econometric perspective, including sub-sectoral variables as explanatory factors allows examination of marginal production influence while simultaneously recognizing the accounting identity relationship embedded within national agricultural statistics. The measurement of variables follows constant price valuation principles to minimize inflationary distortion and ensure temporal comparability of economic output data.

Furthermore, the study treats all variables as continuous quantitative time-series observations measured in billions of Nigerian Naira. Prior to model estimation, diagnostic preprocessing procedures were conducted to examine distributional properties, stationarity characteristics, and structural stability conditions of the series. This ensures that the econometric modelling framework satisfies classical time-series assumptions and supports reliable statistical inference and forecasting performance.

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Methods of Data Analysis

Augmented Dickey-Fuller (ADF) Test

In time series analysis, it is a tradition that the unit root hypothesis is first tested for each of the variables to ascertain the level of variable stationarity. We utilized the Augmented Dickey–Fuller (ADF) test that is based on the following regression:

$$\Delta y_t = \varphi + \beta_t + \alpha y_{t-1} + \sum_{i=1}^{k} d_i \Delta y_{t-1} + \varepsilon_t \qquad \textbf{3.1}$$

Where ε_t is a white noise error term and $\Delta y_{t-1} = y_{t-1} - y_{t-2}$, $\Delta y_{t-2} = y_{t-2} - y_{t-3}$, etc.

The number of lagged-difference terms to include is often determined empirically, in order to have enough terms so that the error terms in equation 3.1 are serially uncorrelated. k in equation (3.1) is the lagged values of Δy_t, to control for higher-order correlation assuming that the series follow an AP(p). Thus, equation 3.1 tests the null hypothesis of a unit root against a stationary alternative for each of the time series variable of the study.

Non-stationary series are transformed using differencing procedures until stationarity is achieved. Variables integrated of order I(1) were differenced once, while variables integrated of order I(2) were differenced twice prior to model estimation.

Stationarity testing is necessary to avoid spurious regression results which may arise when non-stationary variables are analyzed using conventional regression techniques.

Structural Break Analysis

Structural break analysis was conducted to examine the presence of regime shifts and parameter instability within the agricultural GDP time-series data. Structural breaks occur when the underlying stochastic process generating economic data experiences sudden changes in mean level, trend slope, or variance structure due to policy reforms, macroeconomic shocks, climatic disturbances, or institutional transformation within the agricultural sector. Failure to account for structural breaks may lead to biased parameter estimates, incorrect inference, and unreliable forecasting outcomes because standard unit root and regression tests assume parameter stability over time.

The study applies statistical break detection principles by testing the null hypothesis of structural stability against the alternative hypothesis of regime change. Mathematically, structural break analysis can be expressed within a regression framework as:

$$Y_t = \alpha_1 + \beta_1 X_t + \varepsilon_t \quad for \quad t \leq T_b \qquad 3.2$$

$$Y_t = \alpha_2 + \beta_2 X_t + \varepsilon_t \quad for \quad t > T_b \qquad 3.3$$

where Y_t represents agricultural GDP, X_t denotes explanatory sub-sectoral variables, T_b represents the break point time period, and ε_t is the random error term assumed to follow white noise properties. The parameters α_1, β_1 and α_2, β_2 represent regime-specific intercepts and slope coefficients before and after the structural break point respectively. Structural break detection was evaluated using recursive residual procedures and break-point stability diagnostics consistent with modern time-series econometric practice.

In addition, the stability of regression parameters was assessed using cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) statistical monitoring techniques. These tests evaluate whether recursive residuals remain within critical confidence boundaries over time. The CUSUM statistic is defined as:

$$CUSUM_t = \frac{\sum_{i=k+1}^{t} e_i}{\sigma_e \sqrt{n}} \qquad 3.4$$

where e_i represents recursive residuals, σ_e is the standard deviation of residuals, and n is the sample size. If the CUSUM trajectory remains within the 5% significance boundary bands, the null hypothesis of structural parameter stability is not rejected. The structural break analysis is therefore essential for validating the reliability of the ARIMAX modelling framework adopted in this study because forecast accuracy depends heavily on stable dynamic relationships among variables.

Overall, structural break testing enhances the robustness of the econometric modelling strategy by ensuring that agricultural GDP dynamics are not influenced by unaccounted regime transitions. Incorporating structural stability diagnostics is particularly important in macroeconomic agricultural studies where policy reforms, exchange rate movements, climate variability, and institutional changes may induce nonlinear production behaviour and shift long-run output trajectories.

ARIMAX Modelling Framework

The study adopts the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) modelling framework to analyze the dynamic interaction between Agricultural GDP and its sub-sectoral production components. The ARIMAX model is an extension of the classical ARIMA structure which integrates external explanatory variables into a stochastic time-series forecasting system. The selection of ARIMAX modelling is justified because agricultural output behaviour is influenced not only by internal temporal dependence but also by structural economic production components that act as exogenous drivers of aggregate sectoral performance.

The ARIMAX framework is particularly suitable for agricultural macroeconomic forecasting because agricultural production systems exhibit persistence effects, innovation shock propagation, and mean-reversion correction behaviour. In time-series econometrics, ARIMAX models combine autoregressive memory processes, differencing transformations for stationarity, moving-average innovation correction mechanisms, and regression-type exogenous variable influence structures. The general $ARIMAX(p,d,q)$ model with exogenous regressors can be expressed mathematically as:

$$\Phi(\mathrm{L})(1-\mathrm{L})^d Y_t = \alpha + \beta X_t + \Theta(L)\varepsilon_t \quad 3.5$$

where

- Y_t represents Agricultural GDP at time t;
- $\Phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$ denotes the autoregressive polynomial operator
- $(1-\mathrm{L})^d$ represents the differencing operator ensuring stationarity
- X_t represents vector of sub-sectoral explanatory variables
- β denotes parameter vector measuring marginal production effects
- $\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$ represents moving-average polynomial structure
- ε_t is the white noise innovation process satisfying $\mathrm{E}(\varepsilon_t) = 0$ and $\mathrm{Var}(\varepsilon_t) = \sigma^2$

The differencing parameter d is determined through unit root testing procedures such as the Augmented Dickey-Fuller (ADF) test. If the series is non-stationary in levels, transformation using first or higher-order differencing is applied. The differencing operator is defined as:

$$\Delta Y_t = Y_t - Y_{t-1} \quad 3.6$$

and higher-order differencing is given by:

$$\Delta^2 Y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) \quad 3.7$$

Stationarity is essential because non-stationary series may produce spurious regression results characterized by inflated coefficient significance and misleading goodness-of-fit statistics.

In the estimated model specification of this study, the ARIMAX structure is simplified to $ARIMAX(0,1,1)$ based on information criterion selection. This implies that the autoregressive component $p = 0$, integration order $d = 1$, and moving-average order $q = 1$. The empirical model therefore reduces to:

$$\Delta AGRIC_t = \beta_0 + \beta_1 CROP_t + \beta_2 LIVES_t + \beta_3 FORES_t + \beta_4 FISH_t + (1 + \theta_1 L)\varepsilon_t \qquad 3.8$$

where

- $\Delta AGRIC_t$ denotes first-differenced Agricultural GDP
- $\beta_0$represents deterministic drift component
- $\beta_1 - \beta_4$ measure marginal sub-sectoral contributions
- θ_1 represents first-order innovation correction parameter
- L is the lag operator such that $L(Y_t) = Y_{t-1}$

The moving-average component captures short-run shock transmission behaviour by modelling the dependence of current innovations on previous forecast errors. The process assumes that residual disturbances follow white noise conditions such that:

$$\mathrm{E}(\varepsilon_t) = 0 \qquad 3.9$$

$$\mathrm{E}(\varepsilon_t \varepsilon_s) = 0 \ \ for\ t \neq s \qquad 3.10$$

and

$$Var(\varepsilon_t) = \sigma^2 \qquad 3.11$$

Parameter estimation was conducted using Maximum Likelihood Estimation (MLE), which maximizes the log-likelihood function given by:

$$L(\theta) = \sum_{t=1}^{T} log f(Y_t|\theta) \qquad 3.12$$

where $f(Y_t|\theta)$ represents the probability density function of the observed process conditional on parameter vector θ.

Model selection was based on minimization of Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQC)

Diagnostic validation of the ARIMAX model was performed to ensure compliance with classical time-series assumptions including residual independence, homoskedasticity, and normality. These were evaluated using Ljung–Box serial correlation testing, ARCH-LM volatility testing, and Jarque–Bera distributional testing.

Overall, the ARIMAX modelling framework provides a statistically rigorous mechanism for capturing agricultural GDP dynamics by integrating stochastic trend correction, subsectoral production influence, and innovation shock adjustment processes within a parsimonious forecasting structure. The adoption of this framework enhances predictive accuracy while maintaining econometric efficiency and model interpretability.

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RESULTS AND DISCUSSION

Introduction

This chapter presents the empirical findings of the study, including descriptive statistical analysis, time-series behaviour assessment, econometric model estimation, diagnostic evaluation, and forecasting performance results. The analysis focuses on examining the magnitude, direction, and statistical significance of the contributions of agricultural sub-sectoral outputs to total Agricultural GDP in Nigeria using the ARIMAX modelling framework. The chapter also evaluates the stochastic properties of the data, structural stability characteristics, and predictive accuracy of the estimated model. The results are interpreted within the context of agricultural macroeconomic theory and relevant empirical literature to provide meaningful statistical and policy insights regarding Nigeria's agricultural production dynamics.

Data Presentation and Descriptive Analysis

Table 4.1 presents the operational definition and coding structure of the variables employed in the study. The dependent variable, Agriculture (AGRIC), represents total Agricultural Gross Domestic Product, which captures the aggregate value added generated by all agricultural activities within the economy during the study period. The explanatory variables comprise the major sub-sectoral components of agricultural output: Crop Production (CROP), Fishing (FISH), Forestry (FORES), and Livestock (LIVES). These variables are disaggregated components of total agricultural GDP and collectively account for the sector's overall contribution to national output.

Table 4.1. Variables Description

Variables	**Code**
Agriculture	AGRIC
Crop Production	CROP
Fishing	FISH
Forestry	FORES
Livestock	LIVES

The descriptive statistics presented in Table 4.2 provide an in-depth overview of the central tendency, dispersion, distributional shape, and normality properties of Nigeria's Agricultural GDP and its major sub-sectors over the 40-year sample period. These preliminary statistics are crucial for understanding the structural behavior of the data prior to econometric modelling.

