An investigation into the relationship between population growth, technological development and food production in Nigeria

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Abstract
The study explores the relationship between population growth, technological development, and food production. The annual secondary data was extracted from world development indicators between 1991 and 2021. The Philips Perron unit root test undertaken to understand the stationarity order of the variables. The study employed ARDL bound tests of cointegration, short-run and long-run tests. All the variables produced results in line with existing theories and empirical findings of other studies. Population growth negatively affects food production, technological development supports a positive relationship with food production. Furthermore, the study found that there short-run and long-run causality. The results of the study indicate that in order to feed the growing population, food production must rise. The results also showed that technology is used more effectively in agriculture sector, which recommends the government to greatly increase research grant or acquire more technology.

Keywords: Causality, food production, population growth, technology development

1. Introduction

The issue of population growth and food production can be trace in the Malthusian theory, which contends that each child needs a certain quantity of food and that labor is divided between the production of food and manufactured goods. The fundamental assumption is that the labor intensity in the agricultural sector, which is reflected by the trade-off between purchasing manufactured goods and having children, impacts the relative cost of food. The creation of goods and services is made possible by a worldwide network of technological innovation, which makes it simpler and more efficient. On the subject of whether the indicators are related and linked to one another, scholars disagree. Food production may increase as the population grows, or vice versa. Technology improvement boosts food production, but food production also causes population growth. Population growth is what drives the biggest increase in global food production (Michael, Prince, & Bekun, 2018; Mekuria, 2018; Pawlak & Kolodziejczak, 2020). A shift in the intensity of land management can either amplify or temper technical change (Schneider et al., 2011). Despite the belief that more food production is necessary to feed the world's expanding population, experimental and correlational data indicate that food availability has an impact on population growth (Hopfenberg & Pimentel, 2001).

It was thought by Julian (1976); Basso & Antle (2020) claimed that population size influence innovation demand pulled, which happens when a population increases and new demands arise, resulting in stronger incentives for the innovator, and innovation technology pushed, which occurs when a population grows and new demands emerge, which makes it more probable that both will occur. An additional benefit of population growth that could lead to expansionary economic cycles is an uptick in demand for commodities, both for investment and for consumption. Knowledge is now the main focus instead of natural and reproducible physical wealth. It was therefore anticipated that output will not experience the declining returns to scale observed in earlier economic analyses.

The application of digital technologies to agricultural chores is the subject of other studies Chavas (2008); Boye & Arcand (2013); Tsiboe, Asravor, & Osei (2019); Malley, Bronson, Burg, & Klerkx (2020) it has been suggested that the use of digital technologies in agriculture, such as sensors and intelligent machinery, may be a sub-driver of changes in the food production ecosystem and advantages to ecosystem services. Food production is mainly dependent on outside resources like fertilizers and irrigation water, yet these practices are not sustainable. Urbanization growth results in severe arable land resource shortages in key regions due to the unequal distribution of global natural resources and significant regional differences (Wang, 2022). Economic development frequently involves a structural change in which an agrarian economy shifts to one that is more dependent on industry and services. African economies, however, are significantly more dependent on agriculture than the rest of the globe in terms of output and employment. The significant share of agriculture in both GDP and employment in Africa reflects the low GDP per capita of the continent (Herrendorf, Rogerson, & Valentinyi, 2014).

