Analysing Price and Non-Price Drivers of Chickpea Production Dynamics in Tanzania: Insights into Global Market Influence.

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Abstract: *This study examines the supply response of smallholder chickpea production in Tanzania in the context of rising global demand. Using annual time-series data from 1997 to 2022 and applying an Autoregressive Distributed Lag (ARDL) modelling approach, the analysis assesses the influence of global chickpea prices, export performance (as a proxy for global market demand), and rainfall on chickpea area harvested. The results reveal that rainfall plays a critical role in shaping production decisions, exerting a negative effect in the short run—likely reflecting waterlogging risks during planting—and a positive and significant effect in the long run, underscoring the importance of stable moisture conditions for sustained production. Global prices and export performance exhibit positive and significant effects in the short run, indicating that farmers respond to recent market signals, but their long-run effects are statistically insignificant, suggesting weak price transmission and limited integration of smallholders into global markets. Additionally, policy and institutional shifts captured through dummy variables indicate a positive structural break in 2011, coinciding with the first official release of improved chickpea varieties and intensified dissemination efforts, while adverse climatic conditions likely explain the negative effect observed in 2015. Based on these findings, the study highlights the importance of climate-resilient production strategies and improved market infrastructure as key policy priorities for strengthening chickpea production in Tanzania, while noting the need for future research to explicitly examine the roles of labour, technology, and institutional factors.*

Keywords: ARDL Model, Chickpea Production, Global Market Demand, Price and Non-price Factors, Structural Break.

JEL classification: Q11, Q12, Q13, Q17, O13

1.0 Introduction

Chickpeas are one of the most important dry legumes globally, valued for their nutritional content and adaptability to semi-arid climates. The crop is widely distributed across the world (Gaur *et al.,* 2018; Roorkiwa *et al.*, 2020; Fikre *et al.*, 2020), with origins traced to regions around Syria and southeast Turkey during the early Neolithic era (Redden & Berger, 2007). It later spread to secondary centres of diversity, such as the

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Indian subcontinent, Mediterranean Europe, and Northeast Africa. Archaeological findings of wild chickpea varieties in Ethiopia provide evidence of the crop's cultivation in Africa for over 2,500 years (Fikre *et al*., 2020; Admas *et al*., 2021). Despite this extensive history, only a limited number of African countries—Eritrea, Ethiopia, Kenya, Malawi, Niger, South Sudan, Sudan, Togo, Uganda, Zimbabwe and Tanzania—currently cultivate chickpeas.

In Tanzania, chickpeas are typically planted immediately after the long rainy season, averting competition for land with major staple crops. The main chickpea-producing regions include Shinyanga, Mwanza, Geita, Simiyu, Singida, Manyara, Kigoma, and Dodoma, and involve more than 70,000 farmers (URT, 2021). Despite its adaptability to the dry season and its export potential, chickpea production potential remains unexploited, with average yields of just 0.9 tons per hectare, which is well below the global average of 1.7 tons per hectare (FAO, 2025a). However, its importance is increasingly being recognised. According to the Ministry of Agriculture (2025), chickpea has been designated as one of the high-value crops prioritised for strategic trade promotion, alongside sesame and avocado. These crops collectively contributed approximately 10% of Tanzania's agricultural export earnings in the 2023/24 fiscal year (FAO, 2025b). This emerging status under national agricultural priorities underscores the growing policy relevance of chickpeas and their potential to enhance rural livelihoods, improve nutrition, and diversify Tanzania's export base in response to global market demand.

The global demand for chickpeas is rising significantly, driven by factors such as rapid population growth, increasing incomes, urbanisation, and a shift towards healthier dietary choices (Magrini *et al.,* 2017; Savadatti, 2018; Kutepova *et al.,* 2023; Rehm *et al*., 2023). This upward trend is evident in the demand surge, which has grown from less than 500,000 tonnes in 1994 to over 3,000,000 tonnes by 2017 (FAO, 2024a). Due to such large increases in demand, production systems may be under strain, particularly in countries like Tanzania, where productivity and production of chickpeas are still low (URT, 2015). Smallholder farmers in developing countries often take time to respond to market signals. This delay reduces their productivity and limits their ability to capitalise on market opportunities (Magrini *et al.,* 2017). This production gap underscores the importance of examining the factors influencing farmer decisions in Tanzania. Molenaar (2017) emphasises that both price and non-price factors influence pulse production, including chickpeas, in Tanzania. These factors shape farmers' decisions in response to shifting market conditions, industry dynamics, and government policies (Mbunduki, 2024). Analysing such trends over time offers valuable insights into how markets and environmental forces influence agricultural choices. This understanding is crucial for informing policy interventions aimed at supporting smallholder farmers, including price stabilisation, input subsidies, and trade policy design.

Despite the growing importance of chickpeas in Tanzania's agricultural policy agenda and rising global demand, empirical evidence on how Tanzanian farmers respond to

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these incentives remains limited. Existing studies focus on staple and cash crops or South Asian pulses, neglecting Tanzania's specific context for chickpeas, which restricts the development of targeted trade policies and production incentives for smallholder farmers. This study addresses this critical knowledge gap by assessing chickpea supply response using time-series data from Tanzania. The findings provide timely, evidence-based inputs for national policy, particularly as Tanzania aims to scale up high-value agricultural exports, strengthen farming systems, and enhance smallholder participation in global markets. The urgency of this research is further underscored by increasing climate variability and the growing global demand for chickpeas, which requires locally grounded evidence to inform strategic investment and policy planning.

