INNOVATIONS IN AGRICULTURE & PLANT BIOTECHNOLOGY

THE DYNAMICS OF AGRICULTURAL OUTPUT VALUE IN TANZANIA: AN AUGMENTED DICKEY-FULLER ANALYSIS

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Abstract
Despite its existing bottlenecks, Agriculture remains a key driving sector for economic transformation of Tanzania and Africa continent largely. This study analyzes the dynamics of agricultural output value in Tanzania. The novelty of this study is the application of Structural explanation approach; Dickey-Fuller (DF) test and its standard version of Augmented Dickey-Fuller (ADF) Test Model to analyze data on agricultural output value from 1990-2021 for assessing the stationarity and mean-reverting behavior of the sector. The findings indicated that, after differencing, the agricultural output series exhibits stationary characteristics, allowing for reliable forecasting. The results further revealed a significant negative relationship between past and current output levels, suggesting that increases in agricultural production are often followed by declines, reflecting the need for sustainable management practices. Furthermore, the model's diagnostics confirm its robustness, enabling accurate predictions of future output. These insights have important policy implications, emphasizing the necessity for strategies that enhance resilience and sustainability in agriculture. By investing in adaptive practices and technologies, policymakers can better equip farmers to manage production variability and mitigate the impacts of external shocks. This study contributes to the understanding of agricultural output dynamics and provides a framework for effective decision-making aimed at improving food security and economic stability in the sector. Overall, the application of ADF modeling presents a baseline tool for forecasting agricultural output and guiding policy interventions that promote sustainable growth.

Key words: Stationary; Agricultural output; Augmented Dickey-fuller test; Stationary

1.0 INTRODUCTION

Tanzania is currently implementing various strategic plans in various economic sectors to ensure achieving its national development vision 2050. That being the case, Agriculture is the leading and key driving economic sector among others in the country to achieve the envisaged vision. In fact, Agriculture sector is a cornerstone of Tanzania's economy, accounting for approximately 28 percent of the country's GDP and employing more than 65 percent of the workforce (Mpogole *et el,* 2020; Gupta,2020; Kabini, 2022). The sector is primarily composed of smallholder farmers who cultivate various crops, including coffee, tea, cashews, maize, and rice to mention few. Over the past decades, Tanzania has experienced fluctuations in agricultural productivity due to factors such as climate change, land degradation, and varying market access (Gwambene *et al*, 2023). For instance, the National Bureau of Statistics (NBS) of Tanzania reported that, agricultural growth averaged about 3.5 percent annually from 2010 to 2020, with significant variations across different crops and regions (NBS, 2021). This growth is crucial for poverty alleviation and food security, as agriculture supports the livelihoods of millions of Tanzanians (NBS, 2021). Basically, a country being a predominantly agrarian society, understanding the dynamics of agricultural output is crucial for policymakers, researchers, and stakeholders involved in the agricultural sector development.

Despite the sector's potential, challenges persist that hinder consistent agricultural output (Changalima and Ismail,2022; Gwambene *et al*, 2023). The impact of climate variability has been particularly pronounced, with droughts and floods affecting crop yields and leading to food shortages (Wineman *et el*, 2020). For example, the 2016/2017 crop season saw a significant decline in maize production, dropping by over 20 percent compared to the previous season, largely due to adverse weather conditions (Baijukya *et el*, 2020; Ndlovu, 2023). Besides, limited access to modern farming techniques and inadequate infrastructure further exacerbates these challenges (Mussa, 2020). Thus, understanding the trends and performance of agricultural output is vital for policymakers to develop strategies that enhance productivity, improve food security, and promote sustainable agricultural practices in Tanzania. Furthermore, by employing the Augmented Dickey-Fuller test, this study investigated whether the time series data for agricultural output is stationary or non-stationary.

Moreover, Stationarity in time series data refers to the property where the statistical characteristics of the series, such as mean and variance, remain constant over time (Fouedjio, 2021). Non-stationary data can lead to unreliable statistical inferences, making it imperative to identify whether agricultural output values exhibit stationary/dynamics behavior (Salles, *et al*, 2019). The presence of unit roots in the data suggests that shocks to the series can have permanent effects, complicating forecasting and policy formulation (Liu *et al*, 2022). Therefore, establishing the stationarity of agricultural output values is a crucial step for any subsequent analysis, including modeling and forecasting in further studies. Nevertheless, understanding the stationarity of agricultural output is not just a theoretical exercise; it has practical implications for agricultural policy and planning. For instance, if the agricultural output is found to be non-stationary, policymakers may need to consider interventions to stabilize the sector and mitigate the impact of external shocks. Conversely, if the output is stationary, it may indicate a more predictable agricultural environment, allowing for more effective long-term planning and investment.