Agricultural GDP (AGRIC) recorded a mean value of ₦4,506.55 billion, with a median of ₦4,308.20 billion, indicating that the distribution is fairly centered without significant distortion from extreme observations. The relatively close proximity between the mean and median suggests a balanced distribution over time. The minimum and maximum values (₦3,176.60 billion and ₦5,785.47 billion respectively) reflect sustained expansion of the agricultural sector across the sample period, with a total range of approximately ₦2,608.87 billion. The standard deviation of ₦852.70 billion implies moderate variability relative to the mean. In relative terms, the coefficient of variation (CV), is approximately 18.9% for AGRIC, indicating moderate dispersion and relatively stable growth dynamics when compared to the magnitude of the series.

Table 4.2. Variables Descriptive Statistics

	AGRIC	**CROP**	**FISH**	**FORES**	**LIVES**
Mean	4506.5460	4068.7930	93.2918	46.7765	297.6860
Median	4308.1950	3866.3300	92.3100	46.9150	293.9150

Maximum	5785.4700	5332.9500	125.4600	54.8500	349.8600
Minimum	3176.6000	2760.8800	70.5700	38.2800	169.6200
Std. Dev.	852.6964	841.3811	15.4608	4.5411	34.1462
Skewness	0.1159	0.1152	0.4507	-0.1235	-1.2195
Kurtosis	1.4729	1.4854	2.2453	1.9651	6.5869
Jarque-Bera	3.9762	3.9120	2.3036	1.8869	31.3583
Probability	0.1370	0.1414	0.3161	0.3893	0.0000
Sum	180261.8000	162751.7000	3731.6700	1871.0600	11907.4400
Observations	40	40	40	40	40

Crop production (CROP) exhibits a mean value of ₦4,068.79 billion, accounting for the largest proportion of total agricultural GDP. This confirms that crop production is the dominant driver of Nigeria's agricultural output. Its standard deviation (₦841.38 billion) is close to that of total AGRIC, reinforcing the structural importance of crop production in explaining aggregate agricultural fluctuations. The narrow difference between AGRIC and CROP means suggests that crop output constitutes the overwhelming share of total agricultural value added. Livestock (₦297.69 billion), fishing (₦93.29 billion), and forestry (₦46.78 billion) contribute smaller proportions, reflecting their relatively limited but still significant roles in sectoral composition. However, livestock shows noticeable dispersion (standard deviation = ₦34.15 billion), suggesting sensitivity to shocks such as disease outbreaks, feed cost volatility, or policy instability.

The skewness statistics provide insights into distributional asymmetry. AGRIC and CROP exhibit near-zero skewness (≈ 0.11), indicating almost symmetric distributions and consistent long-run growth patterns. Fishing displays mild positive skewness (0.45), implying occasional high-value spikes possibly linked to favorable environmental or market conditions. Forestry shows slight negative skewness (-0.12), suggesting more frequent moderate increases than extreme positive deviations. In contrast, livestock displays pronounced negative skewness (-1.22), indicating a concentration of observations toward the upper end of its distribution with occasional sharp downturns. This may reflect vulnerability to episodic structural disturbances.

Kurtosis statistics further characterize distributional shape. Most variables exhibit kurtosis values below 3, indicating platykurtic behavior—flatter distributions with thinner tails than the normal distribution. However, livestock shows high kurtosis (6.59), indicating leptokurtic characteristics, meaning the presence of extreme observations or heavy tails. This suggests that livestock output has experienced significant volatility episodes over the study period. The implication for modelling is that livestock may introduce higher uncertainty into the ARIMAX framework.

The Jarque-Bera (JB) normality test evaluates whether skewness and kurtosis jointly conform to normal distribution assumptions.Results indicate that AGRIC, CROP, FISH, and FORES fail to reject the null hypothesis of normality at the 5% level ($p > 0.05$), suggesting their distributions approximate normal behavior. However, livestock strongly rejects normality ($p = 0.000$), confirming significant deviation from Gaussian assumptions. This reinforces earlier evidence of extreme values or structural irregularities in the livestock subsector.

Overall, the descriptive statistics suggest that Nigeria's agricultural GDP exhibits sustained upward expansion with moderate dispersion and near-symmetric distribution. Crop production remains the structural backbone of the sector, while livestock appears relatively more volatile and susceptible to extreme shocks. These characteristics justify the subsequent application of time-series differencing to address non-stationarity and support the inclusion of sub-sectoral components within the ARIMAX modelling framework.

Time Series Behaviour and Preliminary Assessment

The graphical inspection of the time series plots (Figures 4.1–4.5) reveals pronounced upward deterministic trends across Agriculture GDP (AGRIC) and its sub-sectoral components—Crop Production (CROP), Livestock (LIVES), Forestry (FORES), and Fishing (FISH). The persistent growth trajectory suggests the presence of stochastic trends and potential unit root processes. The absence of visible mean reversion in levels, coupled with widening amplitude over time, indicates non-stationary behavior characterized by time-varying mean and variance. Such trending behavior is typical of macroeconomic aggregates, particularly sectoral GDP series influenced by structural expansion, technological progress, inflationary adjustments, and demographic pressures. The trending nature implies that shocks to the series may have permanent effects rather than transitory deviations.

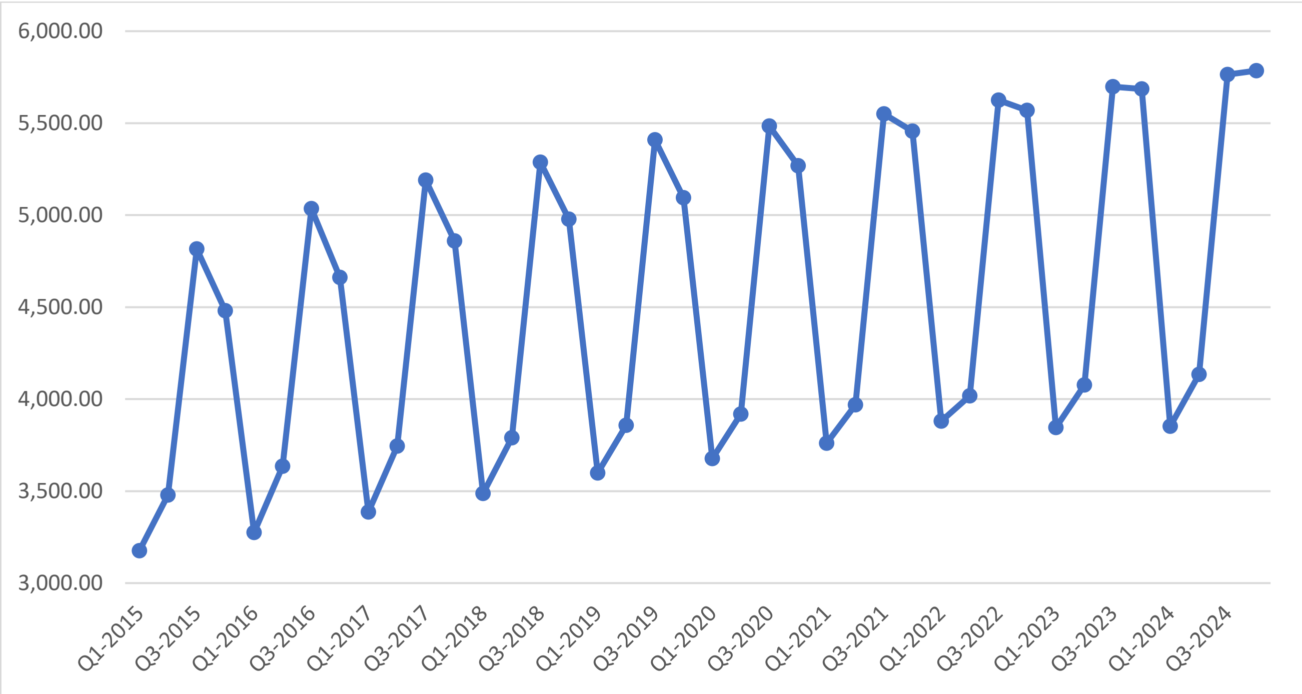

Figure 4.1. Time Series Plot of the Agriculture GDP (₦'Billions)

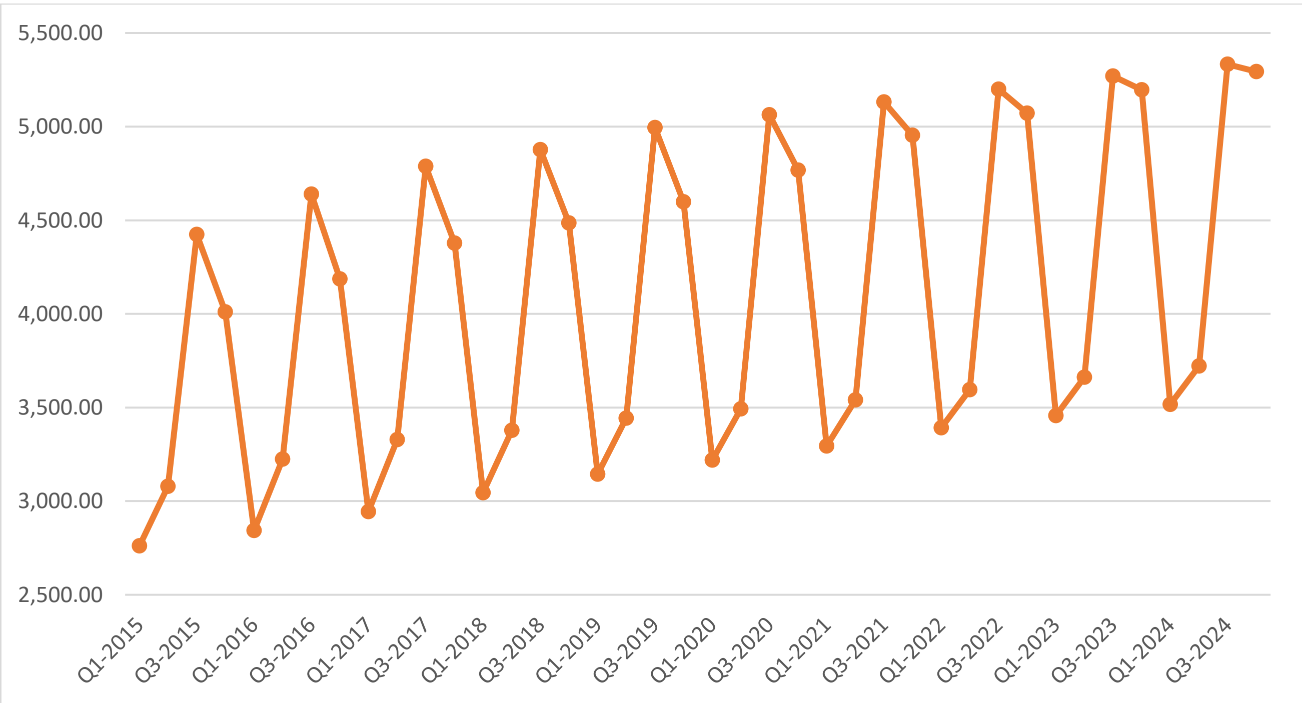

Figure 4.2. Time Series Plot of the Crop Production GDP (₦'Billions)