Idemudia (2012) believed that the inability of successive government in Nigerian to take any action to address the problem of low agricultural output. In most situations low agricultural output raises prices while demand increases (Chand, 2010). Furthermore, more funds will be allocated to technology transfer, which will benefit the area manufacturing and agriculture sectors (Suri & Udry, 2022). Although Nigeria's total agricultural output varies, imports have significantly supported the country's economy. Technology's impact on alterations in food production and the agricultural industry as a whole must be taken into account. Technology has already changed society and has the potential to boost output. Nigeria's economy is based on agriculture, however while being mostly used for subsistence, the agricultural sector has not kept up with the country's rapid population growth. Nigeria's primary source of income before the discovery of crude oil wells was agricultural exports. The main reason for the rise in global food production is population growth (Schneider et al., 2011). Nigeria's economy has struggled to thrive, in part because there hasn't been a fundamental transition. It also claims that a lack of economic diversification has led to a significant dependence on crude oil as a source of income and as its main export good, which is a key factor in this lack of economic development. The great bulk of Nigeria's non-oil exports, which predominately consisted of agricultural products, were made before the 1970s. However, non-oil export shares plummeted and have remained low ever since as global crude oil prices rose in the 1970s. This is due in part to the fact that oil exports are far more profitable than exports of non-oil commodities. As a result, the importance of the oil business and the money made from exporting crude oil has increased. Due to this dependence, the nation faces challenges when the price of crude oil, a vital export good, decreases on a global scale (Moses, 2011; Bala, Chin, Ranjanee, & Ismail, 2017; Orji, Abubakar, & Ogbuabor, 2021). The administration consequently implemented a number of policies to increase non-oil exports and stabilize the economy. The non-oil exports business continues to perform and contribute below par despite these efforts. Performance in the sector has consistently fallen short of projections. This study was conducted to ascertain relationship between population growth, technological development and food production in Nigeria.

2. Literature Review

There is some previous empirical studies conducted that explored the relationship between population growth, technological development and food production. Ervin & López-Carr (2017) discovered that, "Linkages among population, food production, and the environment at multiple scales," that the size and distribution of the human population around the globe have an apparent direct impact on how much food we consume and how we practice agriculture. The relationship between the world's population, food supply, and environment is intricate, non-linear, and scale and local dependent. This section starts off with a theoretical discussion before examining various factors that contribute to the population-food-environment nexus, giving a global overview of population and agricultural statistics from 1970 to 2010, talking about trends and implications for Latin America, and concluding with a few specific multi-scale case studies.

Some studies on population growth and food production Uddin & Zahurul (1992) Molotoks, Smith, & Dawson (2021) the results show that due to anticipated population changes, shared socio-economic pathway (SSP) scenarios have a bigger impact on future food insecurity. Countries with anticipated slower population increase had better food security, whereas those with anticipated rapid population growth suffered the most negative effects. Michael, Prince, & Bekun (2018) the population-food growth associations over the long and short-run from 1982 to 2016 were evaluated using the ARDL Model. The variables are mixed-order integrated, according to the results. The Malthusian theory was supported by the Bounds test, which revealed cointegration between population growth and food production in Nigeria. However, the estimations showed that, both in the long-run and the short-run, population expansion had a positive and significant association with food growth. This demonstrates that Malthus' claim that population growth would negatively affect the availability of food has not yet come to pass. The study of Mekuria (2018) looks at Ethiopia's population growth trends and debates while also examining the connection between population and food production. This analysis shows that both agricultural productivity and population have risen over time. Production growth, however, shows cyclical characteristics when contrasted to population increase. Even if declining mortality and fertility open the door to realizing the demographic dividend, rapid population growth, coupled with land degradation, is one of the main development concerns.

ICT and agricultural output Sennuga (2020) An strategy using two stages of random selection was used to select farming homes for the study. As a result of the ICT Services Short Message (SMS text reminders) 52% of respondents reported seeing quick increases in agricultural productivity and a higher level of life. Technology and food production Geffersa, Agbola, & Mahmood (2019) Research on farm efficiency provides insight into how farms might increase agricultural productivity. This article details a study of technical efficiency (TE) and technology adoption in the Ethiopian maize industry. The study corrected self-selection bias caused by farmers' desires to adopt new crop types and computed TE while accounting for potential technological differences between improved and local maize varieties. In order to estimate TE and account for self-selection bias, the study employed comprehensive household-level data collected in 2011 from Ethiopia's five primary maize-producing districts. The results demonstrate that efficiency estimates and farmer ranking based on efficiency scores are distorted by assuming homogeneous technology for native and improved maize varieties. After controlling for technological variations and self-selection bias, the mean TE of 66.18% showed that, given current input levels and technology, an increase in maize productivity of around 33.82% could be attained. Chavula (2014) conduct research used panel data for 34 African nations from 2000 to 2011 because it is thought that the introduction of ICTs had started to have an effect on the continent during this time period. Antle (1983) used technique and strategy is established by utilizing specific ICTs as input variables. The results show that despite mobile phones having little effect on agricultural productivity, ICTs play a significant part in enhancing it, and despite the widespread use of mobile technology, telephone main lines continue to contribute significantly to agricultural growth.