While it is clear that, there has been a growing body of literature focusing on time series analysis in agricultural economics. Previous studies have employed various methodologies to evaluate the stability and trends of agricultural production, with a particular emphasis on the implications for food security and economic development in various countries. Thus, the novelty of this study it builds upon existing literature by specifically focusing on Tanzania's agricultural output, contributing to the understanding of the sector's behavior over time by employing a well-articulated empirical diagnostic from Augmented Dickey-Fuller model. Moreover, the purpose of this study is to assess the stationarity of agricultural output value in Tanzania using time series data while employing the Augmented Dickey-Fuller diagnostic test, which is essential for making informed decisions on agricultural policy and investment. The study analysis is guided by two Hypothesis namely; Null hypothesis H_0: Agricultural output value is non stationary (it has a unit root) while Alternative hypothesis H_1: Agricultural output value is stationary (it has no unit root). The Augmented Dickey-Fuller (ADF) test, a more robust version of the standard Dickey-Fuller test, was utilized to account for potential autoregressive structures in the data. The findings of this study will offer insights into the nature of agricultural output fluctuations in Tanzania, providing a foundation for future research and policy recommendations. Additionally, by assessing the stationarity of agricultural output, this study will inform stakeholders about the trends and potential risks associated with agricultural production, ultimately contributing to more sustainable agricultural practices, economic growth and improved food security. While that the case, the outcomes of this study will not only enhance the understanding of agricultural output behavior in Tanzania but also contribute to broader discussions on agricultural economics and developmental policy in the Africa region and global at large.

The rest of this paper is arranged as follows; Section 2 explains a literature review, Section 3 presents the data and methods, Section 4 details the results and discussion, and Section 5 presents the conclusion and policy implications of the study.

2.0 LITERATURE REVIEW

2.1 Theoretical framework

The theoretical framework of this study was adopted from the Dickey-Fuller test model (Enders,2014) which serves as the most appropriate theoretical framework in this context. This test is a fundamental tool in time series analysis, particularly for identifying the presence of unit roots in economic data (Islam *et al*, 2018). The test in this study provides that, understanding the stationarity of agricultural output is crucial for making informed decisions regarding agricultural policy and investment. Besides, according to Paparoditis and Politis (2018) the DF test has the following underlying assumptions; First, presence of a unit root-the primary assumption is that the time series may contain a unit root, indicating non-stationarity. The null hypothesis of the Dickey-Fuller test posits that a unit root is present in the series. Second, linearity-the relationship between the current value of the series and its past values is assumed to be linear. This means that the model can be expressed as a linear function of lagged values and error terms. Third, stationarity of error terms-the error terms in the model should be stationary. Non-stationary error terms can lead to unreliable estimates and invalid conclusions. Four, no autocorrelation-the residuals from the regression should not exhibit autocorrelation. If autocorrelation is present, it can distort the test results, leading to incorrect inferences about the presence of a unit root. Five, constant variance-the variance of the error terms should remain constant over time (homoscedasticity). If the variance changes, it may indicate that the model is mis specified. Moreover, the key reasons for choosing to use the Dickey-Fuller Test model in our analytical framework are; first, robustness of the results-the Dickey-Fuller test is widely recognized for its robustness in detecting unit roots in time series data (Wang *et al,* 2021). Its ability to handle various forms of data makes it a reliable choice for agricultural output analysis. Second, simplicity-the test is relatively straightforward to implement and interpret, making it accessible for researchers and policymakers (Roza *et al,* 2022). This simplicity is particularly beneficial in applied settings where clear results are needed. Third, relevance to agricultural economics-given the nature of agricultural output, which is often influenced by various external factors such as climate, market conditions; the Dickey-Fuller test provides a suitable framework for analyzing trends and fluctuations in agricultural production over time (Cai and Omay,2021). Lastly, foundation for further analysis-establishing the stationarity (Otero and Baum, 2018) of agricultural output is a prerequisite for more complex econometric modeling, such as ARIMA (Autoregressive Integrated Moving Average) models, which are commonly used in forecasting agricultural trends.

Nevertheless, the application of the Augmented Dickey-Fuller test in this study is directly linked to the need for understanding the behavior of agricultural output value in Tanzania. By assessing the stationarity of agricultural output values, the study aimed at identifying whether shocks to the agricultural sector have temporary or permanent effects. This understanding is vital for policymakers, as it informs decisions regarding resource allocation, investment in agricultural technologies, and strategies for mitigating risks associated with climate change and market volatility. Furthermore, the results of the Dickey-Fuller test can provide insights into the stability of agricultural output, which is essential for formulating effective agricultural policies and ensuring food security in Tanzania. Thus, by establishing whether the agricultural output is stationary, the study can contribute to a more nuanced understanding of the sector's dynamics, ultimately supporting sustainable agricultural development in the country.

2.2 Empirical review

Given the fact that, there are limited studies which are directly resembled to the theme of this study in Tanzania particularly, we conducted some related literatures regarding agriculture sector and time series with elements of Dickey-Fuller test to establish a research gap to be filled. However, our review touched other countries as well for widening understanding of the application of Dickey-Fuller test application with related studies.