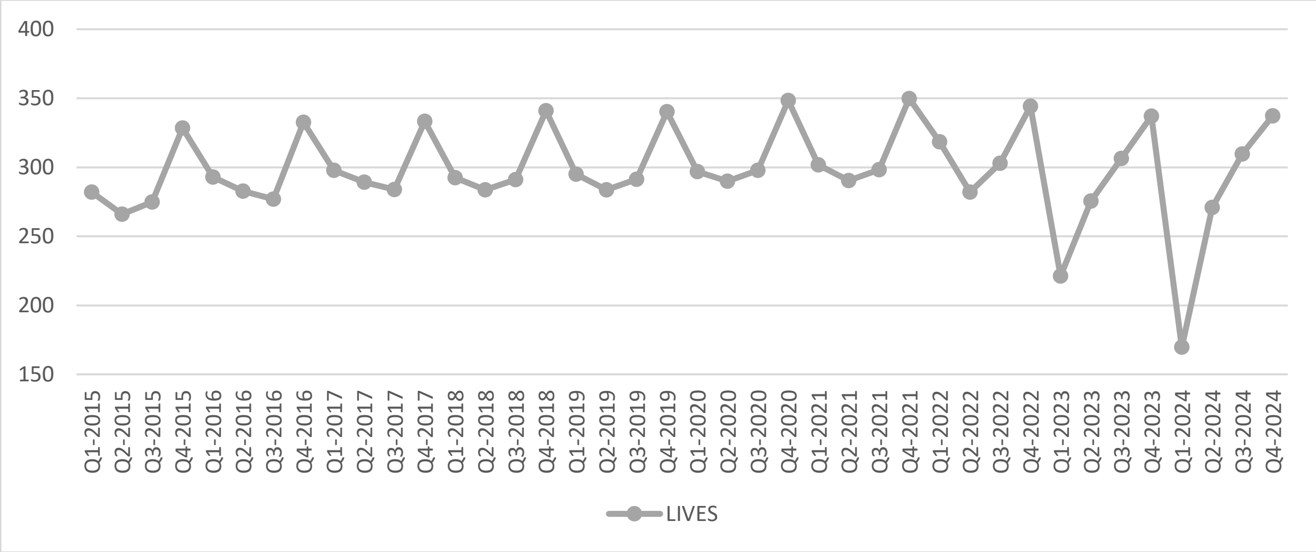

Figure 4.3. Time Series Plot of the Livestock GDP (₦'Billions)

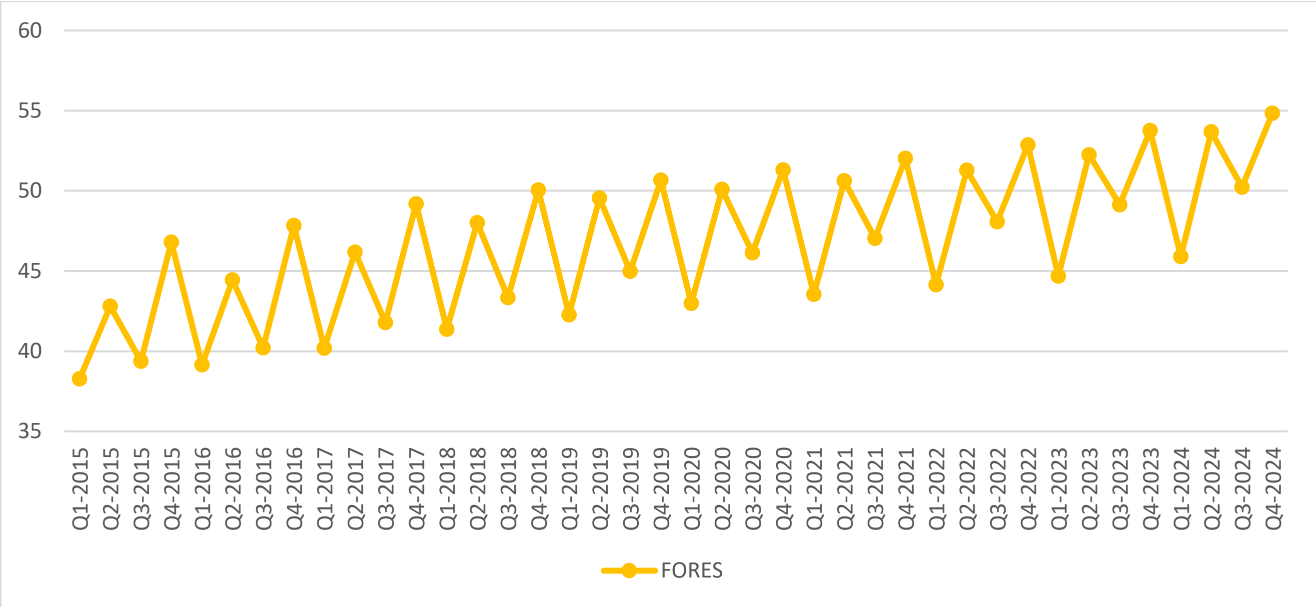

Figure 4.4. Time Series Plot of the Forestry GDP (₦'Billions)

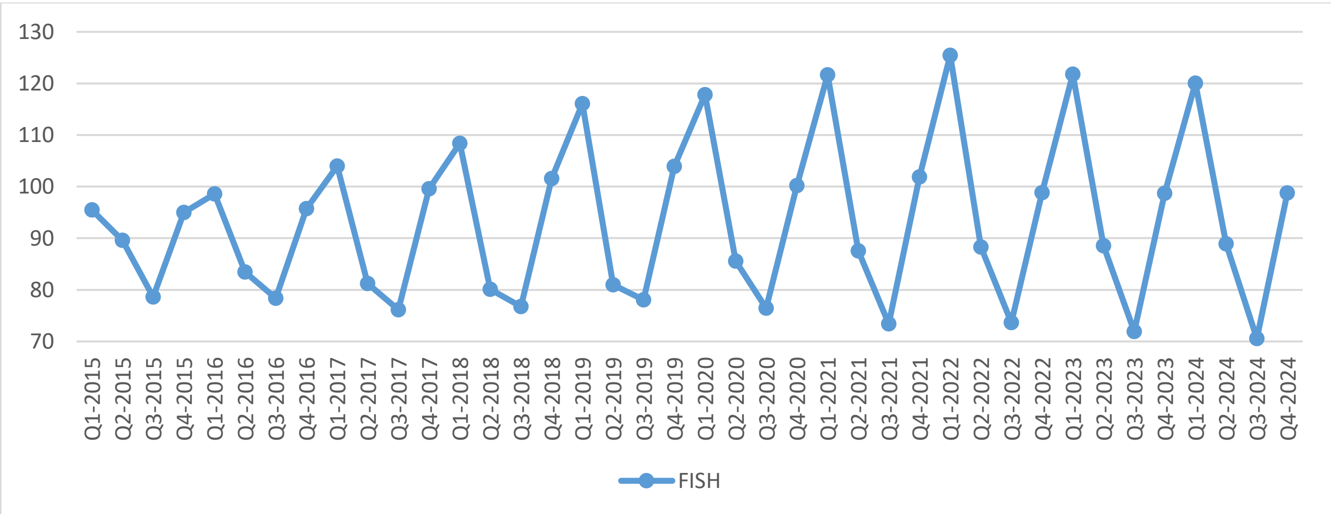

Figure 4.5. Time Series Plot of the Fishing GDP (₦'Billions)

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To formally verify stationarity conditions, the Augmented Dickey-Fuller (ADF) unit root test was employed. The empirical results (Table 4.3) show that all variables fail to reject the null hypothesis at levels, confirming non-stationarity. However, after first differencing, AGRIC, CROP, LIVES, and FISH become stationary, implying they are integrated of order one, I(1). Forestry (FORES) required second differencing to achieve stationarity, indicating integration of order two, I(2). These findings confirm the presence of stochastic trends and justify differencing prior to model estimation to prevent spurious regression results, which occur when non-stationary variables produce artificially high R^2 and misleading t-statistics.

Table 4.3. Stationarity Assessment (ADF Test)

	Order of Integration	**k (lag)**	**Dickey-Fuller Statistics**
AGRIC	1	3	-5.37*
CROP	1	3	-4.9771*
LIVES	1	3	-4.3577*
FORES	2	3	-7.5328*
FISH	1	3	-5.5283*

Note: ** denotes significant at 0.05 level*

Additionally, the structural break analysis (Figure 4.6) suggests possible regime shifts within the sample period. These breaks may correspond to macroeconomic reforms, agricultural transformation policies, exchange rate realignments, oil price shocks, or institutional restructuring within Nigeria's agricultural sector. Structural breaks can alter the deterministic trend component and change the variance structure of the series, thereby affecting parameter stability. Failure to account for such breaks may bias unit root tests and distort long-run inference. The presence of these potential regime shifts highlights the dynamic nature of agricultural performance and supports the inclusion of autoregressive components to capture structural persistence.