2.0 Literature Review

2.1 Analytical Framework

The analytical foundation of this study is rooted in the Nerlovian supply response model, which provides a dynamic framework for analysing how farmers adjust production and land allocation in response to both price and non-price factors. This model combines two key behavioural concepts: the partial adjustment mechanism and the adaptive expectations hypothesis. The partial adjustment framework, introduced by Nerlove (1958), assumes that farmers adjust their actual production and land allocation gradually toward desired levels due to adjustment costs, institutional rigidities, and information constraints. As a result, full adjustment may not be achieved within a single production period (Tchereni, 2013; Savadatti, 2018; Mgeni & Mpenda, 2021). Complementing this framework, the adaptive expectation hypothesis, introduced by Cagan (1956) and Friedman (1957), suggests that farmers often rely on past experiences when forming expectations about uncertain future conditions (Evans & Ramey, 2001). Rather than fully incorporating new market information, farmers tend to revise expectations gradually based on previous observations (Frommel, 2017; Colasante *et al.,* 2017). Building on these two concepts, Askari and Cummings (1976) extended the Nerlovian model by incorporating additional non-price variables that influence farmers' production decisions, thereby improving its relevance for empirical analysis in agricultural settings. This resulted in a revised basic Nerlovian model which is represented by the following equations;

$$Q_t^D = a_0 + a_1 P_t^e + a_2 Z_t + u_t \quad (1)$$

$$P_t^e - P_{t-1}^e = \beta(P_{t-1} - P_{t-1}^e) \qquad (0 < \beta \le 1) \quad (2)$$

$$Q_t - Q_{t-1} = \gamma(Q_t^D - Q_{t-1}) \qquad (0 < \gamma \le 1) \quad (3)$$

whereas; Q_t and Q_t^D are actual and desired output at time t respectively, Q_{t-1} and Q_{t-1}^D are actual and desired output at time t-1 respectively, P_t^e is expected price at time t, P_{t-1} and P_{t-1}^e are actual and expected prices at time t-1 respectively, β and γ are the expectation and adjustment coefficients respectively, a_0, a_1 and a_2 are parameters, Z_t represents the set of non-price factors and u_t accounts for unobserved random factors with zero expected value. These three equations presented above represent three fundamental concepts distinguished by Nerlove (1958). The first equation explains that farmers adjust their output over time to reach desired levels, based on price expectations and non-price factors. The second equation states that farmers revise their price expectations for the coming year in proportion to the error they made in predicting the price of the current year. Lastly, the third equation states that the change in actual output is proportional to the difference between desired and actual output. These equations involve unobservable variables (Q_t^D and P_t^e) and long-term equilibrium. Navayana & Parikh (1981) simplified the original equation by eliminating unobservable variables, resulting in a version that can be estimated using only observable variables and presented as;

$$Q_t = B_0 + B_1 P_{t-1} + B_2 Q_{t-1} + B_3 Q_{t-2} + B_4 Z_t + B_5 Z_{t-1} + U_t \quad (4)$$

Whereas; $B_0 = a_0 \beta\gamma$, $B_1 = a_1 \beta\gamma$, $B_2 = (1 - \beta + 1 - \gamma)$, $B_3 = -(1 - \beta)(1 - \gamma)$, $B_4 = a_2 \gamma$, $B_5 = -a_2 (1 - \beta)\gamma$, and $U_t = \gamma[u_t - (1 - \beta)]u_{t-1}$

Several studies have employed the Ordinary Least Squares (OLS) technique to estimate the Nerlove model (Masese *et al.*, 2022; Jainuddin *et al.*, 2021; Shoko *et al.*, 2016), which assumes that all variables are stationary. However, agricultural time-series data are often non-stationary, making OLS estimates potentially unreliable (Shahzad *et al.*, 2018; Cancino & Cancino-Escalante, 2021; Waqas *et al.*, 2019). Although differencing can correct non-stationarity, it results in the loss of long-term information (Box & Jenkins, 1976; Davidson *et al.*, 1978; Shahzad *et al.*, 2018). To address this, cointegration techniques developed by Engle & Granger (1987) and Johansen & Juselius (1990) allow for the analysis of long-run relationships among variables. However, these methods have limitations: Engle-Granger is restricted to two variables and one cointegrating vector (Waqas *et al.,* 2019; Shahzad *et al.,* 2018), while Johansen's method requires all variables to be integrated of the same order and needs large sample sizes (Shahzad *et al.*, 2018). Given these constraints, this study adopts the Autoregressive Distributed Lag (ARDL) approach developed by Pesaran *et al.* (1999), which is appropriate for small samples and allows for a mix of I(0) and I(1) variables, making it well-suited to agricultural data in developing country contexts.

Building on this statistical framework, the Nerlovian model provides the theoretical foundation for understanding farmers' output adjustment behaviour in response to price and non-price signals under uncertainty. It captures the adaptive and gradual decision-making of smallholder farmers in environments with imperfect information and limited market access, conditions prevalent in Tanzania. However, the Nerlovian model lacks tools to handle the statistical properties of non-stationary time-series data. By integrating the ARDL model's empirical robustness with the Nerlovian model's behavioural insights, this study addresses both the statistical and theoretical challenges of analysing chickpea supply response. The ARDL model's flexibility ensures reliable estimation despite data constraints, while the Nerlovian framework contextualises

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farmer behaviour in Tanzania's semi-arid, smallholder-driven systems. This dual approach overcomes the limitations of each model when used alone, providing nuanced, evidence-based insights into how market dynamics and farmer behaviour shape farming decisions in response to global prices, export performance, and non-price factors like rainfall.

2.2. Empirical Literature

Empirical studies on agricultural supply response consistently show that a combination of price and non-price factors influences farmers' production decisions. For example, Nyerere (2016) used the Nerlovian partial adjustment model and Vector Error Correction Model (VECM) to analyse rice farmers' responses in Tanzania (1991–2015). The study found that selling price, rainfall, and fertiliser use significantly influenced land allocation, with non-price factors, especially rainfall, exerting a greater influence than price. This suggests that environmental constraints dominate decision-making in Tanzania's rain-fed agricultural systems. Similarly, Mbua and Atta-Aidoo (2023) analysed sugarcane production in Tanzania using a Vector Autoregression (VAR) model over the period 1991–2020. Their findings indicate that price variables played a more prominent role than non-price factors in both the short and long run. This contrasts with Nyerere (2016) suggests that supply responsiveness in Tanzania is crop-specific and closely linked to differences in market organisation, infrastructure, and institutional support.