Ilembo and Kassim (2025) conducted a study on “The Power of first differencing in addressing non stationarity time series” to forecast the price of rice in Tanzania using a secondary univariate time series from January 2005 to September 2024 by employing seasonal SARIMA model. The results revealed that, the price of rice in Tanzania will exhibit a consistent upward trend from October 2024 to a peak in March 2027 reflecting a total increase of approximately 121.4% over this period. From April 2027, prices will begin to decline steadily reaching low in August 2029, a reduction of 44.3% from the March 2027 peak. Prices typically dip in late summer, with the sharpest decline observed in August 2025, when prices fall by 32.8% from June 2025. The decline beginning in April 2027 reflects a significant market shift, with an average monthly decrease of approximately 2.1% from April 2027 to August 2029. This may be attributed to increased production or effective market interventions. The policy issues should focus on the areas of price stabilization programs, strengthening trade and export policies putting in place mechanisms to support farmers by giving them access to agro-inputs and ensuring the technical services are availed to farmers through agricultural extension officers. This will increase productivity and address the problem of demand which will in turn solve the entire problem of price volatility. This shall be achieved by influencing consumer behavior and moderating demand, the interventions that help reduce the volatility that arises from sudden spikes in demand, contributing to more stable pricing over time.

Saxena and Mhohelo (2020) investigated on “Modelling and forecasting retail prices of maize for three agricultural markets in Tanzania” using Autoregressive Integrated Moving Average (ARIMA) technique with time series data. The results indicated that, ARIMA (1, 1, 4) model is the most adequate and efficient model for Gairo market, ARIMA (2, 1, 3) model is the most adequate and efficient mode1 for Manyoni market and ARIMA (2, 2, 3) model is the most adequate and efficient model for Kibaigwa market. This was determined by comparing the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) and Mean Absolute Percentage Error (MAPE). Time-series analysis was done using STATGRAPHICS, EXCEL, R software and SAS JPM. The forecast results suggest that, there are expectations of increasing maize prices in Manyoni market from June-2018 to May-2019, the maize prices in Kibaigwa market are also expected to increase with time from January 2016 to December 2016 and the maize prices at Gairo market are expected to keep on increasing with time from June 2018 to May 2019. They asserted that, the results will make better understanding of maize prices situation and future prices will enable producers and consumers to make the right choices concerning buying and selling arrangements of Maize crop in Tanzania.

Oguwuike (2018) examined the effect of agricultural output on economic growth of Nigeria utilizing time series data from 1981-2016; econometrics methods of ordinary least square, Co integration, error correction mechanism was used for the analysis. The outcome of the ADF unit root test show that the variables (GDP, crop production, livestock, fishery and forestry) were stationary. Also, the co-integration result showed that, there exist co integration amongst the variables in the model. The Parsimonious Error Correction Model 2 indicates that the R is 86% meaning that the dynamic model is a good fit. The Durbin Watson value of approximately 2.0, indicates a lesser level of autocorrelation, meaning that the successive values of the error term are serially dependent or correlated. Moreover, the first and third lags of GDP are positively and significantly related to current level of economic growth. The coefficient of crop production is positively signed and statistically significant at 5 percent level with GDP. The coefficient of fishing is positively signed but statistically not significant at 5 percent level with GDP. The coefficient of livestock is positively signed and statistically significant at 5 percent level with GDP. The coefficient of forestry is negatively signed but statistically significant at 5 percent at level with GDP. Based on these results, this study recommends the following: Nigerian government should put good structures in place that allows better and higher agricultural output; The various state government should look beyond the monthly federation allocation account as their major source of revenue for developmental projects but work towards utilization and exploitation of fallow lands in their states for farming; Agricultural institutions should be revived, revamped and some privatized with proper supervision for better productivity; Long term agricultural development plans/projects that are realistic should be created and executed; Nigeria government should increase budgetary allocation to the agricultural sector and ensure effective utilization of the funds/budgets that translates into improved and increased production or output annually; Agricultural credit schemes should be encouraged, strengthened and made easily accessible to farmers for increased agricultural output; Subsidization and availability of agricultural inputs for farmers that translates into higher output; Nigerian government should create secured and enabling environment for commercial farming that minimized subsistence farming and there should be workable and lasting solution towards resolution of crisis between farmers and herdsmen Ramakgasha *et al* (2024) analyzed the intricate relationship between agricultural output and employment in South Africa using time series analysis; they employed a Vector Autoregressive (VAR) model to evaluate the link between agricultural production and the rate of agricultural employment in South Africa spanning from 1990 to 2022. The findings indicated that, both variables passed levels and became stationarity at the first difference when employing ADF, and a long-term equilibrium relationship between the variables was observed using Johansen cointegration test. Over the short term, there was a significant positive correlation among agricultural production and the agricultural employment rate evidenced from ECT coefficient of 0.139 value. The results of the Granger causality tests indicated unidirectional relationship that agricultural employment Granger-causes agricultural production, signifying that agricultural employment can be used to predict the growth of agricultural production. Study recommended that, policies which promote injection of funds to improve production in the agriculture sector needs to be prioritized to maintain and improve employment opportunities.