The studies that investigated the causal relationship of food price Pala (2013) the Johansen cointegration test and Granger causality via VECM were used in this study to examine the nature of the relationship between the crude oil price index and the food price index. Empirical findings for monthly data from 1990:01 to 2011:08 revealed breaks after 2008:08 and 2008:11. The findings show that these series have a distinct long-run connection for both the entire sample and the subsample. The cointegration regression coefficient is negative from 1990:01 to 2008:08, and it is positive from 2008:11 to 2011:08. These figures show how the relationship between the price of crude oil and food has evolved through time.

Nazlioglu (2011) the rising relationship between crude oil prices and the prices of agricultural commodities has rekindled research into how oil prices are transmitted to agricultural commodity prices. With a focus on nonlinear causal interactions, this study contributes to the body of information regarding the correlation between the price of three major agricultural commodities (wheat, soybeans, and maize) and the price of crude oil. This is done by using weekly data from 1994 to 2010 and the Diks-Panchenko nonparametric causality approach and the Toda-Yamamoto linear causality technique. The neutrality theory is supported by the linear causality analysis, which shows that there is no correlation between the prices of agricultural commodities and those of crude oil.

Bala & Chin (2017) the ascertain if variations in oil prices and currency rates are responsible for the unpredictable nature of rising prices from 1976 through 2015 using annual statistics on total inflation and separately analyzed pricing components were reviewed. The Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests were used for integration order of the economic series. To ascertain whether the model's variables are related over the long term, the Johansen Juselius cointegration test was undertaken. The findings indicate that fluctuations in the oil price and the exchange rate have varying effects on a variety of consumer prices. Fasanya & Odudu (2020) analyze the returns and volatility of the spillovers between wheat, rice, soybeans, groundnuts, and palm oil using monthly data from January 1980 to June 2017. The Total Spillover, Directional Spillover, and Net Spillover indices are generated as a result of the study's application of the Diebold & Yilmaz (2012) spillover approach. The outcomes show evidence of interconnection among significant agricultural commodities, according to the spillover indices.

3. Methodology

The methodology of the study, which include model definition, data analysis method, data source, and data analysis tool, are met by this component of the research, which also offers the pertinent theoretical framework needed to accomplish those goals. It may be permissible to incorporate or modify the work of others for analytical objectives.

Theoretical framework

The study made use of the available proxies to precisely determine the relationship between Nigeria's population growth, technology development and food production. The study also adopted a model from Adediran (2012); Michael et al. (2018) population Malthusian hypothesis. Revisiting population growth and food production nexus in Nigeria investigated using the Malthusian population growth model, commonly referred to as a fundamental exponential growth model. The function is assumed to be proportional to the rate at which the function rises in this model.

$$FP = f(PPG,)$$

In order to appropriately capture the relationship, the study used population growth, technology development, food production and GDP. The study applied Malthusian population growth model, sometimes called a simple exponential growth model, based on the idea of the function being proportional to the speed to which the function grows. The linear functional relationship of the model can be expressed as:

$P(t) = P_0 e^{rt}$ ………………………………………………………………………..(1)

Where:

P_0 = p (0) is the initial population size

e = exponential function

r = the Malthusian parameter or population growth rate

t = time

Model specification

$$FP = f(PPG, TCG, RGDP)$$

In econometric form,

$$FP_t = \beta_0 + \beta_1 PPG_t + \beta_2 TD_t + \beta_3 RGDP_t + \mu_t$$

The ARDL model used in equation below determines the unrestricted error correction model (ECM)

$$\begin{aligned}\Delta lnFP_t = \beta_{1t} &+ \sum_{i=1} \alpha_{1i}\, \Delta lnFP_{t-i} + \sum_{i=0} \beta_{1i}\, \Delta lnPPG_{t-i} + \sum_{i=0} \delta_{1i}\, \Delta lnTD_{t-i} \\ &+ \sum_{i=0} \chi_{1i}\, \Delta lnRGDP_{t-i} + \theta_1 lnFP_{t-1} + \theta_2 lnPPG_{t-I} + \theta_4 lnTD_{t-1} \\ &+ \theta_3 lnRGDP_{t-I} + \mu_t\end{aligned}$$

The vector autoregressive model

$A_t = \propto + X_1 A_t - 1 + \ldots + X_{P-1} A_{t-P} + \varepsilon_t$ (1)

Where: A_t represent the cointegration variables in 4 × 1 vector

A_1= Food production

A_2= Population growth

A_3= Technology cooperation grants

A_4= Real GDP

It is anticipated that all four indicators will be stationary following the first differentiation of I(1); however, when the variables are cointegrated in the long run, the VAR model can be specified as the follows:

$\Delta A_t = \propto + \Gamma_1 X_{t-1} + \ldots + \Gamma_{P-1}\, \Delta A_{t-P+1} + \Pi A_{t-1} + \varepsilon t$ (2)

When is cointegrated between $1 < r < 4$, it can be decompressed as Π, where Δ signifies changes in the operator and εt is the residual
white noise of the vector. In this foam, the second equation will also be restated:

$$\Delta A_t = \propto + \Gamma_1 A_{t-1} + \ldots + \Gamma_{P-1}\, \Delta A_{t-P+1} + \alpha(\beta' A_{t-1}) + \varepsilon t \qquad (3)$$

Each variable in Equation 3 is in stationary foam if the rows are regarded as various cointegration vectors, β stand for the coefficient adjustment demonstrating the potential movement to the equilibrium in the long-run, and linear combinations of $\beta' X_{t-1}$ are stationary operations. Using a maximum likelihood approach, the cointegration methods of Johansen (1988) allowed for the detection of the potential quantity of cointegrated equation among non-stationary variables.

Vector error-correction model (VECM)

Population growth (PPG), technical development (TCG), food production (FP), and real GDP are the variables in the models that are used to analyze the causal relationships in the short- and long-run. The VECM was used to build the model. The investigation employed the vector error-correction model (VECM) technique, which produced the following long-run equations:

$$\Delta FP_{1t} = u_1 + \sum_{h=1}^{r} \alpha_{1,h,} ECT_{h.t-I} + \sum_{k=1}^{p-1} B_{11.k}\, \Delta FP_{1t-k} + \sum_{k=1}^{p-1} B_{12,k}\, \Delta PPG_{2t-k} + \sum_{k=1}^{p-1} B_{13.k}\, \Delta TCG_{3t-k} + \sum_{k=1}^{p-1} B_{14.k}\, \Delta RGDP_{4t-k} + \mathcal{E}_{3t}$$

$$\Delta PPG_{2t} = u_2 + \sum_{h=1}^{r} \alpha_{2,h,} ECT_{h.t-I} + \sum_{k=1}^{p-1} B_{21,k}\, \Delta TCG_{1t-k} + \sum_{k=1}^{p-1} B_{22,k}\, \Delta PPG_{2t-k} + \sum_{k=1}^{p-1} B_{23,k}\, \Delta RGDP_{3t-k} + \sum_{k=1}^{p-1} B_{24.k}\, \Delta FP_{4t-k} + \mathcal{E}_{2t}$$

$$\Delta TCG_{3t} = u_3 + \sum_{h=1}^{r} \alpha_{3,h,} ECT_{h.t-I} + \sum_{k=1}^{p-1} B_{31,k}\, \Delta PPG_{1t-k} + \sum_{k=1}^{p-1} B_{32,k}\, \Delta RGDP_{2t-k} + \sum_{k=1}^{p-1} B_{33,k}\, \Delta TCG_{3t-k} + \sum_{k=1}^{p-1} B_{34.k}\, \Delta FP_{4t-k} + \mathcal{E}_{3t}$$

