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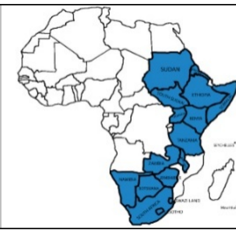

Contribution of Agriculture Sub-Sectors to Gross Domestic Product in Tanzania Mainland 1993 – 2022

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KEYWORDS

Vector Error Correction - Agricultural Subsectors - Gross Domestic Product (GDP) and Forecasts.

ABSTRACT

The primary objective of this study was to assess the contribution of agricultural subsectors on Tanzania mainland GDP, highlighting their crucial role in fostering economic growth and development. This analysis utilized annual time series data from the National Bureau of Statistics, covering the period from 1993 to 2022.Augmented Dicker-Fuller and Zivot-Andrews approach to detect structural breaks and test for stationarity.

The long- and short-run relationships between GDP and the agriculture subsectors were examined in the study using the Vector Error Correction Model. The coefficient of ECT indicates that the rate of adjustment of GDP to its long-run equilibrium is 6.8% annually. Short-run parameters of lagged variables were not very informative. The effects of agriculture sub-sectors on gross domestic product (GDP) reveals that crop and fishery positively impacting GDP, while livestock and forestry had a negative insignificant impact. The study concluded there's significant long-run relationships between GDP and the agricultural sub-sectors. Forecasts indicate positive growth trends for both GDP and the individual agricultural sub-sectors. The study recommends a vertically integrated policy approach to balance out the disparities among the sub-sectors.

1. Introduction

Agriculture is fundamental to the economies of least developed countries (LDCs), where it plays a critical role in driving economic growth, employment, and environmental sustainability (FAO, 2014). In these regions, agriculture contributes between 30 and 60 percent to the GDP, provides substantial foreign exchange, and employs 40 to 90 percent of the population. This sector's importance is highlighted by its role in economic diversification and structural transformation, especially in developing nations. Historical evidence supports the view that agricultural revolutions have been pivotal in promoting economic growth (Danso-Abbeam, Ehiakpor, & Aidoo, 2018).

Globally, agriculture employs approximately 884 million people, representing 27 percent of the global workforce, and has contributed 4 percent to the world’s GDP since 2020. In many LDCs, the sector accounts for over 25 percent of GDP. Between 2000 and 2018, agricultural value-added increased by 68 percent, reaching USD 3.4 trillion. Africa heavily relies on agriculture, with 70 percent of its workforce engaged in the sector, supporting 90 percent of the population's livelihood, and contributing around 25 percent to the continent’s GDP.

In Tanzania, agriculture is the largest sector of the economy, contributing about 30 percent of GDP, 25 percent of export earnings, and supplying over half of the raw materials for industries. About 70 percent of Tanzania's population lives in rural areas, relying heavily on agriculture for their livelihoods. However, the sector's contribution to GDP has been declining, falling from 28.8 percent in 2017 to 26.6 percent in 2019. The growth of Tanzania's agricultural GDP has also slowed, with a drop from 4.9 percent in 2021 to 4.7% in 2022, largely due to rising production costs linked to global factors such as the Ukraine conflict and the adverse impacts of climate change (URT, 2023; National Bureau of Statistics, 2015-2021).

Tanzania’s agriculture faces several challenges despite its significant contribution to the economy. The government’s Agricultural Sector Development Program (ASDP), implemented in phases (2006-2013 and 2018-2025), aims to modernize the sector by improving irrigation, increasing investments, and encouraging the use of modern farming techniques. Despite these efforts, most farming in Tanzania remains small-scale and heavily rain-dependent, leaving it vulnerable to climatic shifts.

Crop production dominates Tanzanian agriculture, occupying 85% of cultivated land (Tiernan, & Nelson, 2012). Other sub-sectors, including livestock, forestry, and fishing, also contribute to the economy, though their impact on GDP has been inconsistent. Understanding the historical contributions of these sub-sectors is essential for effective policy formulation that can foster future growth. This research focuses on assessing how these agricultural sub-sectors have contributed to Tanzania Mainland's GDP, with specific objectives to evaluate their relationship with GDP, analyze their economic impact, and forecast their performance for 2023-2027.

The research serves as a vital tool for various stakeholders. For scholars and students in agricultural economics, it offers valuable insights into the sub-sectors that drive economic growth, encouraging further research. For farmers, it highlights the areas with the greatest potential for economic contribution, helping them prioritize their activities. Policymakers can also use this research to design effective strategies for ensuring the sustainable development of the agriculture sector, addressing present and future challenges.

International studies have also explored the link between agriculture and economic growth in other countries. For instance, Nyamekye et al. (2021) analyzed the relationship between Ghana's agricultural output and overall GDP growth from 1984 to 2018. Their findings revealed both short- and long-term connections between agricultural value-added and GDP growth, emphasizing the importance of agricultural export strategies. Similarly, in The Gambia, Jobarteh and Selemani (2020) examined agricultural sub-sectors' impact on economic growth between 2004 and 2016, revealing that while forestry and livestock positively influenced short-term economic growth, crops and fisheries had a long-term impact.