Ud Din and Haseen (2024) assessed the impact of climate change on India's agricultural sector from 1990 to 2020. The autoregressive distributed lag (ARDL) approach was utilized to determine the short-run and long-run relationships between variables such as carbon dioxide emissions, temperature, energy utilization, and fertilizer consumption. The ARDL method and the Johansen and Juselius cointegration test both supported the existence of a significant and long relationship among the selected variables. The estimated short- and long-run findings showed that, carbon dioxide emissions (CO_2), temperature, and energy consumption affect agricultural yield positively and significantly. These findings have several implications for the Indian economy. With a large population dependent on agriculture, improved productivity can directly impact food security and rural income, consequently leading to the country's overall economic development. Enhanced agricultural output due to these factors may potentially lead to surplus production, allowing India to export more agricultural produce. This can positively impact the country's trade balance and generate revenue through exports.

Overall, the reviewed literatures show that, majority of the studies utilized different models for conclusion of their findings while ADF test was used as part the initial analytical steps in their studies. Also, in most cases they considered more than one variable in their analysis studying various countries. The novelty of this study is that, it adds structural explanation approach and it is specific for Tanzania accounting for the single leading and driving economic transformation sector (Agriculture). Additionally, this study used a single variable and a well-articulated ADF test model was a primary analytical model for the study conclusion. Therefore, this study can address the literature gap and increase the debate in the econometric and Agricultural economics discourse.

3.0 METHODOLOGY

3.1 Research approach and design

The study used purely quantitative approach to analyze numerical data for identifying agricultural output patterns and trends in Tanzania and testing hypothesis. This approach is appropriate for understanding the dynamics of agricultural output and making data-driven recommendations for policy and practice. Besides, the study used longitudinal design (Berman *et al*, 2020) which involves time series data collected over multiple time points, allowing for the examination of trends and changes in agricultural output over time. Thus, by analyzing historical data, the study can effectively identify patterns, fluctuations, and potential unit roots in the time series, which are crucial for understanding the stability and dynamics of agricultural output. This approach provides a comprehensive view of how agricultural output responds to various factors, enabling more accurate assessments of its stationarity and informing policy decisions.

3.2 Data type and source

The study used quantitative time series data obtained from the World Bank development indicators (2023) for the period from 1990 to 2021.

3.3 Estimation method

This study employed Dickey-Fuller test model to estimate the dynamics incorporating a single variable under study which is Agricultural output value. The estimation methods involved testing for stationarity (unit root test) by applying DF test while considering the hypothesis under study. However, the Augmented Dickey-Fuller (ADF) test which is a more robust version of the standard Dickey-Fuller test, was utilized to account for potential autoregressive structures in the data. The hypothesis are as follows;

3.3.1 Hypothesis Testing

Null Hypothesis (H_0): $\gamma=0$ (indicating a unit root, or non-stationarity of agricultural output)
Alternative Hypothesis (H_1): $\gamma<0$ (indicating stationarity of agricultural output)

3.3.2 Econometric model

The econometric model for basic DF test model is given as follow;

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \varepsilon_t$$

where;

$\Delta Y_t = Y_t - Y_{t-1}$ (the first difference of the series); α is a constant; γ is the coefficient for the lagged level of the series and ϵ_t is the error term.

Furthermore, since we understand that, time series suffers for serial correlation problem; and to make our results robust and valid for conclusion, we introduce the standard model of DF test known as Augmented Dickey-Fuller Test Model which is given below. This model is introduced in this study for the purpose of remedies against serial correlation problem and making robust results during analysis into STATA program.

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{\rho} \delta_i \, \Delta Y_{t-i} + \varepsilon_t$$

Where;

$\Delta Y_t = Y_t - Y_{t-1}$ (Represent the first difference of the series); α is a constant; γ is the coefficient for the lagged level of the series; δ_i are the coefficients for the lagged differences; ϵ_t is the error term; ρ is the number of lagged difference terms included and Σ is a summation symbol.

3.3.3 Empirical model

The empirical model of this study is adopted from the basic econometric model of Dickey-Fuller Test Model in 3.3.2, however, this model has been tested using ADF test in the STATA program. This model has only one variable namely "Real agricultural output value" (Real_AGR); this variable considers *Agriculture, forestry, and fishing, value added (*constant 2015 in US$) as its measure. Taking single variable under analysis is due to the main purpose of the study to look at the dynamics in terms of stationarity of agriculture sector output of Tanzania. Here is the empirical model;

$$\Delta Y_t = Y_t - \gamma Real\_AGR_{\,t-1} + \varepsilon_t$$

Where;

γ is the coefficient for the lagged level of the series; α is a constant; $\Delta Y_t = Y_t - Y_{t-1}$ represent the first difference of the series and ϵ_t is the error term.