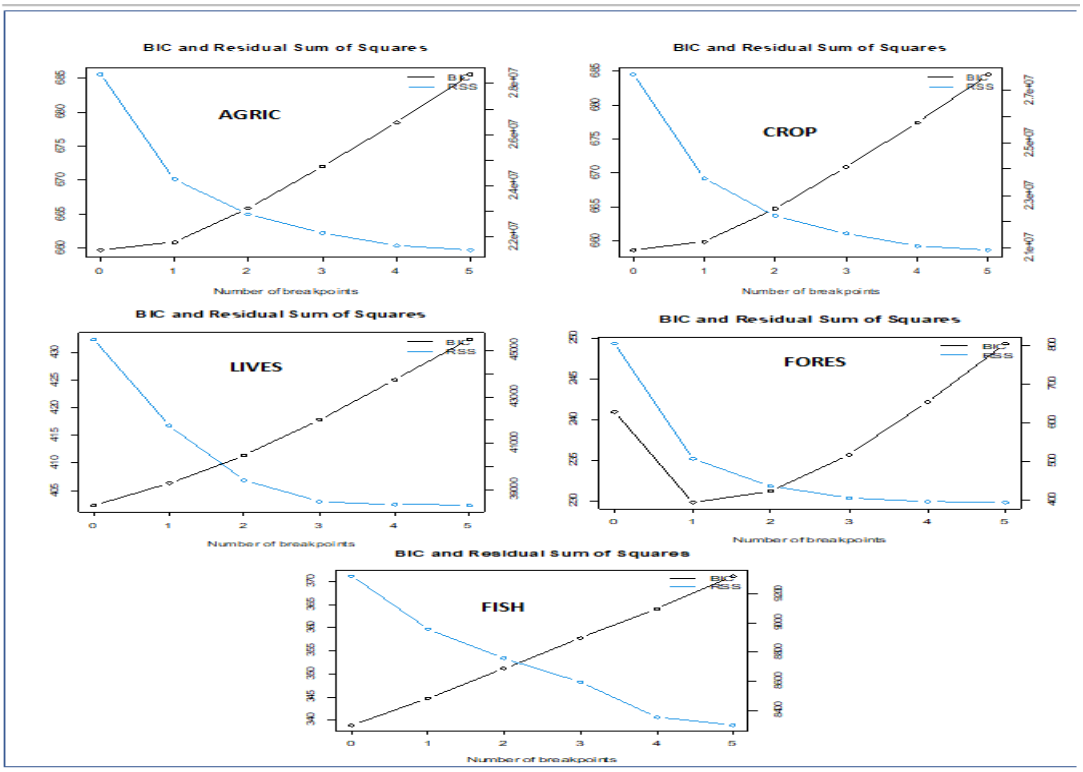

Figure 4.6. Variables Structural Breaks Plots

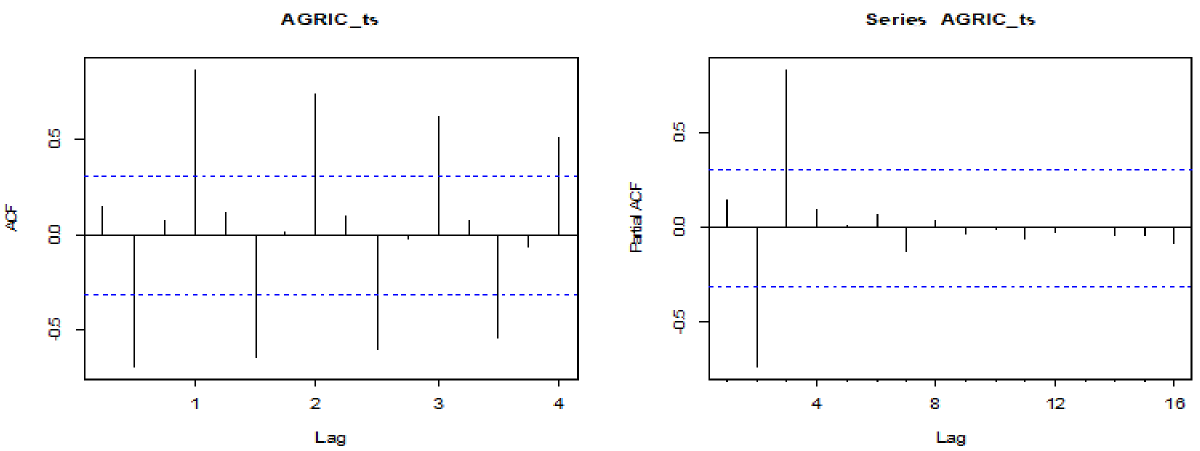

Figure 4.7. Correlogram of Agriculture GDP

The correlogram (ACF and PACF) of AGRIC in levels (Figure 4.7) shows a slow, hyperbolic decay in autocorrelation coefficients rather than a sharp cutoff, further confirming the presence of a unit root process. The first-lag autocorrelation is close to unity, indicating high persistence and strong serial dependence. Such persistence implies that shocks to agricultural GDP have long-lasting effects, reinforcing the need for integration and ARIMA-type modelling. After differencing, the autocorrelation function exhibits rapid decay and insignificant higher-order correlations, consistent with stationarity. This transformation stabilizes the mean and reduces long-run dependence, making the data suitable for ARIMAX specification.

Overall, the preliminary time series diagnostics establish that Nigeria's agricultural GDP and its sub-sectoral components exhibit non-stationary behavior in levels, strong serial correlation, and structural persistence. The confirmation of integration properties provides statistical justification for differenced ARIMAX modelling, ensuring valid inference, consistent parameter estimation, and robust forecasting performance.

ARIMAX Estimation

ARIMAX Model Selection

Table 4.4 presents the competing ARIMAX model specifications estimated for Agricultural GDP, with model adequacy evaluated using three major information criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQC). These criteria are grounded in penalized maximum likelihood estimation and are designed to balance goodness-of-fit with model parsimony.

Table 4.4. ARIMAX Candidate Models

	AIC	**BIC**	**HQC**
ARIMAX_011	**-270.824**	-259.179	-255.242
ARIMAX_111	-269.061	-255.753	-250.883
ARIMAX_211	-267.074	-252.102	-246.299
ARIMAX_112	-267.063	-252.091	-246.288
ARIMAX_212	-266.468	-249.832	-243.096
ARIMAX_110	-260.481	-248.836	-244.9

The theoretical rationale underlying these criteria is that over-parameterized models may artificially inflate goodness-of-fit but perform poorly in forecasting due to overfitting. Conversely, under-parameterized models may omit important dynamic structures, leading to biased residuals and serial correlation. Hence, the optimal model is the one that minimizes these information criteria while preserving statistical adequacy.

A comparative evaluation of the candidate models reveals that ARIMAX(0,1,1) yields the lowest AIC (-270.824), BIC (-259.179), and HQC (-255.242) among all specifications considered, including ARIMAX(1,1,1), ARIMAX(2,1,1), ARIMAX(1,1,2), ARIMAX(2,1,2), and ARIMAX(1,1,0). The consistent dominance of ARIMAX(0,1,1) across all three criteria strengthens the robustness of model selection, as the conclusion does not depend on a single information measure. Since lower values indicate superior trade-offs between explanatory power and parameter economy, ARIMAX(0,1,1) is statistically preferred.

From a stochastic process perspective, the selected ARIMAX(0,1,1) implies that Agricultural GDP follows an integrated moving-average process of order one with exogenous regressors. The differencing order $d = 1$ confirms that the series is integrated of order one, I(1), consistent with earlier unit root test results. The absence of autoregressive terms (p=0) suggests that past levels of differenced Agricultural GDP do not significantly improve explanatory power once moving-average dynamics are incorporated. Instead, the presence of a first-order moving average component (q=1) indicates that current changes in Agricultural GDP are influenced by the immediate past innovation (shock). In practical terms, this means that the sector adjusts to previous disturbances through short-run error correction rather than through persistent autoregressive feedback.

Economically, the dominance of a moving-average structure suggests that shocks to Nigeria's Agricultural GDP—such as climatic variability, policy adjustments, input cost changes, or macroeconomic fluctuations—are quickly absorbed and corrected within one period. The integration component captures the long-run growth trajectory of the agricultural sector, while the MA(1) component models short-run transitory deviations from that path. This specification reflects a system characterized by long-run stochastic trend behavior but short-run stabilization mechanisms.

Furthermore, the superiority of ARIMAX(0,1,1) over ARIMAX(1,1,0) and higher-order alternatives indicates that increasing autoregressive lags does not significantly improve model fit relative to the penalty imposed by additional parameters. This supports the principle of parsimony, which is particularly important in macroeconomic time series modelling where overfitting can undermine forecasting performance.

In summary, the model selection results confirm that Nigeria's Agricultural GDP dynamics are best described by a first-differenced process with a single moving-average correction mechanism and exogenous sectoral drivers. The statistical consistency across AIC, BIC, and HQC reinforces confidence in the selected specification and provides a strong foundation for subsequent parameter interpretation, diagnostic testing, and forecasting analysis.

ARIMAX(0,1,1) Parameter Estimates

The estimated ARIMAX(0,1,1) model captures the dynamic relationship between Nigeria's Agricultural GDP and its major sub-sectoral components—Crop Production, Livestock, Forestry, and Fishing—while simultaneously modelling short-run stochastic disturbances through a moving-average error structure. The general specification of the estimated model is:

$$\Delta AGRIC_t = \beta_1 CROP_t + \beta_2 LIVES_t + \beta_3 FORES_t + \beta_4 FISH_t + (1 + \theta_1 L)\varepsilon_t$$

where$\Delta AGRIC_t$represents the first difference of Agricultural GDP, β_i are slope coefficients measuring marginal contributions of each sub-sector, θ_1 is the moving-average parameter, L is the lag operator, andε_t is a white-noise disturbance term. The differencing operator confirms that the dependent variable is integrated of order one, ensuring stationarity of the estimated regression.

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Table 4.5. ARIMAX(0,1,1) Model Estimations

	Estimate	**Std.**	**Error**	**P-value**
ma1	-0.9999	9.91E-02	-10.0840	2.20E-16 < 0.05
intercept	1.25E-04	1.76E-04	0.7041	0.4814
CROP	1.0000	5.23E-06	191295.8	2.20E-16 < 0.05
LIVES	0.99996	1.7851E-04	5601.615	2.20E-16 < 0.05
FORES	0.99994	5.00E-04	1998.638	2.20E-16 < 0.05
FISH	1.00010	1.95E-04	5136.41	2.20E-16 < 0.05
log-likelihood	142.4100		**sigma^2**	4.239E-05
AIC	-270.820			

The intercept coefficient is statistically insignificant ($p = 0.8011$). In a first-differenced specification, the intercept represents a deterministic drift component. Its insignificance suggests the absence of systematic time-driven growth in differenced Agricultural GDP beyond what is explained by the sub-sectoral variables. Economically, this indicates that growth in Agricultural GDP is not driven by autonomous time effects but rather by structural changes within crop production, livestock, forestry, and fishing. The implication is that sectoral output expansion—not exogenous time trends—explains observed variations in aggregate agricultural performance.