In Tanzania, several studies have focused on the relationship between agricultural sub-sectors and GDP. Mtaturu (2020) analyzed the contributions of Tanzania's agriculture, livestock, and fishing sub-sectors to economic growth from 1971 to 2013, using secondary data. His results showed that all sub-sectors positively contributed to economic growth. Similarly, Chongela (2015) examined the broader impact of Tanzania's agriculture sector on the economy from 1981 to 2010, finding that agriculture contributed 26 percent to the national GDP, with the agriculture sub-sector accounting for 18.9 percent.

Other studies, such as the UNSD and FAO (2019) publication on global trends in GDP and agriculture value-added, have explored the broader context. This study revealed that between 1970 and 2017, global GDP quadrupled, while agriculture’s share grew by just over threefold, reflecting slower growth compared to other sectors. Interestingly, developing countries, including Tanzania, showed the highest growth during this period.

Further analysis of Tanzania’s agricultural sub-sectors is necessary to fully understand their contributions to GDP over time and to forecast their future performance. Historical trends between 1993 and 2022 must be examined, with projections for 2023-2027 providing a foundation for future agricultural policy development. Understanding the varying contributions of sub-sectors like livestock, crops, forestry, and fisheries will offer valuable insights into optimizing agricultural outputs and resource allocation.

Addressing these research gaps will help policymakers craft informed strategies that can sustain agricultural growth and economic development in Tanzania.

The study highlights the relationships within variables. It treated the forestry, livestock, fishery, and crop sub-sectors as explanatory variables, while GDP was considered the predicted variable (Table 1).

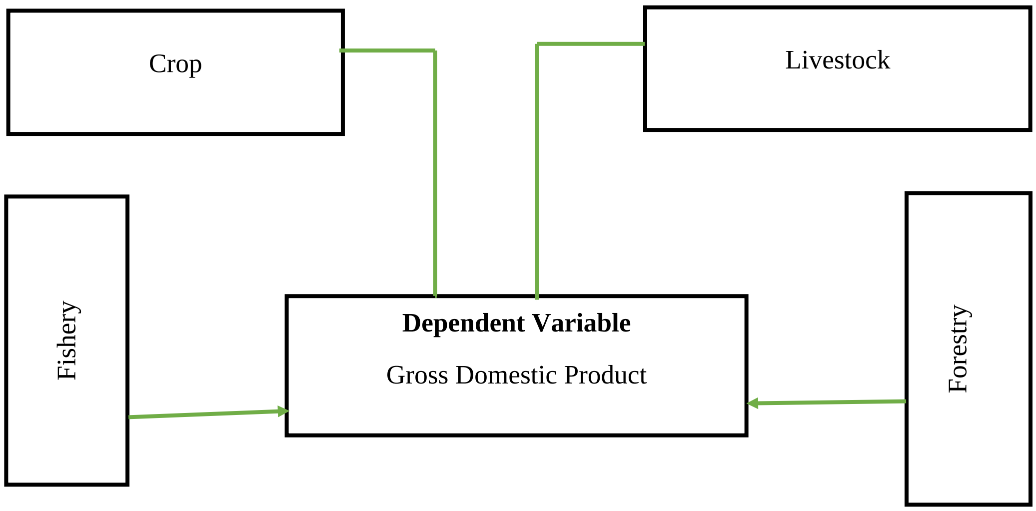

Figure 1: Conceptual framework

Source: Researchers construction from literature review

3. Methodology

The study analyzed annual time series data on real GDP and the gross value added by agriculture, livestock, forestry, and fishery sub-sectors in Tanzania from 1993 to 2022, utilizing 30 observations for each variable obtained from the Tanzania National Bureau of Statistics. Quantitative methods were employed to examine these observations over the specified period.

3.2 Variable Description and Measurement Scale

Table 1: Variable Description

Type of variable	Variable Name	Scale	Measurement
Dependent Variable	GDP	Ratio	Million TZS
	Crop	Ratio	Million TZS
	Livestock	Ratio	Million TZS
	Fisheries	Ratio	Million TZS
	Forestry	Ratio	Million TZS

Source: Researcher's construction

3.3 Model Specification

The regression equations of the VECM is represented as follows:

$$\Delta\, GDP_t = \beta_0 + \beta_{01j}\,\varepsilon_i + \sum_{t-1}^{\rho}\beta_1\,\Delta Cro_{t\text{-}1} + \sum_{t-1}^{\rho}\beta_2\ \Delta Liv_{t\text{-}1} + \sum_{t-1}^{\rho}\beta_3\,\Delta For_{t-1} + \sum_{t\text{-}1}^{\rho}\beta_4\,\Delta Fish_{t\text{-}1} + \varepsilon_t \ \ldots\ldots$$

…………………………………………………………………………………. (0.1)

Where

P Represent the maximum number of lags,

β_0 & β_{01} Represent intercept of the VECM

β_1, β_2, β_3 *and* β_4 Represent the variable coefficients of and

ε_t Represent random error.

The VECM model's error correction term (ECT) indicates how quickly the system is adjusting to the long-run equilibrium relationship. A negative and significant coefficient of ECT suggests that the independent and dependent variables are causally related over the long term. Additionally, it implies that any transient variations in the independent and dependent variables resulted in long-term, stable correlations between them.