Our study used above empirical model because it simplifies the analysis while focusing directly on the primary variable of interest (Real_AGR). Thus, by isolating agricultural output value, the study can more effectively identify whether this series exhibits stationarity or a unit root without the complications introduced by multiple variables. This clarity allows for a more precise evaluation of trends and fluctuations in agricultural output, facilitating easier interpretation of results and providing clear insights into the dynamics affecting agricultural productivity. In addition to that, this approach enhances the validity of the findings, making them more actionable for policymakers and stakeholders in the agricultural sector.

4.0 RESULTS AND DISCUSSION

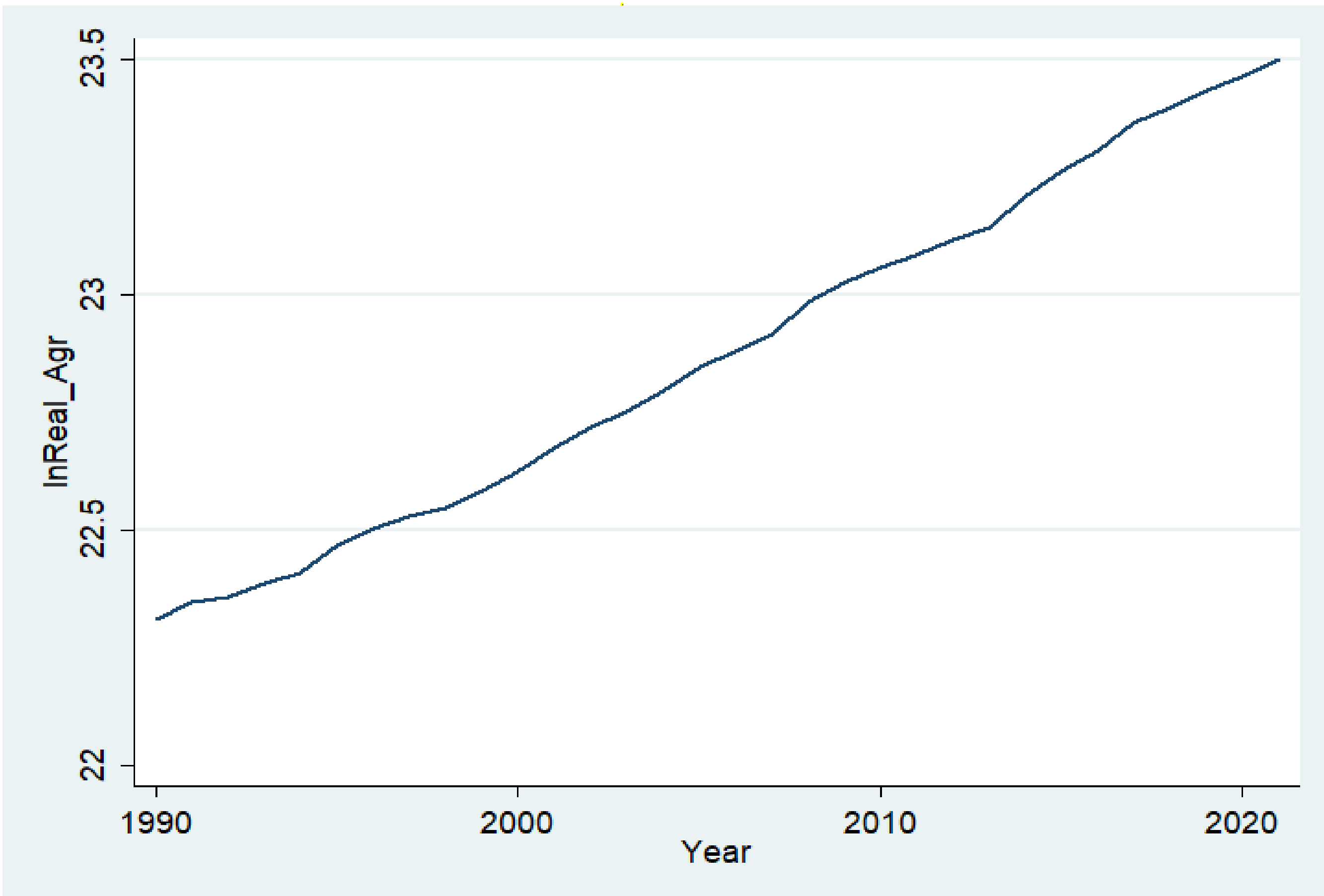
4.1 Regression results of ADF test before differencing