$$\Delta RGDP_{4t} = u_4 + \sum_{h=1}^{r} \alpha_{4,h,} ECT_{h.t-I} + \sum_{k=1}^{p-1} B_{41,k}\, \Delta PPG_{1t-k} + \sum_{k=1}^{p-1} B_{42,k}\, \Delta TCG_{2t-k} + \sum_{k=1}^{p-1} B_{43,k}\, \Delta FP_{3t-k} + \sum_{k=1}^{p-1} B_{44.k}\, \Delta RGDP_{4t-k} + \mathcal{E}_{3t}$$

Where the $\mathrm{ECT}_{h,t-1}$ symbolize the error correction term of the residuals from the initial lagged period of the cointegration equation. Moreover, the causal direction of the variables under VECM approach separates into two different categories short-run causality and long-run causality.

Source of data

The data used in this research are secondary sources in nature and has been downloaded online from World Bank Development Indicator website from 1990 to 2021. Food production index (2014-2016 = 100) based year, annual population growth rate, technical cooperation grants (BoP, current US$) and real GDP per capita.

4. Results and Discussion

The unit root was conducted using Philip Perron (PP) stationarity test. Table 1 presented the results indicated that all the four variables FP, PPG, TCG and RGDP were not stationary at level constant with trend and constant without trend. The unit root test shows the output of the variables. The findings demonstrate that all variables are stationary in first differences when using the Phillips-Perron (PP) test. The result suggests that the null hypothesis has not been rejected or that the constant with and without trend is non-stationary based on their level or I(0). The reason for this is that none of the variables are statistically significant at the 1, 5, or 10% levels. While in the first differences, or I(1), showed that all variables are statistically significant at the 1 and 5% level. After conducting stationarity tests at the initial difference between constants with and without trends, the study found that all four variables became stationary.

In view of the results, certified that ARDL bound test can be used to establish the long-run impact of the independent variables to dependent and Johansen cointegration test and Granger causality via VECM technique can also be suitable.

Table 1 Unit-root test

Variable		Philip Perron (PP)	
		Constant without trend	Constant with trend
FP	$I(0)$	-1.7425	-3.3382
	$I(1)$	-10.357***	-10.451***
PPG	$I(0)$	-0.6519	-0.3982
	$I(1)$	-3.0607**	-3.2892**
TCG	$I(0)$	-1.4151	-2.2055
	$I(1)$	-7.3961***	-7.3624***
$RGDP$	$I(0)$	-0.7251	-1.5612
	$I(1)$	-3.5579**	-3.5087**

Note: **Significant at 5% level. ***Significant at 1% level

Table 2 present the basic statistics description of the data based on the four variables included in the study. It shows that there are 36 observations multiple by 4 variables total of 144 data. All the variables presented with mean, median, maximum, minimum, Std. Dev., skewness, kurtosis, Jarque-Bera, probability, Sum and Sum Sq. Dev. All the data are in positive value. This will give more insight about the nature data under study.

Table 2 Descriptive statistics

	FPI	PPG	TCG	RGDP
Mean	72.73278	2.603632	1.78E+08	1940.816
Median	74.58500	2.594856	1.73E+08	1826.032
Maximum	111.7400	2.764062	3.77E+08	2679.555
Minimum	29.90000	2.406363	43100000	1414.698
Std. Dev.	24.11463	0.095178	1.09E+08	470.9796
Skewness	-0.104236	-0.072868	0.367971	0.266418
Kurtosis	1.993580	2.048065	1.749127	1.388865
Jarque-Bera	1.584512	1.391129	3.159439	4.319507
Probability	0.452822	0.498793	0.206033	0.115354
Sum	2618.380	93.73075	6.40E+09	69869.39
Sum Sq. Dev.	20353.04	0.317062	4.13E+17	7763761.
Observations	36	36	36	36

The lag selection criteria used Akaike information to detect the based combination of lags that will fit the model based on the data. The automatic selection derived 20 different combinations of models. Among the models 2, 0, 0, 0 emerge the best model ended with 2, 2, 0, 2 the lowest combination.