Studies on pulses in South Asia further reveal mixed responses. Abraham and Pingali (2018) explored pulses in India using Nerlove's model and Ordinary Least Squares, revealing that pigeon pea and black gram acreage responded positively to prices, but green gram was price-inelastic in the long run. This inelasticity suggests that non-price constraints, such as input availability, may limit responsiveness, a finding relevant to Tanzania's rain-fed chickpea systems. In contrast, Savadatti (2018) examined chickpea production in India using Nerlove's price expectation model and Ordinary Least Squares (OLS). The study identified past land use, crop yields, and irrigation as key determinants of acreage. The emphasis on irrigation in India reflects infrastructure advantages that limit the direct applicability of such findings to Tanzania's rain-dependent chickpea production.

Additionally, Shahzad *et al.* (2018) employed the Autoregressive Distributed Lag (ARDL) model to analyse tobacco growers in Pakistan (1981–2014), revealing that tobacco prices and lagged production positively influenced short-run production, while wheat prices (a competing crop) had a negative effect. In the long run, tobacco prices and area remained significant, highlighting price responsiveness in structured markets. However, tobacco's cash crop status and market support differ from Tanzania's chickpea sector. However, these studies primarily focus on South Asia, where irrigation, subsidies, and market structures enhance responsiveness (Garg & Saxena, 2023; Vanzetti *et al.,* 2017).

Tanzania's chickpea sector, characterised by rain-fed production and weak market infrastructure (Molenaar, 2017), likely faces distinct constraints, limiting the applicability of South Asian findings.

Overall, the reviewed literature highlights that both price and non-price factors shape agricultural supply response, but the magnitude and timing of these effects vary across crops, regions, and institutional contexts. In Tanzania, existing empirical evidence is largely crop-specific and focuses on staple or established cash crops, offering limited insight into how smallholder farmers producing export-oriented legumes, such as chickpeas, respond to changing market conditions under predominantly rain-fed systems. Studies on pulses from South Asia further emphasise the role of prices and infrastructure, but their findings are difficult to generalise to Tanzania due to differences in irrigation access, institutional support, and market integration. Moreover, variations in econometric approaches across studies complicate direct comparisons of short- and long-run supply responses. These gaps underscore the need for a dynamic empirical framework capable of capturing both price and non-price influences while explicitly accounting for adjustment processes over time. Guided by this motivation, the next section outlines the empirical and analytical framework adopted in this study.

3.0 Methodology

3.1 Data Description

This study utilised annual time-series data from 1997 to 2022 to examine both long-term and short-term factors affecting smallholder chickpea production decisions in Tanzania. Data used were retrieved from Food and Agriculture Organisation (FAO) Statistical Databases and included variables such as chickpea area harvested (hectares), global chickpea prices (USD/ton), and Tanzania's chickpea export volumes (tons). Because the FAO database does not consistently report planted areas for chickpeas in Tanzania, the area harvested is used as a proxy for farmers' land allocation decisions. While harvested area reflects realised production rather than intended planting, it remains a valid indicator of farmers' effective land commitment to chickpea over time.

In a similar manner, limitations in directly observing global demand necessitate the use of an appropriate proxy variable. Therefore, Tanzania's chickpea export volume is employed as a proxy for external market demand, capturing realised international interest in Tanzanian chickpeas. This approach assumes that export performance reflects fluctuations in foreign market demand and market access conditions, which in turn shape domestic production incentives.

Additionally, average rainfall data (measured in millimetres) for the long rainy season months (Masika: March, April, and May) were obtained from the Tanzania Meteorological Authority (TMA) for the period 1997–2022. Instead of relying solely on point-based weather station records, this study utilised satellite-derived monthly total rainfall data, which provide continuous spatial coverage across major chickpea-producing areas. Rainfall estimates were extracted for Mwanza, Manyara, and Shinyanga regions—three leading chickpea-producing regions that together account for approximately 60% of the total chickpea area planted in Tanzania (URT, 2021). The use of satellite-based rainfall data allows for better representation of climatic conditions across farming landscapes, including areas with sparse or unevenly distributed weather stations. For each region, gridded monthly rainfall values were averaged over March, April, and May and then aggregated to construct a regional mean, which was subsequently used to derive a production-weighted proxy of national rainfall conditions affecting chickpea land allocation decisions.

3.2 Model Specification and Estimation

Before analysing the time-series data, preliminary statistical tests were conducted to assess the stationarity of the variables. The Augmented Dickey-Fuller (ADF) test was first applied to determine the order of integration and ensure that no variable was integrated beyond the first order, as required for the ARDL modelling approach (Waqas *et al.,* 2019). However, since the ADF test may fail to detect structural breaks in the data, the Zivot-Andrews unit root test was also employed. This test allows for the identification of endogenous structural breaks within the time series. When a structural break was detected, dummy variables were introduced to capture the shift in the underlying data-generating process. This approach is commonly used in time series analysis to isolate the impact of significant events or policy changes that may alter the trend or level of a variable. Following Alsamara *et al.* (2019), the dummy variable was defined as $DUM_t = 0$ if t < year of the structural break, and $DUM_t = 1$ if t $\geq$ year of the structural break. This helps account for the break in the regression framework, improving model specification and reducing the risk of biased estimates due to unaccounted-for structural changes.
After confirming stationarity and identifying any structural breaks, the study followed the approach outlined by Lema *et al.* (2023). This involved estimating the ARDL model, as presented in equation (5), to examine the cointegration relationship between chickpea acreage and its influencing factors