3.4 Zivot-Andrews Structural Break Trended Unit Root Tests

The Zivot-Andrews (ZA) approach is a statistical method for identifying structural breaks in time series data, particularly useful when changes in the data-generating process are suspected. It builds on the Augmented Dickey-Fuller (ADF) test for unit roots. In the context of analyzing lnGDP, which was found to be non-stationary at both the level and first difference, the ZA method was employed to investigate this non-stationarity further. The ZA technique estimates potential breakpoints in the time series and tests for stationarity within different segments, allowing for varying trends or means before and after the breakpoints. The study aimed to check for unit roots, evaluate whether a model with structural breaks better fits the data than one without, and confirm the existence of structural breaks using the ZA method.

3.5 Optimal lag Selection

Selecting the appropriate lag length is essential in time series analysis to determine the optimal number of lagged values to include in a regression model. This involves using criteria like the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hanna-Quinn Information Criterion (HQIC), with the lag length having the lowest AIC value deemed the best fit for improving model performance.

The study applied the optimal lag selection criterion to effectively identify suitable lag lengths for capturing dynamic relationships with the independent variables.

3.6 Johansen Cointegration Test

The study used Johansen's approach to examine the cointegration between crop, livestock, forestry, fishery sectors, and GDP, but found no cointegration among these variables. To account for potential structural changes over time, the Gregory-Hansen Structural Break Cointegration Test was applied. This test is more robust than traditional methods in detecting cointegration in the presence of structural breaks, ensuring more accurate results. Ignoring such breaks can lead to biased estimates and incorrect conclusions, as noted by Gregory & Hansen, B. E. (1996).

3.7 Vector Error Correction Model (VECM)

The study utilized the Vector Error Correction Model (VECM) to examine the long-run and short-run dynamics between dependent and independent variables, assessing how the independent variables influenced the dependent variable. To evaluate the overall goodness of fit of the VECM models, the study diagnosed the residuals using tests for autocorrelation, R-squared, homoscedasticity (White test), and normality (Jarque-Bera test), employing the Breusch-Godfrey test and the Breusch-Pagan Lagrange Multiplier test.

3.8 Forecasting Techniques

Forecasting methods utilize analytical tools and historical data to predict future trends. In this context, multivariate forecasts are created using cointegrating Vector Error Correction Models (VECMs), which show that forecast errors can increase as the forecast horizon extends. The process of forecasting with VECMs includes several key steps: testing for stationarity and cointegration among variables, conducting diagnostic checks for serial correlation, heteroscedasticity, and model stability, specifying and estimating the model, and finally generating forecasts. Specifically, forecasts are made for first-differenced variables using these co-integrated VECMs.

4. Results and Discussion of the Findings

4.1 Descriptive statistics

The findings present descriptive statistics for five variables, namely; GDP, Crop, livestock, forestry subsectors and fishery. The statistics comprised mean, minimum, maximum values and standard deviation values of the variables.

According to the results, Agriculture subsectors namely Crop, Livestock, Forestry and Fishery contributed to the GDP on an average of 6,772,675 TZS; 3,553,395 TZS; 1,373,476 TZS and 917,865 TZS respectively. For GDP, the highest value was 133,600,000 TZS, for Crop it was 18,295,700 TZS, and for Livestock, it was 10,054,947 TZS for Forestry it was 3,857,006 TZS and for Fishery was 2,503,624 TZS. These values represented the upper range of the data. The minimum value for GDP was 28,425,501 TZS, for Crop it was 432,524 TZS, for Livestock was 105,447 TZS for Forestry was 53,039 TZS and for Fishery it was 35,360 TZS. These values represented the lower range of the data.

Table 2 Summary of Descriptive Statistics in Million TZS

Variable	Observation	Mean	Std. Dev.	Min	Max
GDP	30	67,872,954	33,868,429	28,425,501	133,600,000
Crop	30	6,772,675	6,435,753	432,524	18,295,700
Livestock	30	3,553,395	3,619,473	105,447	10,054,947
Forestry	30	1,373,476	1,456,810	53,039	3,857,006
Fishery	30	917,865	966,635	35,360	2,503,624
lnGDP	30	17.91	0.511	17.163	18.711
lncrop	30	15.116	1.257	12.977	16.722
lnlivestock	30	14.155	1.639	11.566	16.124
lnforestry	30	13.27	1.514	10.879	15.165
lnfishery	30	12.877	1.507	10.473	14.733

Source: Author's computation from STATA 17 (2024)

4.2 Stationarity Test

Economic variables tend to be non-stationary, which can lead to misleading regression results when using vector error correction models, as noted by Granger and Newbold (1974). Consequently, it is crucial to test for stationarity before making any conclusions about the relationships between these variables.

Table 3 presents the ADF test results, showing that while all variables are non-stationary at their levels, livestock, crop, fishing, and forestry become stationary after first differencing, except for GDP, which remains non-stationary.

Table 3: Summary of Unit Root Test of Variable at level and First Difference using ADF

Variables	At level		Firs Difference	
	Statistic	Critical value at 5%	Statistic	Critical value at 5%
lnGDP	-1.803	-3.588	-2.056	-3.592
lnCrop	-2.404	-3.588	-4.260***	-3.592
lnLivestock	-2.076	-3.588	-4.256***	-3.592
lnForestry	-2.374	-3.588	-4.247***	-3.592

lnFishery	-2.471	-3.588	-4.427***	-3.592

Source: Author's computation from STATA 17 (2024)

Note: the asterisks (***) denote significance at the 5% level.