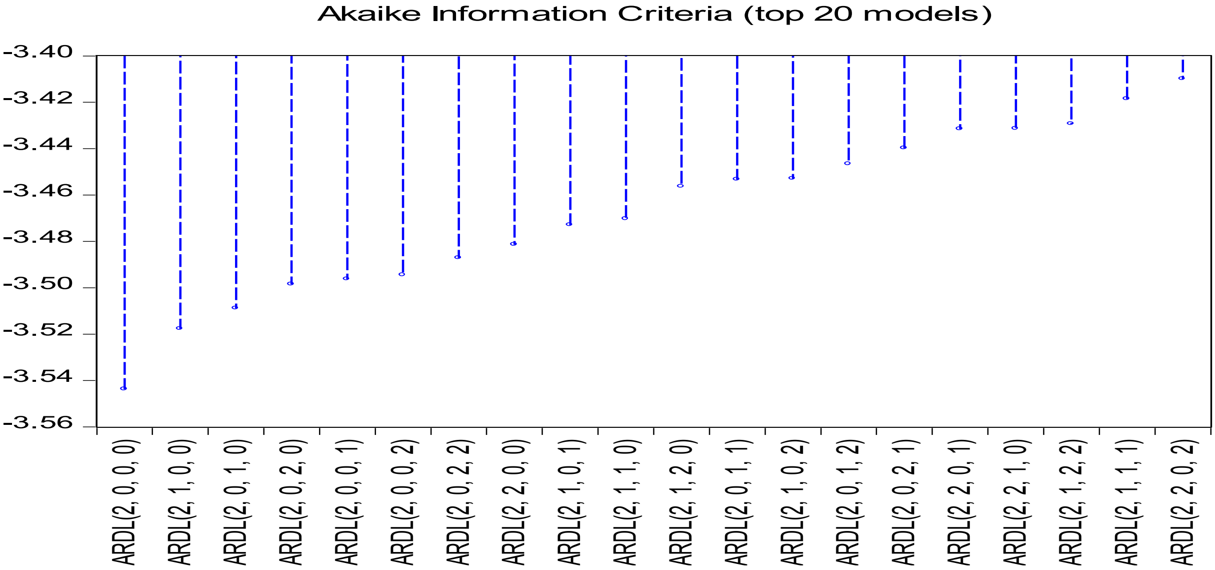

Figure 1: Optimal lag selection

Table 3 presented the ARDL bound test results of cointegration, there is highly recommended area to be considered based on the ARDL procedure. There are constant tabulated F-statistics values from the table in four different significant stages 1%, 2.5%, 5% and 10% level of significant. The calculated F-statistics based on the model indicate 13.0158 which are greater than the tabulated value at 1% level of significant of 4.66. The study concluded that the model has long-run relationship. Furthermore, we can continue to find-out the long-run and short-run coefficient sign and significant level.

Table 3 ARDL bound test

Model	**F – Statistics**	**Lag**	**Significance Level**	**Bound Test Critical Values (Constant Level)**	
	13.0158			**I(0)**	**I(1)**
$FPI = f(PPG, TCG, RGDP)$		2	10%	2.37	3.2
			5%	2.79	3.67
			2.5%	3.15	4.08
			1%	3.65	4.66

Table 4 consist the coefficients of long-run and short-run variables, from the left-hand side is the short-run results, long-run results in the right-hand side while diagnostic checks result at the end of the table.