$$\begin{aligned}\Delta \ln AREA_t = b_0 + \sum_{i=1}^{P} \psi_i \ln AREA_{t-1} + \sum_{i=0}^{q_1} \theta_{i1} \Delta \ln PriceW_{t-1} + \sum_{i=0}^{q_2} \theta_{i2} \Delta \ln TzExport_{t-1} \\ + \sum_{i=0}^{q_3} \theta_{i4} \Delta \ln Rain + \delta_1 AREA_{t-1} + \delta_2 \ln PriceW_{t-1} + \delta_4\, ln\, TzExport_{t-1} \\ + \delta_4\, ln\, Rain_{t-1} + Dum_t + \mu_t \qquad (5)\end{aligned}$$

$$\begin{aligned}\Delta \ln AREA_t = b_0 + \sum_{i=1}^{P} \delta_1 \ln AREA_{t-1} + \sum_{i=0}^{q_1} \delta_2 \ln PriceW_{t-1} + \sum_{i=0}^{q_2} \delta_3 \ln TzExport_{t-1} \\ + \sum_{i=0}^{q_3} \delta_4 \ln Rain + \mu_t \qquad (6)\end{aligned}$$

$$\begin{aligned}\Delta \ln AREA_t = b_0 + \sum_{i=1}^{P} \psi_i AREA_{t-1} + \sum_{i=0}^{q_1} \theta_{i1} \Delta \ln PriceW_{t-1} + \sum_{i=0}^{q_2} \theta_{i2} \Delta \ln TzExport_{t-1} \\ + \sum_{i=0}^{q_3} \theta_{i3} \Delta\, ln\, Rain + Dum_t + \vartheta ecm_{t-1} \qquad (7)\end{aligned}$$

Whereas; $AREA$ is chickpeas area harvested in Tanzania, $PriceW$ is the global price of chickpea, $TzExport$ is Tanzania chickpea exports, $Rain$ is average rain, ψ_i and θ_i represent short-run multipliers, δi are the long-run multipliers, Dum_t is a dummy variable, b_0 is the intercept, Δ is the difference operator μt are the white noise errors and ϑecm_{t-1} is the error correction term .

This model was developed to study whether a long-term relationship exists between various variables. The analysis focuses on the coefficients of lagged variables to determine if a significant connection exists, using the F-test and t-test. The optimal lag length for the study was identified by utilising the Akaike Information Criterion (AIC), which is effective for estimating lag lengths in small samples (Mwakabungu & Kauangal, 2023). Since the study was conducted on an annual basis, a maximum lag of 2 was applied (Kripfganz & Schneider, 2023; Narayan, 2004). The analysis aimed to obtain both short-term and long-term variables by estimating the equations previously presented as (6) and (7).

To ensure the model's accuracy, several post-estimation diagnostic tests were conducted. The Breusch-Godfrey test checked for autocorrelation, while the White test assessed heteroskedasticity. The CUSUM test helped determine whether parameters remained stable over time. Additionally, the Jarque-Bera test evaluated if the residuals followed a normal distribution. These tests verified the model's reliability, reinforcing confidence in the findings.

4.0 Results and Discussion

4.1 Descriptive Statistics

The descriptive statistics for the variables used in the study are summarised in Table 1. The average chickpea area harvested (AREA), used as a proxy for farmers' land allocation decisions, was 75,227 hectares, with a standard deviation of 33,303 hectares. The harvested area ranged from a minimum of 25,560 hectares to a maximum of 198,112 hectares, highlighting considerable variability in farmers' effective land commitment to chickpea production over time.

The global chickpea price (PriceW) averaged $620.41 per ton, with a standard deviation of $152.02, ranging from $364.24 to $885.13 per ton, indicating significant price fluctuations. Tanzania's chickpea exports (TzExport) showed an average volume of 37,337 tons, with a standard deviation of 41,591 tons. Export volumes ranged widely, from as low as 1,728 tons to a peak of 167,547 tons, reflecting variability influenced by production and market dynamics. Rainfall during the planting season (Rain) averaged 182.59 mm, with a standard deviation of 51.32 mm and a range from 100.37 mm to 283.05 mm. Agronomic evidence suggests that chickpea performs best under moderate and well-distributed rainfall, typically between 100 and 150 mm during the planting and establishment period, when adequate soil moisture is required for germination and early crop development (Mthulisi & Mcebisi, 2020). The observed rainfall range, therefore, indicates that while some seasons fell within optimal moisture conditions, others exceeded crop water requirements, potentially increasing the risk of waterlogging and crop stress in rain-fed systems. These statistics provide essential context for understanding the factors influencing chickpea production and market dynamics in Tanzania.

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Table 1: Descriptive Statistics

Variable	Observations	Mean	Std. dev.	Min	Max
AREA	26	75227.12	33303.17	25560.00	198112.00
PriceW	26	620.41	152.02	364.24	885.13
TzExport	26	37336.98	41591.16	1728.00	167547.40
Rain	26	182.59	51.32	100.37	283.05

Source: Author's Calculations Based on Data.5hujj

4.2 Chickpea Production Dynamics in Tanzania

Figure 1 illustrates the trends in Tanzania's chickpea production, harvested area, global prices, rainfall, and exports over the past two decades (2003–2022), shaped by a dynamic interplay of local and international factors, including significant structural breaks in 2011 and 2015. Production stood at 29,885 tons in 2003, with a harvested area of 66,006 hectares, and grew steadily to a peak of 119,984 tons in 2012 on 198,112 hectares. This expansion coincided with rising global chickpea prices—from USD 412 per ton in 2003 to USD 831 per ton in 2011—and increasing exports from 27,226 tons in 2003 to 29,042 tons in 2012.