4.3 Zivot-Adrews Structural Break Trend Unit Root Test Result

The Zivot-Andrews (ZA) approach was used to check if GDP was truly non-stationary at the first difference level, accounting for structural breaks, unlike the standard Augmented Dickey-Fuller (ADF) test. The results from the analysis showed a structural break in the data, and the null hypothesis of a unit root was rejected. After first differencing, the variables became stationary, meaning they are integrated of order I(1). This suggests that the series has a persistent structure over time, confirmed by the test statistic exceeding the critical value.

Table 4: Zivot-Andrewa Structural Break Trended Unit Root Test

Variable	At Level		Critical Value at 5% level	Fist Difference		Critical Value at 5% level	Integration Level
	Statistic	Break Point		Statistic	Break Point		
InGDP	-2.510	2010	-4.800	-4.892	2010	-4.800	I(1)
lnCrop	-4.305	1998	-4.800	-6.070	1998	-4.800	I(1)
lnLivestock	4.508	2007	-4.800	-6.534	2007	-4.800	I(1)
lnForestry	-3.115	2012	-4.800	-6.219	2007	-4.800	I(1)
lnFishery	-3.333	2012	-4.800	-6.340	2014	-4.800	I(1)

Source: Author's computation from STATA 17 (2024)

4.4 Optimal lag Selection

The selection of an appropriate lag length in time series analysis is critical to avoid model errors. In this study, the Akaike Information Criterion (AIC), Hanna-Quinn Information Criterion (HQIC), and Schwarz Bayesian Information Criterion (SBIC) were used to determine the optimal lag. All three criteria indicated that a lag length of 4 is ideal. With 4 lags, the AIC is -17.7283, HQIC is -16.2652, and SBIC is -12.6475, showing a significant improvement in the model's fit.

Table 5 Optimal Selection Results

lag	AIC	HQIC	SBIC
0	-2.6315	-2.5618	-2.3895
1	-12.0164	-11.5983	-10.5647
2	-11.9776	-11.2112	-9.3162
3	-12.375	-16.2603	-8.5039

4	-17.7283*	-16.2652*	-12.6475*

Source: Author's computation from STATA 17 (2024)

4.5 Johansen Cointegration Test

The number of co-integration equations between the variables (lnCrop, lnlivestock, lnForestry, lnFishery, and lnGDP) in this study was determined using Johansen's approach.

The findings show that there is no evidence of a co-integration relationship among the variables. The trace statistic value (67.5802) for the hypothesis R≤0R is lower than the critical value (68.52) at a 5% significance level. Both the trace statistic and Eigenvalues fall below the critical values, leading to the conclusion that there is no co-integration. As a result, the long-term relationships between the variables cannot be analyzed.

Table 6: Johansen Cointegration Test Results

Hypothesis	Trace Statistic	5% Critical Value	Maximum Eigenvalue	5% Critical Value
R=≤0	67.5802	68.52	33.4655	33.46
R≤1	34.1147	47.21	13.0279	27.07
R≤2	21.0869	29.68	9.9982	20.97
R≤3	11.0887	15.41	8.7058	14.07
R≤4	2.3829	3.76	2.3829	3.76

Source: Author's computation from STATA 17 (2024

The issue with the Johansen cointegration results in Table 6 is that they do not account for structural breaks in the data series. To address this limitation, the Gregory-Hansen cointegration method was employed, as it accommodates the structural break identified by the Zivot-Andrews trended unit root test

4.6 Gregory –Hansen Structural Break Cointegration Test

This test is an extension of the traditional Angle-Granger cointegration test, which assumes that the cointegrating relationship remains stable over time.

Table 7 displays the Gregory-Hansen cointegration results. It demonstrates that the null hypothesis of no cointegration is rejected. When the absolute value of the ADF statistic surpasses the critical value at a 5% level of significance. Thus, the null hypothesis is rejected, indicating the presence of cointegration with structural breakdowns.

Table 7 Gregory-Hansen Structural Break Cointegration Test

Gregory-Hansen Models	ADF	Zt	Za

	Statistic	Breakpoint	Statistic	Breakpoint	Statistic	Breakpoint	Critical Value at 5% Level
Intercept shift	-5.79	2006	-5.58	2006	-31.06	1997	-5.31
Intercept shift with the trend	-5.98	2006	-6.08	2006	-29.6	2006	-5.59

Source: Author's computation from STATA 17 (2024)

4.6 Vector Error Correction Model Results

The VECM was used to analyze the long-run and short-run dynamics between the dependent and independent variables, it also measured the influence of the independent variables on the dependent variable. The results of the diagnostic tests, as well as the long-run and short-run dynamics and coefficients, are shown in Tables 8 and 9, which include the VECM outcomes.

4.7 Long-Run Relationship

The estimated Vector Error Correction Model indicates a stable long-run relationship among the system's variables. As shown in Table 8, the vector error correction Model results confirm the presence of a long-run relationship between lnGDP and lnCrop, lnLivestock, lnForestry, and lnFishery over the period from 1993 to 2022.