Table 4 Long-run and short-run results

Short-run	DV LFPI Coefficient	Std. error	long-run	Coefficient	Std. Error
$D(LFPI(-1))$	-0.5678*** (-4.7677)	0.1190	$LPPG$	-2.7531** (-2.4730)	1.1132
$D(LPPG)$	-0.7506 (-1.5025)	0.4995	$LTCG$	0.4528** (2.3529)	0.1924
$D(LTCG)$	0.0676** (2.1771)	0.0310	$LRGDP$	-0.4788 (-0.8533)	0.5611
$D(LRGDP)$	-0.1070 (-0.5709)	0.1874	C	2.2797 (1.1767)	1.9373
$CointEq(-1)$	-0.1799*** (-8.3879)	0.0214			
	F-statistics	**P-value**			
Heteroscedasticity	1.5251	0.2140			
Serial correlation	0.6521	0.5292			
Normality	0.2559	0.3838			

Note: **Significant at 5% level. ***Significant at 1% level

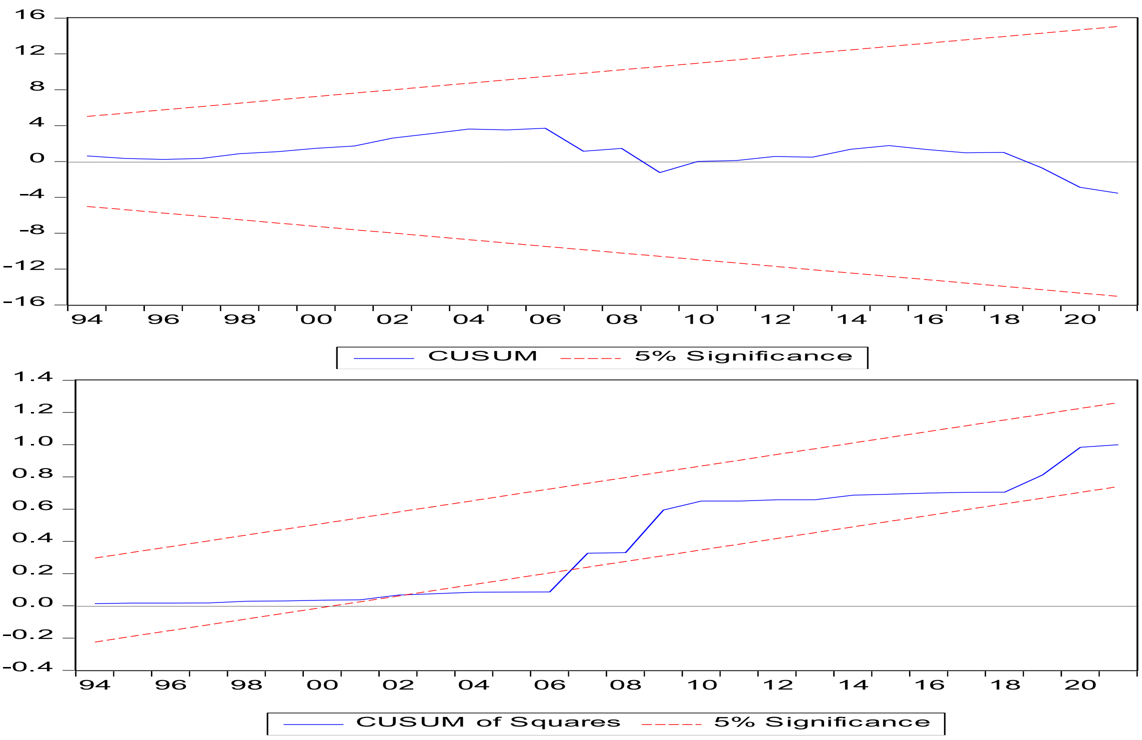

Figure 2: CUSUM and CUSUM of squares

Johansen cointegration test was used to determine the cointegration relationship of applicable variables. Table 5 and 6 provide the results in both trace statistics ($\lambda trace$) and maximum eigenvalue test (λmax) in Johansen procedure is chosen because it has the ability as to detect more than one cointegrating relationship in the long-run rather than the Philips Ouliaris method which can detect only one cointegration relationship in the model. The results from the Johansen test are obtained from two tests, Trace test and Max-Eigen value. However, the tests are nearly alike, but they may cause small differences if the sample is small. The cointegration equation used maximum of two (2) lags in the two tests. The results reveal that there are two cointegrating equation at 1 percent level of significant in both the two procedures of Trace test and Max-eigenvalue test.