The analysis with STATA program considered the analysis of the variable in ADF test model with trends and with drift trends. Test with trends can significantly influence the behavior of agricultural output over time, reflecting factors such as economic growth, technological advancements, or changes in agricultural practices (Liu *et al*, 2022). While test with drift trends is essential because it accounts for the possibility of a deterministic trend in the data. Drift trends capture systematic upward or downward movements in the agricultural output over time, reflecting factors such as technological advancements, policy changes, or shifts in market conditions (Otero and Baum, 2018). Moreover, to resolve the problem of non-stationarity, we transformed the variable data by introducing natural log to make it non linearity; we also introduced lags up to lags 8 to check whether the results may depict stationary condition. The results in **Table 1** indicated that, since the p-Z(t) values are greater than all critical values without absolute sign, we fail to reject the null hypothesis of a unit root at the 5%, significance level. Also, t-statistics value is less than the critical value at 0.05 level, we fail to reject null hypothesis. This suggests that, the agricultural output value is non-stationary when accounting for trends. The lagged level coefficient (L1) in most models is negative and statistically significant ($p < 0.05$), indicating negative relationship meaning that past values can significantly influence the current agricultural output (Table 1). Furthermore, the trend coefficient is statistically significant at the 5% ($p<0.05$) level, suggesting a positive relationship with agricultural output over time, potentially indicating a gradual increase in output. Overall, the analysis indicates that, the agricultural output value in Tanzania is non stationary when accounting for trends, as evidenced by the p-Z(t) values exceeding critical values. The significant positive coefficient of the lagged level suggests a stable and predictable relationship in agricultural output over time, while the constant term does not provide significant information about the baseline level. Figure 1 depict the non-stationarity of the agricultural output; the trend shows unpredictable output and complexity in policy making.

Moreover, this non-stationarity implies that (Kyojo *et al,* 2024) shocks to the agricultural sector, such as fluctuations in rainfall or market demands, can have lasting effects on output levels. For example, if the production of crops like maize is non-stationary, it indicates that, significant declines in yields due to climate change or pest infestations may not be followed by a recovery to previous levels. This can complicate planning for food security, as the agricultural output becomes less predictable and more vulnerable to external influences. Besides, the implications of non-stationarity are profound for policymakers and agricultural stakeholders in Tanzania. This might involve adopting more adaptive agricultural practices or investing in infrastructure to buffer against shocks, such as improved irrigation systems or crop insurance programs to mitigate production risk of farmers. Furthermore, the findings assert that, understanding the underlying causes of non-stationarity such as the impact of climate variability or socio-economic factors like financing production can help in formulating targeted interventions. Thus, (Paul and Lema,2018) addressing these root issues, policymakers can work towards enhancing the resilience of the agricultural sector, ultimately ensuring sustainable productivity and food security in the face of ongoing challenges.

Overall, the findings also highlight the importance of considering drift trends in understanding the dynamics of agricultural productivity. Furthermore, the findings assert for the need for caution in making forecasts or policy decisions based on this data, as the underlying dynamics appear to lack predictability and stability. Thus, this weakness of the results in Table 1 lacking stationary condition triggered us to go for first differencing of the variable data and further subsequent analysis as presented in the next tables. Basically, differencing is used to remove trends and stabilize variance, making the time series data stationary; this transformation is essential for valid statistical modeling and forecasting, as many methods assume the data is stationary (Paparoditis and Politis, 2018).

Figure 1: A structural explanation of agricultural output value in Tanzania



Source: World Bank (2022)

The graph above figure 1 show that, agricultural output does not change significantly over times from 1990 to 2021 which is not always the case under normal circumstances due to existing of shock such as climatic change and market variation.

Table 1. Regression table results for ADF Test before Differencing

Variable Real Agricultural output value (in Natural log)	**Lags**	**Coefficients & std error**	**T-statistic-Z(t)**	**p-value for Z(t)**	**5%Critical value**
	L1	-.2618573(.0952126)**			
	_trend	.0108187(.0037987)**	-2.750	0.2158	-3.576
Origin Model	Constant	5.850377(2.115546)			
	L1	-.3545679(.1037837)**			
1st Model_lags1	LD.	.1747878(.1643995)			
	Trend	.0145783(.0041686)**	-3.416	0.0492**	-3.580
	Constant	7.901773(2.304551)			
	L1.	-.3430374(.1302887)**			
	LD.	.1747545(.1713083)			
2nd Model_lags2	L2D.	-.0105677(.1792855)			
	Trend	.0141059(.0052651)**	-2.633	0.2650	-3.584
	Constant	7.6463(2.891038)			
	L1	-.3911861(.1498991)**			
	LD.	.2262067(.1901895)			
3rd Model_lags3	L2D.	-.0076462(.1809146)			
	L3D.	-.1237977(.1847822)	-2.610	0.2755	-3.588
	Trend	.0162165(.0060705)**			
	Constant	8.714839(3.323348)			
	L1	-.3441572(.1782608)			
	LD.	.1646179(.208692)			
	L2D.	-.0694898(.2093044)			
4th	L3D.	-.1336918(.1905734)			
Model_lags4	L4D	-.1645042(.2015722)	-1.931	0.6386	-3.592
	Trend	.0144353(.0072363)			
	Constant	7.680329(3.948909)			
	L1	-.5283797(.1654428)**			