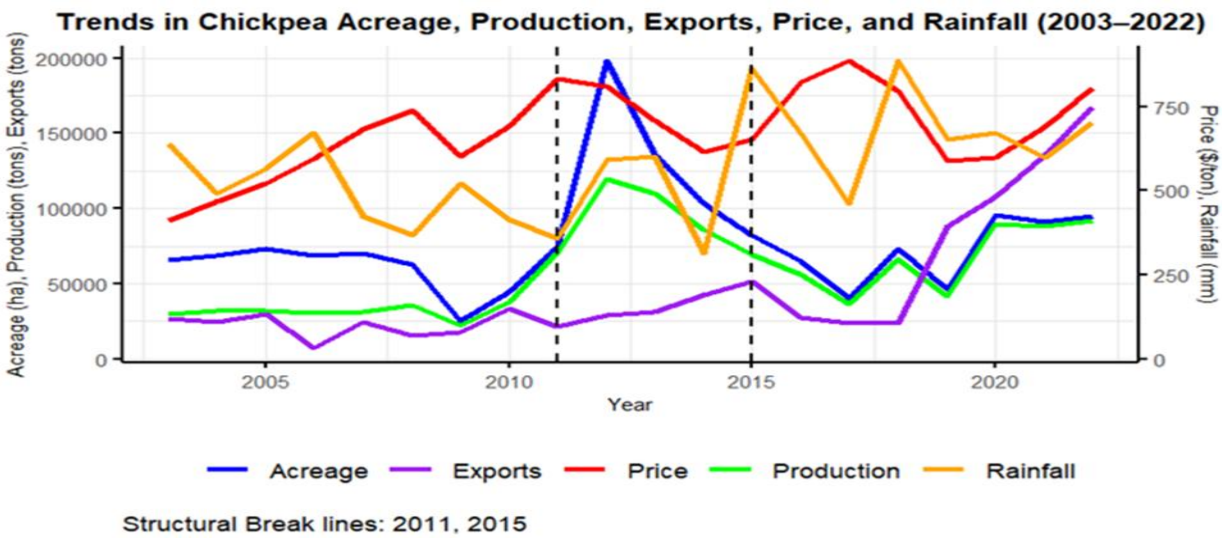

Figure 1: Chickpea Production Dynamics
Source: FAO statistics and TMA

A structural break in 2011, marked by supportive agricultural policies, may have boosted this expansion, as noted by Molenaar (2017), who highlighted growing farmer confidence despite weak market structures. However, production and area declined after 2012, falling to 56,170 tons and 64,724 hectares by 2016. This contraction occurred despite rising global chickpea prices, which were largely driven by strong demand in India between 2012 and 2015 (Singh *et al.*, 2017). The fact that Tanzanian production did not expand in response to these favourable price conditions suggests that domestic supply constraints such as climatic variability, limited access to quality seed, and weak market infrastructure may have outweighed price incentives and constrained farmers' ability to capitalise on emerging export opportunities.

A recovery in chickpea production began in 2017, with output rising to 90,000 tons in 2020 and 92,246 tons in 2022, alongside an expansion in harvested area to 95,213 hectares by 2022. This rebound may reflect farmers' adaptive responses to climate variability and pest pressures affecting traditional crops. For instance, Nyaombo (2022) reports that in Singida, 65% of farmers adopted pulses—including chickpeas—as a more resilient alternative to climate-sensitive staples. Overall, these trends illustrate that Tanzania's chickpea sector is shaped by an interaction of global price movements, export opportunities, policy shifts, and climatic conditions, with the 2011 and 2015 structural breaks reflecting, respectively, institutional/technological influences and environmental constraints.

4.3 ARDL Error Correction Mode

4.3.1 Pre-estimation Tests

Before estimating the ARDL model, several tests were conducted on the data. These tests include the stationarity test, structural break test and cointegration test. The Augmented Dickey-Fuller (ADF) test revealed that only rainfall was stationary at its level. In contrast, the Zivot-Andrews test, which accounts for potential structural breaks, identified area, rainfall, and price as stationary at their levels. After first differencing, the remaining series achieved stationarity, confirming their integration order as $I(1)$. Since the Johansen cointegration approach is not appropriate when combining $I(0)$ and $I(1)$ variables, using the ARDL model for analysis is deemed appropriate.

Table 2: The Augmented Dickey-Fuller (ADF) and Zivot-Andrews test results

ADF			**ZANDREWS**			
Variable	At level	After 1st dif.	At level	Break	After 1st dif.	Break
ln_AREA	-2.794	-3.159**	-5.133**	2011	-	
ln_PriceW	-1.696	-5.025***	-5.306**	2006	-	
ln_TzExpor	-1.333	-3.320**	-3.735	2011	-6.922***	2004
ln_Rain	-3.654**	-	-5.727***	2015	-	

***, ** and * represents stationary at 1, 5 and 10 per cent levels of significance respectively

Source: Results Based on Data.

In the analysis, structural break dummies for 2004, 2006, 2011, and 2015 were initially included, based on evidence from the Zivot-Andrews unit root test (Table 2). However, only the dummies for 2011 and 2015 were found to be statistically significant. These findings highlight that the structural changes in 2011 and 2015 had a measurable impact on the model, likely reflecting key events that occurred in that period. The optimal model was identified as ARDL (1,1,2,2), and a bound test was performed. The results of the bounds test indicated that the estimated F-statistic (6.872) and t-statistics (-4.349) exceeded the lower and upper bound critical values at 5% significance levels (3.23 - 4.35) and (2.860 - 3.780), respectively, confirming the presence of a long-run cointegration relationship between the dependent variable and the explanatory factors.