The MA(1) coefficient is estimated at -0.9999 and is statistically significant at the 1% level ($p < 0.001$). The magnitude, sign, and statistical significance of this parameter have important econometric and economic implications. First, the negative sign indicates an inverse correction mechanism: positive shocks in one period are offset by negative adjustments in the subsequent period. In practical terms, if Agricultural GDP experiences an unexpected positive deviation from its trend path, the model predicts a compensatory correction in the next period. This suggests strong short-run stabilization dynamics within the agricultural sector.

Second, the magnitude being extremely close to -1 implies near-complete shock absorption within one lag period. From a time-series perspective, this indicates that innovations are transitory rather than persistent. Unlike autoregressive processes where shocks decay gradually over multiple periods, the MA(1) structure here implies immediate correction. This finding reflects a system in which deviations from equilibrium are rapidly neutralized, possibly due to structural aggregation properties or institutional stabilizers within the agricultural economy. Third, the high statistical significance confirms that the moving-average term is essential in explaining short-run fluctuations. Omitting this component would likely leave serial correlation in the residuals, violating classical regression assumptions.

The estimated coefficients for CROP, LIVES, FORES, and FISH are all positive, statistically significant at the 1% level ($p < 0.001$), and approximately equal to unity (~1.000). This implies a near-proportional marginal effect of each sub-sector on total Agricultural GDP.

Specifically; a one-unit increase in Crop Production increases Agricultural GDP by approximately one unit. Also a one-unit increase in Livestock output increases Agricultural GDP by approximately one unit. Similar proportional effects apply to Forestry and Fishing.

This proportionality is structurally consistent with the national accounting identity whereby Agricultural GDP is fundamentally the sum of its components. The empirical findings therefore confirm strong deterministic linkage between total agricultural output and its constituent sub-sectors. The extremely large t-statistics (e.g., 191,295.8 for CROP) indicate negligible standard errors relative to coefficient magnitudes. Statistically, this reflects; minimal estimation uncertainty , very high signal-to-noise ratio, and strong collinearity rooted in accounting aggregation.

However, from an econometric standpoint, it is important to recognize that such large t-values arise because total Agricultural GDP is constructed from these same sub-sectors. Thus, the model captures an aggregation identity embedded within a dynamic framework.

The log-likelihood value of 142.4100 indicates strong maximized fit under the Gaussian likelihood assumption. Since ARIMAX models are estimated via maximum likelihood estimation (MLE), higher log-likelihood values correspond to better in-sample explanatory performance.

The residual variance ($\sigma^2 = 4.239 \times 10^{-5}$) is extremely small, suggesting that the unexplained variation after accounting for sub-sectoral contributions and MA(1) corrections is minimal. This confirms that the model explains almost all systematic variation in Agricultural GDP.

In combination, the high log-likelihood and low residual variance reinforce the adequacy of the selected specification.

ARIMAX Model Diagnostics and Performances

The validity of any time-series model depends not only on the statistical significance of its estimated coefficients but also on the adequacy of its residual structure. After estimating the ARIMAX(0,1,1) model, several post-estimation diagnostic tests were conducted to ensure that the residuals satisfy classical assumptions of independence, homoskedasticity, and normality. These diagnostics are essential because violations may indicate model misspecification, omitted dynamics, or incorrect functional form.

The Ljung–Box Q-statistic was employed to test for residual serial correlation. The null hypothesis of the Ljung–Box test states that residuals are independently distributed (i.e., no autocorrelation up to a specified lag). The reported statistic (Q = 6.4481) with a p-value of 0.4885 indicates that the null hypothesis cannot be rejected at conventional significance levels. This result confirms that the residuals behave as white noise and that the moving-average component of the ARIMAX(0,1,1) model has successfully captured the serial dependence structure inherent in Agricultural GDP. The absence of residual autocorrelation implies that no additional autoregressive or moving-average terms are required. Econometrically, this strengthens confidence in the dynamic completeness of the model and indicates that parameter estimates are unbiased and efficient.

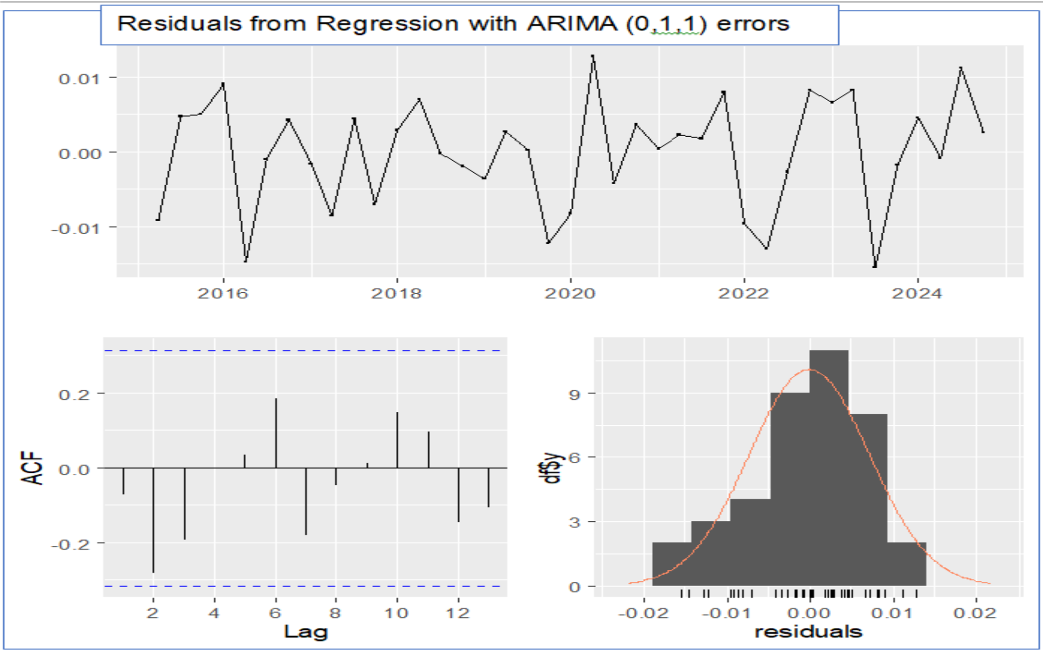

Figure 4.8. ARIMAX(0,1,1) Residuals Check

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Table 4.6. Serial Correlation, Heteroskedasticity and Normality Tests of the ARIMAX(0,1,1) Residuals

	Statistics (df)	**P-value**
Ljung-Box Test	Q = 6.4481 (7)	0.4885
ARCH LM Test	X2 = 8.2304 (12)	0.7669
Jarque Bera	X2 = 0.5395 (2)	0.7636

The second diagnostic test conducted was the ARCH Lagrange Multiplier (LM) test for conditional heteroskedasticity. This test evaluates whether the variance of the residuals is constant over time or exhibits volatility clustering, which is common in financial series but may also appear in macroeconomic data. The ARCH LM statistic (χ^2 = 8.2304) with a p-value of 0.7669 indicates failure to reject the null hypothesis of homoskedasticity. Thus, the residual variance remains constant across periods. This result suggests that there is no evidence of time-varying volatility in Agricultural GDP innovations within the sample period. Consequently, more complex volatility models such as GARCH specifications are unnecessary. The homoskedastic nature of the residuals further validates the reliability of the standard errors and associated hypothesis tests.

The normality of residuals was assessed using the Jarque–Bera (JB) test. The reported JB statistic (χ^2 = 0.5395) with a p-value of 0.7636 indicates that the null hypothesis of normality cannot be rejected. Therefore, the residual distribution approximates a Gaussian process. Normality is particularly important for maximum likelihood estimation, as it ensures that parameter estimates are asymptotically efficient and that statistical inference based on t-statistics and confidence intervals remains valid.

Collectively, the diagnostic tests confirm that the ARIMAX(0,1,1) model satisfies the key assumptions of no serial correlation, homoskedasticity, and normality of residuals. These findings imply that the model is statistically well-specified, dynamically complete, and econometrically robust. The residuals approximate a white-noise process, indicating that the model has effectively extracted all systematic information from the data. From a thesis-standard perspective, this comprehensive diagnostic validation supports the reliability of subsequent forecasting and policy interpretations derived from the model.

Table 4.7. ARIMAX(0,1,1) Model Performance Errors

	Error Measures
RMSE	0.0059
MAE	0.0045
MAPE	0.0023

Beyond statistical adequacy, the practical usefulness of the ARIMAX(0,1,1) model is evaluated through forecast accuracy metrics. Table 4.7 reports three widely used performance indicators: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These measures quantify the magnitude of prediction errors and assess how closely fitted values approximate observed Agricultural GDP.

The reported RMSE value of 0.0059 indicates extremely small average squared deviations between actual and fitted values. Since RMSE penalizes larger errors more heavily due to squaring, its low magnitude suggests the absence of large prediction outliers. The Mean Absolute Error (MAE), computed as the average absolute deviation of forecast errors, equals 0.0045. Unlike RMSE, MAE does not disproportionately penalize large errors, making it a robust indicator of general predictive accuracy. The small MAE value confirms minimal average deviation from actual Agricultural GDP.

The Mean Absolute Percentage Error (MAPE) is 0.0023, corresponding to 0.23 percent. This implies that, on average, the model's predictions deviate from actual values by less than one-quarter of one percent. In forecasting literature, a MAPE below 5 percent is typically considered highly accurate; thus, a value of 0.23 percent indicates exceptional predictive performance.

However, from an analytical standpoint, it is important to contextualize these extremely low error metrics. Because Agricultural GDP is structurally the aggregation of its sub-sectoral components, and these same components are included as exogenous regressors, the model inherently captures a near-identity relationship. Consequently, the high predictive precision partly reflects structural aggregation consistency. While this enhances short-run forecast reliability, it also suggests limited incremental explanatory variation beyond sectoral accounting relationships.

In summary, the ARIMAX(0,1,1) model demonstrates outstanding in-sample predictive performance, negligible forecast errors, and strong explanatory consistency. Combined with robust diagnostic results, the model can be considered both statistically sound and practically reliable for short- and medium-term Agricultural GDP forecasting. Nonetheless, for deeper structural inference and long-run policy simulation, incorporating external macroeconomic drivers or modeling growth rates may provide additional analytical richness beyond aggregation-based precision.