The model used for measuring the effect of agriculture sub-sectors on lnGDP when lnGDP is a function of the variables below

$$\text{lnGDPt} = \beta_0 + \beta_1 \text{ lnCopt} + \beta_2 \text{ lnLiveSt} + \beta_3 \text{ lnFort} + \beta_4 \text{ lnFisht}$$

Where;

lnGDPt is gross domestic product value added

The terms lnCopt, lnLiveSt, lnFort, and lnFisht, respectively, stand for the gross value added for crops, livestock, forestry, and fisheries respectively. Conversely, the coefficients of the explanatory variables are $\beta_{1,}$ $\beta_{2\,,}$ β_3 and β_4.

The equation for measuring the effect of agriculture sub-sectors on lnGDP when lnGDP is a function of other variables become:

lnGDP = 7.2518 + 5.6408 lnCrop - 3.4853 lnLivestock - 2.9533 lnForestry + 5.1140 lnFishery.. (0.2)

The results indicate that the agricultural subsector significantly contributed to GDP growth, where a 1 million TZS increase in crop gross value added led to a long-term GDP growth of 5.6408 million TZS. However, for the livestock subsector, a similar increase in gross value added caused a long-term GDP decline of 3.4853 million TZS. Similarly, in the forestry subsector, a 1 million TZS increase in gross value added resulted in a 2.9533 million TZS decline in long-term GDP growth. All findings were significant at the 1% level.

Table 8: Long-run results of VECM (Johansen normalization restrictions imposed)

Variable	Coefficient	Std.Error	Z-Statistic	P-value
lnGDP	1			
lnCrop	-5.6408***	1.5406	-3.66	0.0000
lnLivestock	3.4853***	0.9273	3.76	0.0000
lnForestry	2.9533***	0.5192	5.69	0.0000
lnFishery	-5.1140***	1.2014	-4.25	0.0000
Constant	-7.2518			

Source: Author's computation from STATA 17 (2024))

Note: * Significance at 10% level, **at 5% level and ***at 1% level.

4.8 Short Run Dynamic

The Vector Error Correction Model is commonly applied in econometrics to analyze short-term fluctuations in variables while maintaining their long-run equilibrium relationship. The error correction terms (ECT) indicate the rate at which variables like lnGDP and (lnCrop, lnLivestock, lnForestry, lnFishery) adjust in the short run to return to long-run equilibrium. Table 9 presents the short-run adjustment parameters for each variable contributing to this equilibrium. The ECT coefficient for lnGDP is -0.068.

4.9.1 R-Squared

The R-squared value in the diagnostic test indicates that 97.6%. It's quite high, suggesting a good fit.

4.9.2 Lagrange Multiplier Test for residual autocorrelation

The Lagrange Multiplier test was employed to evaluate the presence of residual autocorrelation. Table 9 indicates that the test does not yield significant evidence of autocorrelations in the time series data at the 5 percent significance level, based on the p-value of 0.792.

4.9.3 Jague-Bera Normality Test

Jarque-Bera Normality Test Tests with p-value (0.756) at the 5% level of significant indicating that, the residuals are normally distributed across the model.

Table 9: Short-run Dynamics and Diagnostic Test

Variable	Coefficient	Std.Error	t-statistic	P-value
ECT	-0.068***	0.021	-3.06	0.000

Variable	Coefficient	Std.Error	t-statistic	P-value
lnGDP_1	0.012	0.347	0.03	0.516
lnGDP_2	-0.622	0.448	-1.39	0.973
lnGDP_3	0.570	0.514	1.11	0.165
lnCrop_1	0.839	0.463	1.81	0.267
lnCrop_2	1.204*	0.516	2.34	0.070
lnCrop_3	0.046**	0.047	0.98	0.020
lnlivestock_1	-0.477	0.364	-1.31	0.326
lnLivestock_2	-1.078	0.427	-2.53	0.189
lnLivestocK_3	0.092**	0.043	2.14	0.012
lnForestry_1	-0.630**	0.255	-2.47	0.032
lnForestry_2	-0.006**	0.222	-0.03	0.013
lnForestry_3	-0.259	0.16	-1.62	0.980
lnFishery_1	0.295	0.095	0.71	0.475
lnFishery_2	0.757	0.413	1.62	0.105
lnFishery_3	1.304**	0.467	2.43	0.015
Constant	0.046*	0.536	1.69	0.091
Diagnostic Tests Results				
R-Squared	0.976			
Chi-square	368.921			0.000
LM test (Chi-square)	19.109			0.792
Jague-Bera Normality Test	0.560			0.756

Source: Author's computation from STATA 17 (2024)

Note: * Significance at 10% level, ** at 5% level and *** at 1% level

4.10 Eigenvalue Stability Condition

A root test was conducted to determine the positions of components of AR and MA inside the circle to satisfy the Eigenvalue stability condition of the model for both AR and MA. It is clear from the Eigenvalue stability test in Figure 1 that none of the companion matrix's other Eigenvalues are bigger than one, and only one Eigenvalue of the VECM equals unity. As a result, the stability checks shows that the specifications of our model are correct.