4.3.2 ARDL Model Estimation

The results of the ARDL (1,1,2,2) model estimation for acreage response to price and non-price factors are presented in Table 3. The model includes both long-run (LR) and short-run (SR) variables, the adjustment coefficient (ADJ) and the constant term (_cons). The R-squared value of 0.800 and the adjusted R-squared of 0.616 indicate that the model explains a large portion of the variability in the chickpea area. The low root mean square error (RMSE) of 0.259 also shows the model's strong fit, suggesting that the selected predictors effectively capture the key factors influencing chickpea cultivation.

Table 3: Results of ARDL Error Correction Model Estimation

	Variables	Coefficient	Newey–West Std. err.	t	P>t	[95% conf. interval]	
ADJ	ln_AREA	-0.741	0.170	-4.350	0.001***	-1.113	-0.370
LR	ln_PriceW	-0.022	0.677	-0.030	0.975	-1.496	1.453
	ln_TzExport	-0.017	0.121	-0.140	0.888	-0.282	0.247
	ln_Rain	1.912	0.859	2.230	0.046**	0.041	3.786
SR	D.ln_PriceW	1.572	0.534	2.950	0.012**	0.409	2.735
	D.ln_TzExport	0.328	0.160	2.050	0.062*	-0.020	0.675
	LD.ln_TzExport	0.154	0.129	1.200	0.255	-0.127	0.435
	D.ln_Rain	-0.499	0.334	-1.490	0.161	-1.226	0.228
	LD.ln_Rain	-0.433	0.221	-1.960	0.074*	-0.914	0.049
	DUM1	0.885	0.241	3.680	0.003***	0.361	1.409
	DUM2	-1.102	0.263	-4.200	0.001***	-1.674	-0.530
	_cons	1.023	5.570	0.180	0.857	-11.112	13.158

***, ** and * represents variable significance at 1 %, 5% and 10% levels respectively

$\boldsymbol{No.\ of\ Obs}$=24, $\boldsymbol{R^2}$ = 0.800, $\boldsymbol{Adj\ R^2}$ = 0.616, and RMSE = 0.259, Breusch-Godfrey LM Test Chi(2) = 14.533 and p-value = 0.000, White's test Chi (2) = 24.00 and p-value = 0.404, Jarque-Bera normality test for residual: Chi (2) = 0.231 and p-value = .891

Source: Model Estimates Based on Data.

The adjustment coefficient is an important measure to evaluate how the model fit data and creates a long-term equilibrium. According to Mbua & Atta-Aidoo (2023), this coefficient must be negative and statistically significant to meet theoretical and practical requirements. It is observed that the coefficient is -0.741 and is significant at a 1% level, which suggests a strong error correction mechanism. This negative sign shows how well the model restores equilibrium, which indicates that about 74% of any deviation from the long-run equilibrium is corrected each year.

The results from our ARDL model showed that rainfall has significantly influenced chickpea area harvested in both the short-run and long-run. In the short run, a negative effect (coefficient = -0.433, p = 0.074) from rainfall suggests that above-normal or poorly distributed rainfall during planting and early growth stages reduces the area ultimately harvested under chickpea, reflecting crop losses or abandonment rather than farmers' initial planting intentions. This finding matches with Monyo *et al.* (2014), who identified waterlogging as one of the key constraints to chickpea production in Tanzania. However, the positive and significant long-run relationship (coefficient = 1.912, p = 0.046) between rainfall and area shows how rainfall is important for sustainable production since steady rainfall ensures enough soil moisture. These findings show the need for adaptive water management strategies, especially in the face of increasing climate change. Chickpea's drought-tolerant nature makes it suitable for semi-arid regions, but the crop still relies on moderate and well-distributed rainfall for maximum productivity.

The analysis reveals a significant short-term relationship (coefficient = 1.5720, p = 0.012) between chickpea prices and area, suggesting that Tanzanian farmers are responsive to global price changes. This is particularly noteworthy given the context of limited market infrastructure, where formal price information systems are not widely accessible. The observed responsiveness may be explained by farmers relying on indirect clues—such as past price trends, community knowledge, or observed trader behaviour—to inform planting decisions. This aligns with findings from related literature, which highlight that in environments with weak information systems, farmers often adapt through experiential learning and social networks (Barrett, 2008; Magesa *et al.,* 2014). Therefore, even in the absence of direct price access, behavioural adaptations may enable farmers to partially align their farming decisions with global market trends. In the long run, however, the relationship between prices and harvested area is positive but statistically insignificant (coefficient = -0.022, p = 0.975), suggesting that price changes have a limited influence on land allocation decisions over time. This weak impact might be due to market inefficiencies and limited price transparency. As Molenaar (2017) noted, the absence of robust price discovery mechanisms in Tanzania allows intermediaries to exploit price gaps along the supply chain, disproportionately benefiting at the expense of farmers. This may cause farmers to view price signals as unreliable and prefer income stability and reducing risk over them. Similarly, Magesa *et al.* (2014) found that inadequate access to market information, such as prices, quality standards, and quantity demands, reduces farmers' bargaining power and promotes uncompetitive markets, which further force them to rely on non-price factors. These findings collide with Dlamini's (2018) study in Swaziland, where long-run price effects on potato acreage were not significant due to market uncertainties and price volatility, while short-term price effects were significant.