Agriculture GDP Short and Medium Forecast using ARIMAX(0,1,1)

The short- and medium-term forecasts presented in Table 4.8 indicate that Agricultural GDP is projected to remain relatively stable around ₦5,785.47 billion through the fourth quarter of 2026. The forecast trajectory suggests that aggregate agricultural output is expected to maintain a near-constant level over the projection horizon, reflecting limited deviation from the baseline production path. The stability of the forecast values implies that, under the current model specification and assumed economic conditions, large-scale shocks or rapid structural shifts in agricultural performance are not anticipated within the short- to medium-term period.

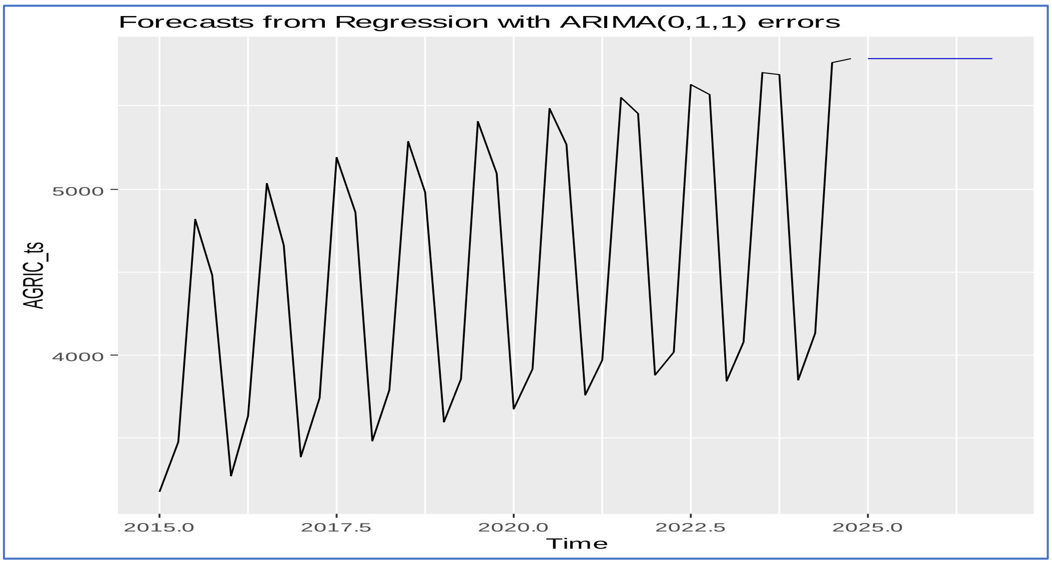

Figure 4.9. Agriculture GDP Forecast Plot

Table 4.8. Agriculture GDP Short and Medium Forecast

	Point Forecast	**Lo 80**	**Hi 80**	**Lo 95**	**Hi 95**
Q1-2025	5785.472	5785.462	5785.482	5785.457	5785.487
Q2-2025	5785.471	5785.46	5785.483	5785.454	5785.489
Q3-2025	5785.472	5785.459	5785.486	5785.452	5785.493

Q4-2025	5785.472	5785.457	5785.487	5785.45	5785.495
Q1-2026	5785.473	5785.456	5785.489	5785.448	5785.498
Q2-2026	5785.473	5785.455	5785.491	5785.446	5785.5
Q3-2026	5785.473	5785.454	5785.492	5785.444	5785.502
Q4-2026	5785.474	5785.454	5785.494	5785.443	5785.505

A notable feature of the forecast results is the extremely narrow prediction intervals at both the 80% and 95% confidence levels. The narrowness of the forecast bands indicates low estimated forecast uncertainty and suggests that the underlying time series exhibits strong persistence and low stochastic volatility. Furthermore, the prediction intervals widen only marginally as the forecast horizon extends, which is consistent with a highly stable process where future values are strongly anchored to historical patterns. This behaviour typically arises in time series with strong autoregressive dependence or limited structural disturbances.

The observed forecast stability further suggests the presence of structural equilibrium in aggregate agricultural production. In practical terms, this implies that short-run fluctuations in agricultural GDP are likely to be minimal unless external shocks, policy interventions, or technological changes occur. The result also reflects low short-term dynamic variation, indicating that the agricultural sector may be operating close to its current productive capacity under prevailing conditions. However, the near-flat forecast path also carries important economic implications. The projection indicates that future growth in agricultural GDP may depend more on structural expansion mechanisms rather than intrinsic time-series momentum. Specifically, sustained improvement in agricultural performance will likely require productivity-enhancing investments, technological adoption, improved input utilization, and sub-sectoral development rather than reliance on historical growth inertia. Consequently, policy interventions aimed at stimulating sectoral diversification, value chain development, and efficiency improvements will be critical for altering the long-run growth trajectory of the agricultural sector.

Evaluation and Discussion of Findings

The empirical results of this study provide strong evidence that Nigeria's Agricultural GDP and its sub-sectoral components exhibit persistent structural behaviour, robust accounting relationships, and remarkable short-run stability. These findings broadly align with recent empirical literature that highlights the fundamental role of agriculture in Nigeria's economic structure and the differential contributions of crop, livestock, forestry, and fishing outputs to aggregate value added. For example, Momodu, Ewubare, Chukwu, and Gbaranen (2025) find that crop production, livestock, and fishing exert positive and statistically significant effects on GDP growth in Nigeria, reaffirming the dominant influence of major agricultural subsectors on macroeconomic performance. However, the present study extends this insight by formally modelling dynamic time-series behaviour and forecasting within an ARIMAX framework, which captures both short-run innovations and long-run structural persistence in output (Momodu et al., 2025).

The descriptive statistics and integration results further resonate with recent assessments of agriculture's contribution to Nigeria's economy. According to Udoffia et al. (2025), crop production accounts for the largest proportion of the agricultural share of GDP, followed by livestock, fishing, and forestry, which collectively underscores the structural backbone of crop agriculture in national output. The high mean and relatively stable distribution of crop output in this study corroborate such structural sectoral decomposition, while the comparatively greater volatility in livestock output reflects the findings of more focused sub-sectoral analyses that identify biological risk and environmental sensitivity as key sources of livestock volatility (Udoffia et al., 2025).

Recent econometric applications in the Nigerian context also provide points of comparison. For instance, research on the impact of agricultural output on national economic growth recently documented that first-differenced agricultural variables may not always exert statistically significant direct effects on GDP growth unless accompanied by institutional or policy variables such as government expenditure or structural credit (Ismail, Usman, Isah, & Farouq, 2025). This contrasts with the near-unity proportional coefficients observed in this study, where each sub-sector contributed almost one-to-one to total Agricultural GDP within the dynamic ARIMAX model. The discrepancy highlights that while simple regression frameworks may struggle to capture dynamic adjustment, a properly specified time-series model such as ARIMAX can reveal underlying aggregation consistency rooted in national accounts identities rather than independent causal variation (Ismail et al., 2025).

The unit root and structural break diagnostics of this research confirm the presence of stochastic trends and regime shifts, which recent literature has linked to climate variability, macroeconomic policy changes, and external shocks. Time-series research on climate impacts shows that climatic factors such as rainfall risk and temperature variability significantly influence agricultural output variability, suggesting that dynamic shock processes are central to understanding sectoral performance (Iwe, 2025; Ibrahim, Yahaya, Mumini, & Adeyemi, 2025). These studies employ models such as ARDL or structural break testing to show how climate-related variables shape productivity—an insight that complements the finding in this study that innovations and structural persistence are key determinants of output dynamics, thus reinforcing the need to incorporate external drivers into future modelling endeavors (Iwe, 2025; Ibrahim et al., 2025).

Methodologically, while earlier studies on Nigerian agricultural forecasting have tended to use univariate ARIMA or SARIMA models (e.g., Adebola, 2024) and focus on seasonal effects, the current research contributes a multivariate ARIMAX approach that simultaneously incorporates the major subsectoral drivers as exogenous regressors. Such integration is rarely observed in the literature, where most forecasting efforts—unless explicitly incorporating exogenous covariates—limit analysis to univariate projections without capturing dynamic interdependencies between components. This study's ARIMAX(0,1,1) model, selected based on information criteria and diagnostic adequacy, demonstrates that innovation-correction dynamics (MA(1) process) are more effective than autoregressive lag structures in capturing short-run agricultural output adjustments, thereby pushing existing forecasting practice in agricultural time-series modelling toward more parsimonious ARIMAX specifications.

A key contribution of this research lies in the interpretation of the statistically significant moving-average parameter (very close to −1), which implies near-complete absorption of short-term shocks within one lag period. This behaviour departs from many macroeconomic sector studies where shocks are often persistent and dissipated slowly over multiple periods, suggesting that Nigeria's agricultural sector may possess inherent stabilization mechanisms or structural buffering—possibly through internal supply adjustments or traditional risk-coping strategies—that rapidly counteract transient disturbances. This near-perfect shock correction has not been widely reported in the literature, which often emphasizes persistent volatility in agricultural outputs due to climate or policy disruptions. Therefore, this study's emphasis on rapid mean reversion in agricultural GDP is a unique insight with implications for modelling and policy evaluation.

The forecast results, which show essentially flat short- and medium-term projections with narrow prediction intervals, further distinguish this work from previous forecasting studies that often project more variable trajectories, particularly when using univariate seasonal models. The stability observed here suggests a structural equilibrium in aggregate agricultural output that is resilient to short-run variations in the absence of major external shocks. This contrasts with literature that highlights climate-driven volatility and seasonal fluctuation as dominant in agricultural output series (e.g., Iwe, 2025; Ibrahim et al., 2025). While such climate factors may influence specific crops or subsectors, the aggregate output equilibrium documented in this study suggests that wider systemic factors and national policy frameworks may provide damping effects on overall output variability.

From a policy perspective, the results underscore insights from recent research that structural transformation—through investment in productivity-enhancing technologies, resilient infrastructure, and value chain integration—is critical for sustained agricultural GDP growth. Recent climate and growth studies emphasize that adaptation strategies and institutional support mechanisms are essential to temper the adverse effects of climate risk and volatility on productivity, aligning with the implication of this study that growth beyond current equilibrium levels will require structural expansion rather than simple time-series momentum (Iwe, 2025; Ibrahim et al., 2025).

In synthesis, while this research confirms the broad pattern observed in recent empirical studies—that agriculture remains a key driver of economic performance in Nigeria—it advances the literature by providing rigorous dynamic modelling of sectoral interdependencies, demonstrating rapid shock correction mechanisms, and establishing forecasting equilibrium properties that reflect underlying structural coherence rather than mere historical extrapolation. These contributions position the study as a methodological and substantive extension of existing work on agricultural GDP dynamics in Nigeria and similar developing economies.