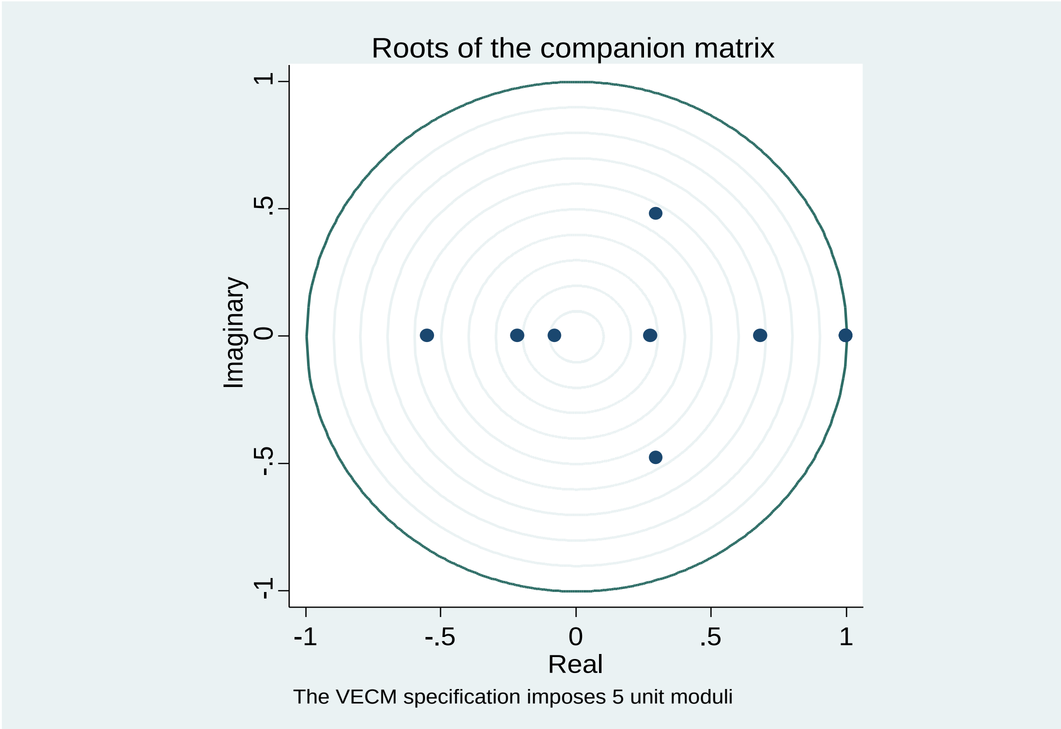

Figure 1: Eigenvalue Stability Condition Results
Source: Author's computation from STATA 17 (2024)

4. 11 Variables Forecasts

Findings from Table 10 show that the forecasted GDP is increasing over the years from 2023 to 2027, as seen in the GDP forecasts column accompanied by standard errors, indicating the level of uncertainty associated with the forecasts. In 2023, the forecasted GDP is 134,733,872 million TZS, with a standard error of 1.012734. The lower and upper boundaries of the 95% confidence interval for the GDP projections are represented by the 95% confidence interval for this forecast, which provides a range within which the actual GDP is anticipated to fall. It is 131,433,552 to 138,117,056 million TZS.

Similarly, the forecasted values for Crop, Livestock, Forestry, and Fishery are provided for each year. In 2023 the forecasted Crop, Livestock, Forestry, and Fishery are; 28, 227, 486, 15, 082, 579, 6,375, 031 and 4, 476, 710 million TZS respectively.

The null hypothesis, which states that there would be no change in gross domestic product or agriculture subsectors over the next five years, is rejected. On the whole, the forecasts point to positive growth trends in both GDP and the individual agriculture subsectors.

Table 10: Variables Forecast Results

					GDP Forecasts			
Year	Crop	Livestock	Forestry	Fishery	GDP Forecasts	Str.Error _GDP	95% C.I (LCL)	95% C.I (UCL)
2023	28,227,486	15,082,579	6,375,031	4,476,710	134,733,872	1.0127	131,433,552	138,117,056
2024	51,849,612	38,479,888	12,230,832	7,470,570	138,957,472	1.0203	133,584,200	144,546,896
2025	41,293,880	18,699,440	7,416,622	4,760,122	144,373,296	1.0291	136,480,048	152,723,056
2026	53,191,732	25,362,260	10,171,582	6,542,556	147,828,112	1.0421	136,359,504	160,261,312
2027	83,322,144	41,881,720	15,972,532	10,382,234	154,711,136	1.0558	139,079,520	172,099,648

Source: Author's computation from STATA 17 (2024)

The asymptotic confidence intervals for the dynamic projections in the levels of the variables; Crop, Livestock, Forestry, Fishery, and GDP are derived and plotted. The lengths of the confidence intervals increase as the prediction horizon gets closer, as predicted (Figure 2).