5^{th} Model_lags5	LD.	.340009(.1989493)	-3.194	0.0857	-3.596
	L2D.	-.0378956(.1848156)			
	L3D.	.0242324(.18104)			
	L4D	-.1604347(.1703476)			
	L5D	-.2456995(.1724184)			
	Trend	.0222927(.0067285)**			
	Constant	11.75673(3.661988)			
6^{th} Model_lags6	L1	-.7100292(.2080499)**	-3.413	0.0497**	-3.600
	LD.	.3810961(.2032013)			
	L2D.	.1660032(.2229213)			
	L3D.	.1077239(.1900145)			
	L4D	-.015695(.1917969)			
	L5D	-.2489622(.1719484)			
	L6D	.0909779(.182168)			
	Trend	.0296777(.0085399)**			
	Constant	15.76602(4.604141)			
7^{th} Model_lags7	L1	-.8228648(.2853974)**	-2.883	0.1681	-3.600
	LD.	.4647726(.2334919)			
	L2D.	.1362429(.2435758)			
	L3D.	.1608995(.2407043)			
	L4D	-.0380595(.2115627)			
	L5D	-.2420753(.1980966)			
	L6D	.0561743(.191899)			
	L7D	-.1520402(.189624)			
	Trend	.0345502(.0117754)**			
	Constant	18.26823(6.312234)			
	L1	-.9378574(.3858332)**			
	LD.	.5050478(.3088415)			
	L2D.	.2775773(.3051405)			
	L3D.	.1222401(.2550482)			

	L4D	-.0077127(.268961)			
8th Model_lags8	L5D	-.320158(.2174993)	-2.431	0.3634	-3.600
	L6D	.0035957(.2137229)			
	L7D	-.1718661(.1967558)			
	L8D	-.2693783(.226235)			
	Trend	.0395177(.0159866)**			
	Constant	20.82348(8.529513)			

Source: WorldBank(2022)

*Note*** $p<0.05$

4.2 Regression results of ADF test after differencing

Table 2. Regression results of ADF Test with trend after Differencing

After differencing the results in **Table 2** indicated that, given the p-Z(t) value is less than the critical values at all significance levels, we reject the null hypothesis of a unit root test. This indicates that, the agricultural output is stationary after differencing. The lagged level coefficient is negative and is statistically significant ($p < 0.05$), indicating a strong negative relationship. This suggests that, increases in past agricultural output led to significant declines in current output, reflecting a mean-reverting behavior as well. Meanwhile, the trend coefficient is not statistically significant ($p > 0.05$), indicating that, the trend does not have a meaningful impact on the differenced agricultural output. The results further indicate in **Table 3** that, since the p-Z(t) value is less than the critical values at all significance levels, we reject the null hypothesis of a unit root test. This indicates that, the differenced agricultural output is stationary even without trend. The lagged level coefficient-L1 is statistically significant ($p < 0.05$), indicating a strong negative relationship. This suggests that, increases in past agricultural output led to significant declines in current output, reflecting a mean-reverting behavior, again this may be due to factors such as climatic changes, policy change and market dynamics.

Overall, when agricultural output is stationary after differencing, it indicates that, the time series exhibits consistent statistical properties over time (see figure 2), allowing for reliable analysis and forecasting using traditional statistical methods. This stationarity implies that, any fluctuations or shocks in output are temporary and will revert to a long-term mean, suggesting a mean-reverting behavior in the data. For example, if fluctuations in maize production due to drought conditions are followed by a recovery in yields during subsequent years, the stationary nature of the series would suggest that such shocks do not lead to lasting changes in overall productivity levels. Consequently, policymakers can make informed decisions based on stable relationships within the data, as the underlying dynamics of agricultural productivity are predictable and less susceptible to persistent disturbances. additionally, achieving stationarity enhances the robustness of analyses and the effectiveness of strategies aimed at improving agricultural output.

Moreover, as evidenced in (Paul and Lema, 2018; Mhagama *et al,* 2023), a stationary agricultural output series depicted in this study can facilitate the development of targeted interventions that can boost productivity and food security. Example, if the coffee sector in Tanzania displays stationarity, stakeholders can focus on improving farming techniques, such as adopting climate-smart agriculture, knowing that the long-term average output will remain stable. Actually, these study results provide understanding that can enable the implementation of sustainable practices that can mitigate short-term shocks, such as investing in irrigation systems to ensure consistent water supply during dry seasons. Above all, by recognizing the stationary nature of agricultural output, policymakers can create a conducive environment for growth, ultimately contributing to economic stability and enhanced livelihoods for farmers across the country.