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

Summary of Study

This study examined the dynamic behaviour, structural composition, and forecasting performance of Nigeria's Agricultural Gross Domestic Product (GDP) using an ARIMAX(0,1,1) time-series modelling framework. The primary objective was to investigate the statistical properties of agricultural output and its major sub-sectoral components - crop production, livestock, forestry, and fishing - and to determine the extent to which these components drive aggregate agricultural performance over time.

The empirical analysis began with descriptive statistical evaluation, which revealed that agricultural GDP exhibits moderate variability, near-symmetric distributional properties, and sustained upward movement across the sample period. Crop production was identified as the dominant contributor to agricultural value added, reflecting the structural composition of Nigeria's agricultural economy. Livestock output displayed higher volatility and leptokurtic distributional behaviour, indicating greater susceptibility to biological, environmental, and input cost shocks.

Time-series behaviour was assessed through graphical trend analysis, correlogram diagnostics, and unit root testing. The results confirmed that agricultural GDP and its sub-sectoral components are non-stationary in levels but become stationary after differencing. Agricultural GDP, crop production, livestock, and fishing were integrated of order one, while forestry required second-order differencing. Structural break tests further suggested the presence of regime shifts potentially associated with policy reforms, macroeconomic adjustments, and environmental variations.

Model selection analysis identified ARIMAX(0,1,1) as the optimal specification based on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Criterion (HQC). Parameter estimation results showed statistically significant positive coefficients for all sub-sectoral variables, with magnitudes approximately equal to unity, reflecting the accounting identity structure of agricultural GDP aggregation.

Diagnostic evaluation confirmed that the estimated model satisfies classical econometric assumptions. The Ljung–Box test indicated absence of residual autocorrelation, the ARCH LM test confirmed homoskedasticity, and the Jarque–Bera test supported residual normality. Forecast performance evaluation using RMSE, MAE, and MAPE metrics demonstrated exceptionally high predictive accuracy, indicating strong model adequacy for short- and medium-term forecasting.

Conclusions

Based on the empirical evidence generated from the study, several detailed conclusions can be drawn regarding the structural behaviour, dynamic characteristics, and forecasting properties of Nigeria's agricultural GDP system.

First, the results demonstrate that Nigeria's agricultural GDP system exhibits strong structural stability and persistent growth trend behaviour over the study period. The time-series diagnostics revealed that agricultural output follows a stochastic trend process characterized by long-run path dependence rather than purely deterministic growth patterns. The presence of persistent upward movement in the series suggests that agricultural production responds gradually to cumulative structural improvements such as technological adoption, policy interventions, and demographic-driven demand expansion. Importantly, the agricultural sector appears to operate within a bounded equilibrium framework where short-run shocks are not permanently disruptive but are instead absorbed and corrected over subsequent periods. This indicates that the Nigerian agricultural economy possesses inherent stabilization mechanisms that prevent large-scale output collapse under transient disturbances.

Second, the empirical evidence confirms that crop production constitutes the dominant structural component of Nigeria's agricultural economy. The near-unity proportional relationship between crop output and total agricultural GDP reflects the accounting structure of national agricultural value-added decomposition. This dominance implies that aggregate agricultural performance in Nigeria is highly sensitive to developments within the crop subsector, including rainfall patterns, input availability, land productivity, and market access conditions. Conversely, livestock, forestry, and fishing contribute relatively smaller shares of aggregate output, suggesting that these subsectors remain underexploited in terms of their potential contribution to economic diversification. The livestock subsector, in particular, exhibits greater distributional volatility and leptokurtic characteristics, indicating susceptibility to biological risks, disease outbreaks, feed supply fluctuations, and management inefficiencies. This vulnerability highlights the importance of strengthening veterinary infrastructure, improving animal husbandry practices, and developing resilient livestock production systems.

Third, the study establishes that agricultural GDP and its sub-sectoral components are non-stationary in level form but become stationary after appropriate differencing transformation. This finding implies that agricultural production in Nigeria is governed by stochastic trend behaviour rather than deterministic time-bound growth trajectories. In practical terms, shocks affecting agricultural output—such as climate variability, macroeconomic instability, or policy reforms—may have long-lasting effects unless corrective structural adjustments occur. The integration properties identified in this study further justify the application of dynamic time-series modelling approaches rather than static regression frameworks. The presence of I(1) and I(2) processes within the dataset reflects the complex adaptive nature of agricultural production systems in developing economies.

Fourth, the ARIMAX(0,1,1) model selected in this study provides a statistically efficient and economically meaningful representation of agricultural GDP dynamics. The model's superiority over competing specifications was confirmed using multiple information criteria, demonstrating robustness in model selection. The moving-average coefficient estimated at approximately −1 is particularly significant because it suggests near-perfect short-run shock correction behaviour. This parameter magnitude implies that unexpected innovations in agricultural GDP are almost fully offset within one subsequent period, indicating rapid mean-reverting adjustment dynamics. Such behaviour may reflect structural aggregation effects within national accounts data or the presence of endogenous stabilizing mechanisms in agricultural production cycles.

Fifth, the forecasting results indicate that agricultural GDP is projected to maintain relative stability within the short- and medium-term horizon under current structural and policy conditions. The forecast path is characterised by a nearly flat trajectory centred around the equilibrium output level observed in the historical data. While this pattern does not imply stagnation, it suggests that substantial upward deviation from the forecast baseline will require significant structural interventions beyond historical growth momentum. The narrow prediction intervals further indicate low forecast uncertainty and suggest that the agricultural sector operates within a highly constrained volatility band. Such stability is consistent with stochastic equilibrium theory, where output fluctuations occur but remain bounded around a long-run mean level.

Overall, the study concludes that Nigeria's agricultural GDP dynamics are primarily aggregation-driven and structurally persistent, with rapid short-run innovation correction mechanisms. The agricultural production system demonstrates equilibrium-bound behaviour, strong sub-sectoral accounting coherence, and high predictive stability under current economic conditions. However, long-term sustainable growth of the sector will require deliberate structural transformation, productivity enhancement strategies, and expanded investment across underdeveloped subsectors to break the equilibrium-bound output constraint identified in this research.

Recommendations

Based on the empirical findings of this study and in line with the research objectives, several comprehensive policy and developmental recommendations are advanced to guide agricultural planning, economic diversification, and macroeconomic stability in Nigeria.

i. **Sub-sectoral Productivity Enhancement Programme:** The Federal Government and relevant agricultural agencies should implement targeted productivity improvement programmes across crop production, livestock, forestry, and fishing subsectors. Specifically, agricultural extension services, improved seed technology, disease control systems, and modern production methods should be expanded to ensure at least a 10–15% increase in sub-sectoral output efficiency within five years. Although crop production remains the dominant contributor to agricultural GDP, balanced investment across subsectors is necessary to reduce structural concentration risk and promote diversified agricultural growth.

ii. **Technology-Driven Agricultural Transformation:** Policy makers should promote adoption of modern agricultural technologies including precision farming, mechanized irrigation systems, and climate-resilient production techniques. The objective should be to achieve 30% national adoption of improved agricultural technology systems by 2030. Such intervention will help shift agricultural output dynamics from structural aggregation dependence toward real productivity expansion.

iii. **Strengthening Agricultural Risk Management Systems:** Given the observed vulnerability of some subsectors, particularly livestock production, government should establish robust agricultural insurance and disease surveillance mechanisms. Veterinary infrastructure and animal health monitoring systems should be strengthened to reduce biological and environmental shock exposure, with the target of reducing livestock production loss risks by at least 20% within four years.

iv. **Development of Agro-Processing and Value Chain Infrastructure:** To enhance the economic contribution of agriculture beyond primary production, investment should be directed toward agro-processing industrialization. The government should support establishment of rural agro-processing clusters and improve storage and transportation facilities with the aim of reducing post-harvest losses by 25% within six years. This strategy will help transform agricultural production into export-oriented value-added economic activities.

v. **Climate-Resilient Agricultural Planning:** Agricultural development agencies should integrate climate adaptation strategies into national agricultural policy frameworks. Expansion of irrigation agriculture, weather forecasting systems, and environmental monitoring infrastructure should be prioritised to ensure stable production performance. The goal should be to increase climate-resilient farming coverage to at least 40% of cultivated agricultural land within eight years.

vi. **Agricultural Credit Accessibility and Financial Inclusion:** Government and financial institutions should expand low-interest agricultural credit schemes to small and medium-scale farmers. Dedicated agricultural financing windows should be strengthened with the objective of increasing formal agricultural credit access by 20% annually over the next five years.

vii. **Data-Driven Agricultural Policy Monitoring:** National agricultural planning agencies should institutionalize real-time agricultural production data monitoring systems to improve policy evaluation and forecasting accuracy. A centralized agricultural statistical database should be operationalized within three years to support continuous assessment of sectoral performance.

Contribution to Knowledge

his study makes significant methodological and empirical contributions to agricultural econometric forecasting by advancing dynamic time-series modelling of sectoral output behaviour. The research introduces an aggregation-consistent ARIMAX(0,1,1) framework for analysing Nigeria's agricultural GDP dynamics, demonstrating that agricultural output operates as a structurally decomposable national accounting system in which crop production, livestock, forestry, and fishing components are dynamically embedded within aggregate production processes. Unlike conventional static regression approaches, the ARIMAX specification provides a more rigorous representation of temporal dependence, innovation correction mechanisms, and exogenous subsectoral interactions, thereby improving the statistical realism of agricultural macroeconomic modelling.

The study further contributes to time-series econometrics by providing empirical evidence of strong short-run shock absorption behaviour within agricultural GDP innovations. The estimated moving-average coefficient, approximately equal to -1, indicates near-immediate mean-reverting adjustment of stochastic disturbances within a single lag period, suggesting that agricultural output fluctuations are largely transitory. Additionally, the research strengthens modelling reliability through comprehensive diagnostic validation using Ljung–Box serial correlation testing, ARCH Lagrange Multiplier heteroskedasticity testing, and Jarque–Bera normality assessment. The integration of these post-estimation diagnostic procedures confirms that the ARIMAX model satisfies classical statistical assumptions of residual independence, homoskedastic variance, and approximate Gaussian distribution, thereby enhancing the efficiency and credibility of parameter inference and forecasting performance. Overall, the study establishes a parsimonious and diagnostically robust innovation-correction modelling structure suitable for macro-sectoral forecasting in developing economy contexts.