The influence of global market demand, proxied by Tanzania's chickpea export volume, was assessed across both long-run and short-run dynamics. In the long run, export volume did not exhibit a statistically significant effect on chickpea area (coefficient = -0.017, p = 0.888), indicating that sustained increases in external demand do not strongly shape smallholder investment decisions. Although Tanzania ranked among the top ten chickpea exporters globally in 2024 (FAO, 2025b), its export volumes remain modest relative to major producers and exporters such as India, Australia, and Canada. As a result, Tanzania's participation in global chickpea trade is characterised more by opportunistic export engagement than by strategic, market-led production planning. Moreover, chickpea exports in Tanzania are largely supply-driven, reflecting fluctuations in domestic production conditions—most notably rainfall variability, and, more broadly, agronomic challenges common to rain-fed systems—rather than deliberate long-term expansion in response to global demand signals. This limits the transmission of global market incentives to smallholder farming decisions over the long run, even though export opportunities may remain important in specific production seasons. In contrast, the short-run coefficient was positive and marginally significant (coefficient = 0.328, p = 0.062), implying that farmers may respond to recent improvements in export performance, possibly through observed demand at collection points or price premiums. This distinction underscores the importance of strengthening real-time market access and trade information systems to enhance farmer responsiveness to global demand trends.

Lastly, the dummy variables for 2011 and 2015 exhibited statistically significant effects on chickpea acreage, with coefficients of 0.8853 (p = 0.003) and −1.1023 (p = 0.001), respectively. The positive effect observed in 2011 coincides with the implementation of the First Five-Year Development Plan (FYDP I, 2011–2015) and the Long-Term Perspective Plan (2011–2025), which emphasised agricultural growth, crop diversification, and export-oriented value chains. Although chickpea was not explicitly prioritised as a standalone crop within these policy frameworks, 2011 marked the first official release of improved chickpea varieties in Tanzania, accompanied by intensified dissemination of improved agronomic practices and seed system development in major producing regions (Kileo *et al.,* 2014). These efforts were supported by development partners, notably ICRISAT, in collaboration with national research and extension institutions. Taken together, these policies, technological, and institutional developments likely enhanced farmer awareness, reduced seed access constraints, and improved confidence in chickpea production, thereby contributing to increased land allocation during this period. On the other hand, the negative effect observed in 2015 is likely associated with episodes of excessive distributed rainfall in major chickpea-producing regions (TMA, 2016). Such conditions can lead to waterlogging, increased disease incidence, and disruptions to field operations in predominantly rain-fed systems, ultimately reducing the area harvested under chickpea. This highlights the vulnerability of chickpea production to rainfall extremes, despite the crop's general tolerance to drought.

This study examined the effects of price and non-price factors on farmer acreage response in Tanzania, from 1997 to 2022. While the analysis was limited to this timeframe due to data availability, it still provided an understanding of agricultural decision-making. Despite constraints on the period, this study effectively utilised the ARDL model to analyse available data, as evidenced by the Post-estimation Diagnostic Tests conducted in the next section.

4.3.3 ARDL Post-estimation Diagnostic Tests

Several diagnostic tests were carried out to evaluate the stability and reliability of the ARDL model results. In Table 2, the model was estimated using Newey-West standard errors instead of the original ones to address autocorrelation. The presence of autocorrelation was confirmed by the Breusch-Godfrey LM test, which reported a Chi-square statistic of 14.533 and a p-value of 0.0001. As mentioned by Lema *et al*. (2023), Newey-West standard errors are robust against both autocorrelation and heteroskedasticity, making them a reliable adjustment for parameter estimation. A second test was White's test for heteroskedasticity, which yielded a chi-square statistic of 24.00 and a p-value of 0.4038. These results confirm that heteroskedasticity was not a concern in the model. Another test conducted was the Jarque-Bera test for residual normality, which had a Chi-square value of 0.231 and a p-value of 0.8909, confirming that the residuals followed a normal distribution.

Stability tests were also conducted to make sure the ARDL model coefficients were stable over time. The CUSUM test was used to identify systematic changes in the regression coefficients, and the CUSUM of Squares (CUSUMSQ) test evaluated the stability of the residual variance. According to the results from Figures 2 and 3, the cumulative sums in both tests stayed under the key 5% boundaries showing no indication of instability in the model, according to the results from Figures 2 and 3. Together, these diagnostic findings support the robustness and reliability of the ARDL model employed in the research.

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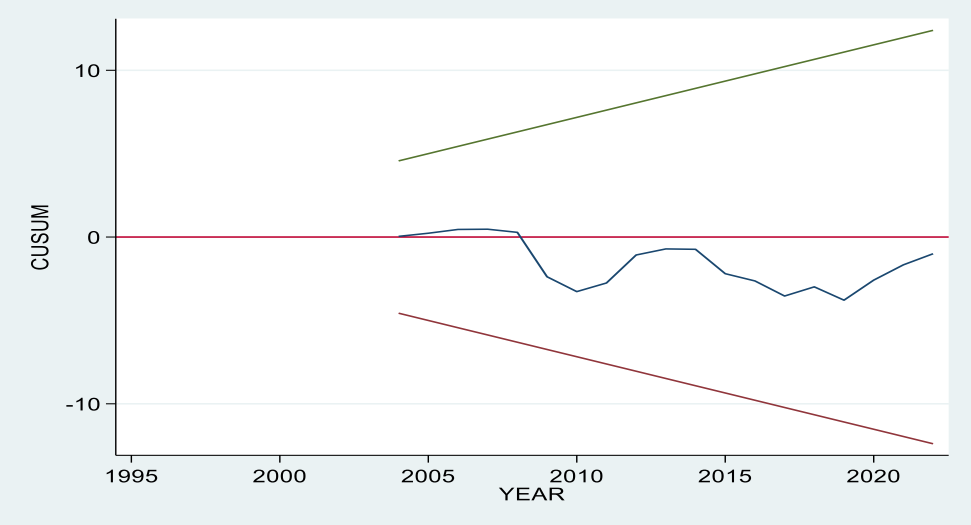

Figure 2: CUSUM Stability Test for ARDL Model
Source: Author's Calculations Based on Data.