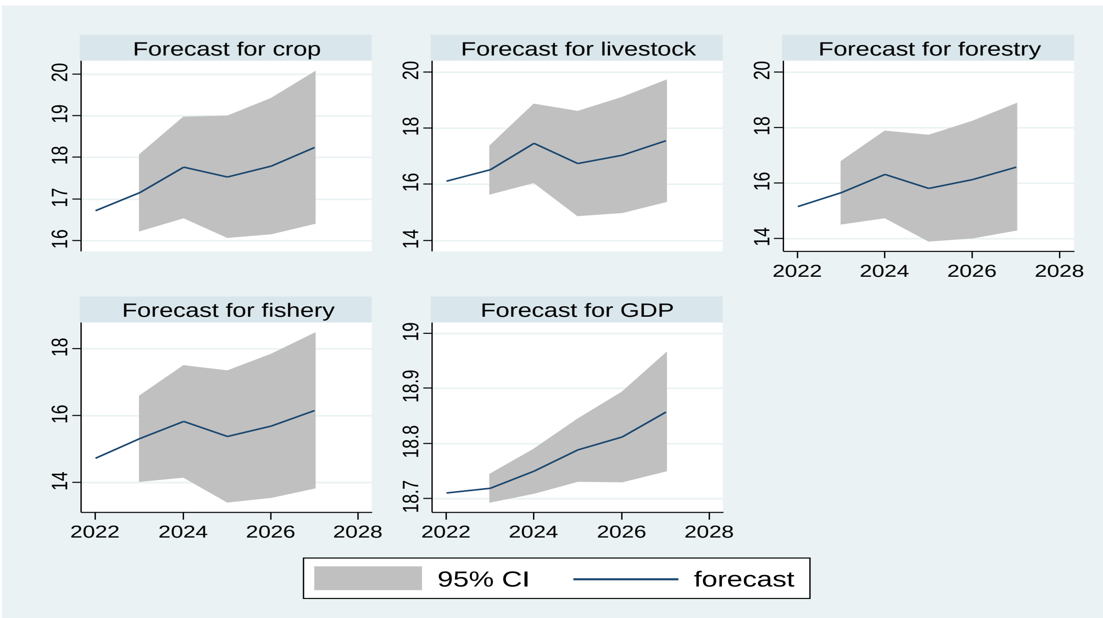

Figure 2: Dynamic Forecasts of Crop, livestock, Forestry, Fishery and GDP

Source: Author's computation from STATA 17 (2024)

4.12 Diagnostic Test

4.12.1 Jague-Bera Normality Test

The Jarque-Bera Normality Test determines if the residuals are normally distributed, as shown in Table 9. It is suggested that the residuals are normally distributed by the p-value (0.756) at the 5% level.

4.12.2 Heteroscedasticity Test

Table 11 presents the evidence that the Breach-Pagan-Godfrey test's computed probability of 0.1875) was sufficient to reject the null hypothesis. The residuals were therefore determined not to be heteroscedastic.

Table 11 Breuch-Pagan for Heteroscedasticity Test

Assumption	Normal error terms	
H0	Constant variance	
chi2(1)		6.16
Prob > chi2		0.1875

Source: Author's computation from STATA 17 (2024)

4.12.3 White's test for Homoscedasticity

The test statistic has a value of Chi2(25) = 26.0000 and a Chi-squared distribution with 25 degrees of freedom. The p-value associated with it is Prob > chi2=0.4076.

The null hypothesis cannot be rejected, since the p-value of 0.4076 is greater than usual significance level requirements (such as 0.05 and 0.01). As such, there isn't any indication that the regression model exhibits homoscedasticity that is statistically significant.

Table 4.12 White's Test for Homoscedasticity

H0	Homoscedasticity	
Ha	Unrestricted heteroscedasticity	
Chi2(25)		26.0000
Prob > chi2		0.4076

Source: Author's computation from STATA 17 (2024)

4.13 Discussion of the Results

The results in Table 8 indicate that agriculture sub-sectors have positively contributed to GDP over time, with the fishery subsector showing significant positive effects, while the livestock and forestry subsectors did not negatively impact GDP. Tables 8 and 9 further confirm a strong correlation between GDP and agricultural sub-sectors, though many short-run coefficients of lag factors lack significance. The diagnostic test's R-squared value of 97.6% suggests that the independent variables effectively explain the variation in the dependent variable, indicating a strong fit of the model.

A study by Jobarteh and Selemani (2020) explored the impact of agricultural subsectors on The Gambia's economic development using time series data from 2004 to 2016 from the Gambia Bureau of Statistics. The research focused on crops, livestock, forestry, fisheries, and their contributions to economic growth.

Results indicated that crops and fisheries significantly contribute to economic growth, while forestry and livestock have a negligible long-term impact. These findings align with trends observed in Tanzania, where crops and fisheries positively influence GDP, whereas forestry and livestock negatively affect it.
Mtaturu (2020) assessed the contribution of Tanzania's agricultural subsectors to economic growth using time series data from 1971 to 2013, employing Newey-West and OLS methods. The findings indicated that all subsectors, except forestry, positively influenced economic growth in both the short and long term. Conversely, Kabir (2018) utilized the Vector Error Correction Model to examine the relationships between GDP and agricultural GDP in Bangladesh. Post-estimation tests confirmed the model's accuracy, allowing for reliable dynamic projections of the variables lnGDP and lnAGDP.
The forecasted variables indicate an increasing GDP from 2023 to 2027, with positive growth trends also observed in the Crop, Livestock, Forestry, and Fishery sectors. The findings include standard errors and confidence intervals, which reflect some uncertainty in the forecasts. This supports the study's null hypothesis that both GDP and the agricultural sub-sectors will rise over the specified period.