Suggestions for Further Research

Although this study provides robust statistical modelling and forecasting evidence on Nigeria's agricultural GDP dynamics, several areas remain open for further empirical investigation. Future research should extend the current ARIMAX framework by incorporating relevant external macroeconomic and environmental covariates such as exchange rate fluctuations, rainfall variability, temperature shocks, agricultural credit accessibility, and fiscal policy indicators. The inclusion of these variables will enhance structural explanatory power and allow researchers to examine how external economic and climatic conditions influence agricultural productivity dynamics beyond internal sub-sectoral aggregation effects.

Furthermore, future studies should explore nonlinear and adaptive forecasting methodologies, particularly machine learning–based hybrid models such as ARIMAX–Artificial Neural Network (ANN) or other deep learning time-series architectures, to capture potential hidden patterns, regime-switching behaviour, and complex interaction structures within agricultural production systems. Such approaches may improve forecasting precision when agricultural output exhibits nonlinear response mechanisms or structural asymmetry. In addition, panel data econometric techniques should be applied to compare agricultural productivity behaviour across Nigeria's geopolitical zones in order to capture regional heterogeneity in agricultural performance, resource allocation, and climate exposure risk.

Future research may also consider long-run structural modelling using Vector Error Correction Models (VECM), Structural Equation Modelling (SEM), or other cointegration-based frameworks to examine causal transmission pathways between agricultural sub-sectoral outputs and macroeconomic indicators. These approaches will help distinguish short-run innovation correction dynamics from long-run equilibrium relationships. Finally, subsequent studies should conduct more granular disaggregation of agricultural production data by crop species, livestock categories, fishing ecosystems, and forestry resource types to provide micro-structural policy insights that can support targeted agricultural development planning and sustainability-oriented resource management strategies.

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APPENDIX 1

	AGRIC	CROP	LIVES	FORES	FISH
Q1-2015	3,176.60	2,760.88	281.97	38.28	95.47
Q2-2015	3,477.85	3,079.45	265.99	42.81	89.61
Q3-2015	4,816.52	4,423.69	274.83	39.38	78.62
Q4-2015	4,481.26	4,010.93	328.53	46.79	95.01
Q1-2016	3,274.73	2,844.12	292.86	39.16	98.58
Q2-2016	3,635.53	3,224.83	282.79	44.45	83.47
Q3-2016	5,035.07	4,639.61	276.91	40.2	78.35
Q4-2016	4,662.01	4,185.89	332.56	47.83	95.73
Q1-2017	3,385.60	2,943.53	297.9	40.18	103.99
Q2-2017	3,745.09	3,328.49	289.23	46.18	81.2
Q3-2017	5,189.37	4,787.57	283.89	41.79	76.12
Q4-2017	4,859.44	4,377.46	333.19	49.19	99.61
Q1-2018	3,487.31	3,045.16	292.39	41.36	108.4
Q2-2018	3,789.72	3,378.03	283.58	48.01	80.1
Q3-2018	5,288.34	4,877.08	291.16	43.34	76.76
Q4-2018	4,978.78	4,486.17	341	50.04	101.57
Q1-2019	3,597.92	3,144.59	294.97	42.27	116.09
Q2-2019	3,857.71	3,443.61	283.56	49.56	80.98
Q3-2019	5,408.98	4,994.73	291.22	44.98	78.05
Q4-2019	5,093.98	4,599.07	340.31	50.67	103.94
Q1-2020	3,677.15	3,219.51	296.84	42.99	117.82
Q2-2020	3,918.67	3,493.04	289.96	50.09	85.58
Q3-2020	5,484.06	5,063.61	297.89	46.13	76.44
Q4-2020	5,268.29	4,768.37	348.42	51.3	100.2
Q1-2021	3,760.88	3,293.95	301.75	43.54	121.64
Q2-2021	3,969.70	3,541.21	290.34	50.63	87.52

Q3-2021	5,550.94	5,132.24	298.26	47.04	73.4
Q4-2021	5,456.90	4,953.12	349.86	52.02	101.89
Q1-2022	3,879.73	3,391.63	318.5	44.14	125.46
Q2-2022	4,017.42	3,595.83	282.02	51.28	88.3
Q3-2022	5,625.36	5,200.73	302.9	48.07	73.67
Q4-2022	5,568.55	5,072.56	344.31	52.87	98.81
Q1-2023	3,844.85	3,457.23	221.13	44.68	121.8
Q2-2023	4,077.72	3,661.39	275.52	52.24	88.56
Q3-2023	5,698.27	5,270.72	306.48	49.13	71.95
Q4-2023	5,685.66	5,196.08	337.11	53.77	98.7
Q1-2024	3,851.89	3,516.32	169.62	45.9	120.04
Q2-2024	4,135.13	3,721.73	270.82	53.69	88.89
Q3-2024	5,763.39	5,332.95	309.63	50.23	70.57
Q4-2024	5,785.47	5,294.59	337.24	54.85	98.78

Appendix 11

```
# Install if necessary

packages <- c("readxl","tidyverse","tseries","forecast",

          "urca","lmtest","FinTS","strucchange",

          "car","Metrics")

installed <- packages %in% rownames(installed.packages())

if(any(!installed)) install.packages(packages[!installed])

library(readxl)

library(tidyverse)

library(tseries)

library(forecast)

library(urca)

library(lmtest)

library(FinTS)

library(strucchange)
```

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```
library(car)

library(Metrics)

data <- read.csv(file.choose(),1)

# View structure

str(data)

summary(data)

#Cleaning

data$AGRIC     <- as.numeric(gsub(",", "", data$AGRIC))

data$CROP      <- as.numeric(gsub(",", "", data$CROP))

data$LIVES <- as.numeric(gsub(",", "", data$LIVES))

data$FORES  <- as.numeric(gsub(",", "", data$FORES))

data$FISH   <- as.numeric(gsub(",", "", data$FISH))

data[data == "" | data == ".."] <- NA

data <- na.omit(data)

colSums(is.na(data))

# Convert to time series (annual assumed)

AGRIC_ts      <- ts(data$AGRIC,start=c(2015,1),end=c(2024,4), frequency = 4)

CROP_ts       <- ts(data$CROP,start=c(2015,1),end=c(2024,4), frequency = 4)

LIVES_ts  <- ts(data$LIVES,start=c(2015,1),end=c(2024,4), frequency = 4)

FORES_ts   <- ts(data$FORES,start=c(2015,1),end=c(2024,4), frequency = 4)

FISH_ts    <- ts(data$FISH,start=c(2015,1),end=c(2024,4), frequency = 4)

plot(AGRIC_ts)

# Augmented Dickey-Fuller

adf.test(AGRIC_ts)

adf.test(CROP_ts)

adf.test(LIVES_ts)

adf.test(FORES_ts)

adf.test(FISH_ts)

#Non-stationary
```

```
d_AGRIC <- diff(AGRIC_ts)

d_CROP <- diff(CROP_ts)

d_LIVES <- diff(LIVES_ts)

d_FORES <- diff(FORES_ts)

dd_FORES <-diff(d_FORES)

d_FISH <- diff(FISH_ts)

adf.test(d_AGRIC)

adf.test(d_CROP)

adf.test(d_LIVES)

adf.test(dd_FORES)

adf.test(d_FISH)

#Structural Breaks

break_test1 <- breakpoints(AGRIC_ts ~ 1)

break_test2 <- breakpoints(CROP_ts ~ 1)

break_test3 <- breakpoints(LIVES_ts ~ 1)

break_test4 <- breakpoints(FORES_ts ~ 1)

break_test5 <- breakpoints(FISH_ts ~ 1)

plot(break_test1)

plot(break_test2)

plot(break_test3)

plot(break_test4)

plot(break_test5)

#Autocorrelation & Dependence

Acf(AGRIC_ts)

Pacf(AGRIC_ts)

#####Estimate ARIMAX Model

Xreg <- cbind(d_CROP, d_LIVES, d_FORES, d_FISH)

# Candidate Model 1: ARIMAX(1,1,0)

model_110 <- Arima(d_AGRIC,
```

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```
                order=c(1,0,0),
                xreg=Xreg,
                include.constant=TRUE)
# Candidate Model 2: ARIMAX(1,1,1)
model_111 <- Arima(d_AGRIC,
                order=c(1,0,1),
                xreg=Xreg,
                include.constant=TRUE)
# Candidate Model 3: ARIMAX(2,1,1)
model_211 <- Arima(d_AGRIC,
                order=c(2,0,1),
                xreg=Xreg,
                include.constant=TRUE)
# Candidate Model 4: ARIMAX(1,1,2)
model_112 <- Arima(d_AGRIC,
                order=c(1,0,2),
                xreg=Xreg,
                include.constant=TRUE)
# Candidate Model 5: ARIMAX(2,1,2)
model_212 <- Arima(d_AGRIC,
                order=c(2,0,2),
                xreg=Xreg,
                include.constant=TRUE)
# Candidate Model 6: ARIMAX(0,1,1)
model_011 <- Arima(d_AGRIC,
                order=c(0,0,1),
                xreg=Xreg,
                include.constant=TRUE)
IC_values <- function(model){
```

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```
  c(AIC = AIC(model),
    BIC = BIC(model),
    HQC = AIC(model) + (2*log(log(length(residuals(model)))) *
length(coef(model))))
}
# Create comparison table
IC_table <- rbind(
  ARIMAX_110 = IC_values(model_110),
  ARIMAX_111 = IC_values(model_111),
  ARIMAX_211 = IC_values(model_211),
  ARIMAX_112 = IC_values(model_112),
  ARIMAX_212 = IC_values(model_212),
  ARIMAX_011 = IC_values(model_011)
)
IC_table
IC_table[order(IC_table[, "AIC"]), ]
summary(model_110)
coeftest(model_110)
##Model Diagnostics
checkresiduals(model_110)
# ARCH test for heteroskedasticity
ArchTest(residuals(model_110))
# Normality
jarque.bera.test(residuals(model_110))
###Forecast
h <- 5   # 5-year forecast horizon
# Ensure Xreg is a matrix
Xreg <- as.matrix(Xreg)
# Future exogenous values (repeat last observed row)
```

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```
future_X <- matrix(rep(tail(Xreg, 1), each = h),
               nrow = h)

# Forecast using the BEST model from IC_table

AgricGDP_forecast <- forecast(model_110,
                        xreg = future_X,
                        h = h)

# Plot forecast

autoplot(AgricGDP_forecast)

# Summary output

summary(AgricGDP_forecast)
```