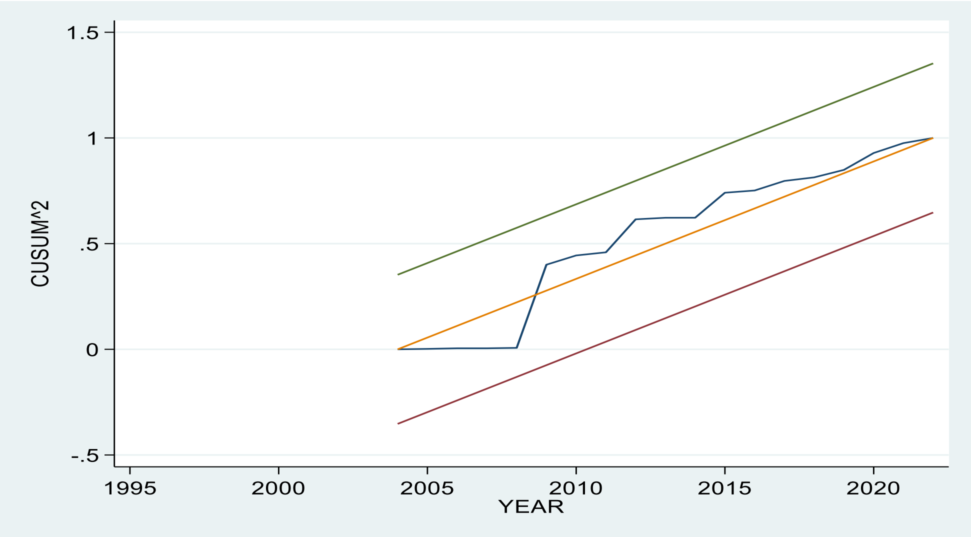

Figure 3: CUSUM-square Stability Test for ARDL Model
Source: Author's Calculations Based on Data.

5.0 Conclusion and Recommendations

5.1 Conclusion

This study sheds light on the complex dynamics influencing chickpea production in Tanzania, particularly the interplay between local production decisions and global market forces. By integrating long-term time-series data, the analysis provides nuanced evidence that while Tanzanian farmers are not entirely disconnected from international demand, their production decisions are more strongly shaped by environmental conditions and immediate price signals than by sustained global trends. The weak long-term influence of global market demand and prices reflects structural challenges, such as inadequate market infrastructure, limited access to reliable information, and weak price transmission mechanisms, that continue to insulate smallholders from global opportunities. In contrast, the strong role of rainfall in both the short and long run reinforces the vulnerability of production to climatic variability and underscores the need for climate-resilient farming systems.

5.2 Recommendations

Based on the empirical findings from the ARDL analysis, several policy-relevant recommendations emerge. First, the statistically significant influence of rainfall on chickpea acreage in both the short run and long run highlights the central role of climatic conditions in shaping production decisions. This underscores the need to strengthen climate-resilient production systems, particularly through the promotion and scaling up of drought-tolerant chickpea varieties and improved agronomic practices suited to rain-fed environments. While this study does not directly test specific adaptation technologies, the strong rainfall effects observed suggest that investments in soil moisture conservation and small-scale water management could help stabilise production under increasing climate variability.

Second, the presence of significant short-run price responsiveness indicates that farmers do react to price incentives when signals are timely and observable. This implies that improving price transmission mechanisms, such as enhancing market information systems, reducing intermediation costs, and strengthening trade logistics, could increase farmers' ability to align production decisions with market opportunities. Although market infrastructure variables were not directly included in the model, the weak long-run price effects observed point to structural market inefficiencies that warrant policy attention.

Third, the limited long-run influence of global market demand, proxied by export volumes, suggests that Tanzania's chickpea sector remains largely supply-driven rather than demand-led. This calls for complementary interventions aimed at improving market integration, including strengthening export coordination, quality standards, and institutional linkages along the value chain, to enable smallholders to benefit more consistently from global demand.

Finally, future research should extend the current analysis by incorporating additional institutional and production variables such as input access, labour dynamics, technology adoption, policy interventions and other non-price factors, using richer datasets where available. Such extensions would allow for a more comprehensive assessment of the mechanisms through which policy and institutional reforms affect chickpea supply response over time.

The study analysed the effect of sectoral employment composition on Tanzania's tax revenue. The time series data was used from 1970 to 2018 and utilised the ECM within

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the ARDL model for estimation. We employed the tax revenue as the dependent variable and regressed it with the independent variable, sectoral employment composition, and additional control variables. The control variables encompassed GDP per capita and trade openness. The current study's analysis has demonstrated that sectoral employment composition has a statistically significant impact on Tanzania's tax revenue generation, both in the short and long run. The practical contribution of this study is that the government and policymakers will be able to improve tax revenue by focusing on the specific sector which significantly affects it. This is because the study provides the effect of employment composition in each specific sector on tax revenue. Therefore, the government and policymakers need to work with the composition of employment in the service and industry sectors to address the challenge of low tax revenue. The government should also consider the sectoral employment transformation policy to enhance tax revenue collection in Tanzania. Furthermore, the authorities recommended focusing on trade openness as a means to enhance tax revenue. Theoretically, this study addresses the gap by offering empirical evidence regarding the impact of the sectoral employment composition for specific sectors on tax revenue. This current study provides empirical evidence to expand the understanding of the mechanisms by which sectoral employment composition affects tax revenue. This contributes to prior studies that examined the impact of aggregate employment on tax revenue across various contexts.

While the current research significantly enhances the understanding of the impact of sectoral employment composition on tax revenue, various limitations and considerations and suggested for further research. First, the study concentrated on total tax revenue. Future research could focus on disaggregate tax revenue to evaluate different tax categories as dependent variables. Secondly, due to the restricted focus of this study, it is advisable for future research efforts to include multiple countries in order to conduct a more thorough analysis. Lastly, this study exclusively relies on quantitative data. Future research should consider incorporating mixed methods to improve the understanding of the factors under study, as this strategy has the potential to yield different results.

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