5. Conclusions and Recommendations

5.1 Conclusion

The study aimed to assess the impact of various agricultural sub-sectors on Tanzania's mainland GDP. It found that these sub-sectors positively contribute to long-term economic growth, rejecting the null hypothesis of no long-term effect with statistically significant results at the 1% level. Specifically, while forestry and livestock had a negative correlation with GDP, crop production and fisheries showed a positive correlation. Additionally, the independent variables (livestock, forestry, fisheries, and crop productivity) explained 97.6% of the variation in GDP, highlighting agriculture's significance in this context. However, the study accepted the null hypothesis regarding short-run effects, as the short-run parameters were not significant at the 5% level.
The study concludes that agricultural subsectors are crucial for the long-term economic growth of mainland Tanzania. It suggests that targeted investments, legislative changes, and sustainable development initiatives can enhance agriculture's positive impact on GDP. Although the short-term contributions of these subsectors to GDP are limited, developing strategies to mitigate short-term fluctuations is essential for economic stability. Additionally, anticipating positive changes in the next five years can aid in establishing realistic economic targets and aligning national development strategies.

5.2 Recommendations

The study recommended the following

The Tanzanian government should implement a vertically integrated strategy to balance contributions across agricultural sectors, reducing the dominance of crops and fishing while boosting forestry and fishery sectors for poverty alleviation and economic growth.

Forestry practitioners should prioritize sustainable management, reforestation, processing facilities for higher-value products, and advancements in research and development in forestry.

Improving animal breeding and husbandry is vital for productivity. Expanding veterinary services, ensuring access to vaccines and medications, and investing in infrastructure for water supply and feed storage are crucial. Affordable financing for small and medium enterprises should also be available.

More research is needed to understand the limited effects of short-run agricultural changes on GDP, the economy's structure, and intersectoral relationships.

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Reference

Chandio A. A., Yuansheng J. and Magsi H. (2016). Agricultural Sub-Sectors Performance: An Analysis of Sector-Wise Share in Agriculture GDP of Pakistan. International Journal of Economics and Finance, 8, 156. https://doi.org/10.5539/ijef.v8n2p156

Chongela, J. (2015). Contribution of Agriculture Sector to the Tanzanian Economy. American Journal of Research Communication, 3 (7), pp. 57 70.

Department of Economic and Social Affairs, Statistics Division, (2008). International Standard Industrial Classification of All Economic Activities, Revision 4. Sales No. E.08.XVII.25 ISBN: 978-92-1-161518-0. United Nations, New York.

Danso-Abbeam, G., Ehiakpor, D. S., & Aidoo, R. (2018). The global agricultural sector acts as a catalytic agent that accelerates the pace of structural transformation and diversification of the economy. Journal of Agriculture and Sustainability,10(2),45-60.

FAO. (2014). The State of Food and Agriculture Innovation in family farming.

https://doi.org/10.1017/S1876404512000115

Gregory, A. W., & Hansen, B. E. (1996). "Residual-based tests for cointegration in models with regime shifts". Journal of Econometrics, 70(1), 99-126.

Granger, C.W.J., and Newbold, P. (1974). Spurious regressions in econometrics. Journal of Econometrics, 2(2), 111-120.

Humayun Kabir. (2018). Econometric investigation of short-run and long-run relationships between GDP and agricultural GDP of Bangladesh: Application of the Vector Error Correction Model (VECM).

Jobarteh, A., & Selemani, K. (2020). Assessing the effect of agriculture sub-sectors on the Gambia’s economic growth using time series econometric models. *International Journal of Agricultural Economics, 5(4), 142-149.* https://doi.org/10.11648/j.ijae.20200504.17

Lütkepohl, H. (2006). "Structural vector autoregressive analysis for cointegrated variables". In: New Introduction to Multiple Time Series Analysis. Springer, Berlin, Heidelberg.

Mtaturu, Z. A. (2020). Agricultural Production and Economic Growth in Tanzania: Implication for Sub-Sectoral Contribution. Business Education Journal(BEJ), Volume IV, Issue I, 15 Pages. www.cbe.ac.tz/bej

Nyamekye, A. B., Tian, X., & Cheng, F. (2021). Investigating the relationship between Ghana's agricultural sector and economic growth: An analysis using time series data from 1984 to 2018. Open Journal of Business and Management, 9, 1297-1311. https://doi.org/10.4236/ojbm.2021.93070

Tanzania National Bureau of Statistics. (2016). Concepts and Definitions for Official Statistics in Tanzania. Ministry of Finance and Planning- Dar es Salaam.

UNSD & FAO. (2019). “Global Trends in GDP, Agriculture Value Added, and Food-Processing Value Added”.

WinemanA, Jayne TS, Isinika Modamba E, Kray H. The changing face of agriculture in Tanzania: Indicators of transformation. Dev Policy Rev. 2020; 38:685– 709. https://doi.org/10.1111/dpr.12491

Zivot, E., & Andrews, D. W. K. (1998). Further evidence on the great crash, the oil price shock, and the unit-root hypothesis. Journal of Business & Economic Statistics, 16(2), 139–146. DOI: 10.1080/07350015.1998.10524733.