Source: World Bank (2022) *Note: **p<0.05*

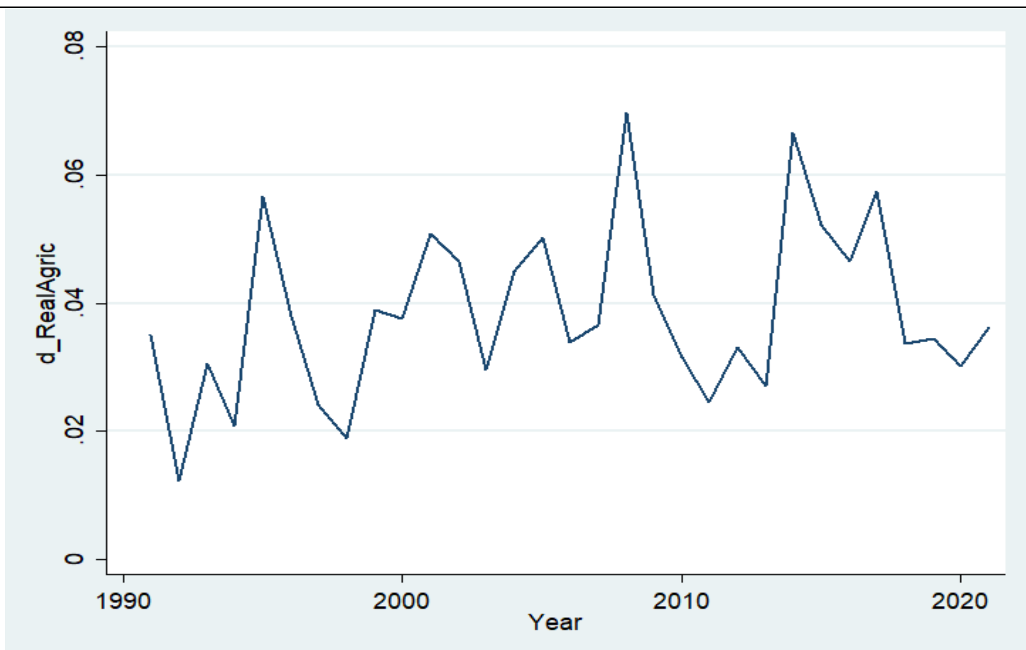
Variable Real Agricultural output value	**Lags**	**Coefficients & std error**	**T-statistic-Z(t)**	**p-value for Z(t)**	**5%Critical value**
Model: dfuller d_RealAgric, trend regress lags(0)	L1 _trend Constant	-.8955586(.192661) ** .0003629 (.0002982) .0288733(.0079148)	-4.648	0.0009**	-3.580

Source: World Bank (2022) *Note: **p<0.05*

Figure 2: A structural explanation of agricultural output value in Tanzania

Table 3. Regression results of ADF Test without trend after Differencing

Variable Real Agricultural output value	**Lags**	**Coefficients & std error**	**T-statistic-Z(t)**	**p-value for Z(t)**	**5%Critical value**
Model: dfuller d_RealAgric, drift regress lags(0)	L1 Constant	-.8278996(.1860375) ** .0318949 (.0075793)	-4.450	0.0001**	-1.701



Source: World Bank (2022)

The graph above (figure 2) shows that, agricultural output tends to change over times from 1990-2021 due to fluctuations/dynamics in production as a result of factors such as technological change, market dynamics, climate changes such as drought and over rainfall; policy change that happens in the country and global.

5.0 CONCLUSION AND POLICY IMPLICATIONS

This study assessed the dynamics of agricultural output in Tanzania using the ADF test model while utilizing time series data from 1990-2021. The results indicated that, agricultural output is non stationary before differencing while the differenced agricultural output series is stationary, suggesting that, fluctuations in output are temporary and revert to a long-term mean. This mean-reverting behavior implies that, agricultural productivity is influenced by consistent underlying factors, making it possible to predict future trends more reliably. The significant negative relationship with lagged output indicates that, periods of high production may lead to adjustments in subsequent periods, highlighting the importance of managing resources sustainably.

Overall, the findings suggest that, policymakers should focus on implementing strategies that enhance the resilience and sustainability of agricultural production. This includes investing in adaptive agricultural practices, such as crop diversification and soil health improvement, to mitigate the impact of adverse weather conditions and market fluctuations. Besides, promoting access to technology and data-driven decision-making can help farmers optimize yields while reducing resource depletion. Establishing robust support systems, such as financial assistance and risk management tools, will further enable farmers to manage production variability effectively. Thus, by fostering a stable agricultural environment that anticipates and adapts to changes, policymakers can ensure long-term food security and economic stability in the sector.
The limitation of this study is that, the agricultural output is influenced by number of factors, hence it is crucial for future study to account for causal relationship of different factors such as technology, weather changes, financial access and market dynamics into the model. Also, after differencing the data variable and become stationary, future studies may go for further analysis by utilizing forecasting models such as ARIMA (Auto-Regressive Integrated Moving Average).

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