Table 5: Trace unrestricted cointegration rank test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.623914	62.47429	47.85613	0.0012
At most 1 *	0.521549	34.11412	29.79707	0.0150
At most 2	0.316119	12.73528	15.49471	0.1249
At most 3	0.057460	1.716117	3.841466	0.1902

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values

Table 6: Maximum Eigenvalue unrestricted cointegration rank test

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.623914	28.36017	27.58434	0.0397
At most 1 *	0.521549	21.37883	21.13162	0.0462
At most 2	0.316119	11.01917	14.26460	0.1533
At most 3	0.057460	1.716117	3.841466	0.1902

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values

To confirm the causal relationship between population growth, technology, food production, and economic growth Granger causality of a minimum of the unidirectional way must occur when the variables in the equation move in a mutual and exclusive manner (Granger, 1988). Because cointegration just shows that causality exists, it does not show which way the relationship between them. The causal relationship could be established using the vector error correction model (VECM), which was created directly from the cointegration vectors. In the study, Johansen cointegration vectors were used to further approximate the VECM base causality tests. Table 7 shows the results from VECM Granger causality, the null hypothesis stated that there is no causal relationship between the variables under consideration until the probability become significant. Since the method explained the potential for both short-run and long-run causality effects. Both the t-test and the f test are used to determine whether the null hypothesis is accepted or rejected.

Table 7: VECM Granger causality

Variable	ΔFP	ΔPPG	ΔTCG	ΔRGDP	ECT_{it-1}
ΔFP	-	0.0512 (0.2263)	2.4430 (0.1180)	4.7725** (0.0289)	-0.1978*** (-3.4713)
ΔPPG	1.2554 (0.2677)	-	14.9295*** (7.4647)	1.8155 (0.9077)	0.0152*** 2.9835
ΔTCG	1.0540 (0.5954)	19.26*** (0.0000)	-	6.38** (0.0465)	-0.04** (-2.3332)
$\Delta RGDP$	3.0842 (0.2191)	1.5774 (0.4545)	4.8240 (0.0824)	-	0.31*** (2.9583)

Note: $\boldsymbol{ECT_{it-1}}$ is the error correction term indicating the long-run causality *, **, *** shows the significance levels at the 10%, 5%, and 1%, respectively.

5. Conclusion and Recommendations

The study aims to investigate the effects and connections between population growth, technological development, and food production. Secondary data was derived from global development indicators between 1991 and 2021. The cointegration and long-term effects of the independent factors on the dependent variable were examined after the pre-testing. The research used ARDL bound tests, short-run testing, and long-run tests, all of which produced outcomes that were in line with what was anticipated from the case study. Although population growth has a negative effect on food production, technological advancements have a positive effect. Furthermore, short run and long run causality also found in the study. The study recommended that the government encourage foreign farmers to adopt new technology and aim to build domestic substitutes through technology transfer, allowing the government to significantly enhance agricultural research. The study's findings revealed that technology is being used more efficiently in agriculture and that food production must increase output to feed the world's growing population.

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References

Adediran, O. A. (2012). Effect of population on economic development in Nigeria: A quantitative assessment. *International Journal of Physical and Social Sciences*, *2*(5), 1–14.

Antle, J. S. (1983). Infrastructure and aggregare agriculture productivity: International evidence. *Economic Development and Cultural Change*, *31*(3), 609–619. https://doi.org/http://dx.doi.org/10.1086/451344

Bala, U., & Chin, L. (2017). Oil price, exchange rate and disaggregate consumer prices: causality, impulse response, and variance decomposition. *International Journal of Economics, Commerce and Management*, *5*(6), 37–59.

Bala, U., Chin, L., Ranjanee, S., & Ismail, N. W. (2017). The impacts of oil export and food production on inflation in African OPEC members. *International Journal of Economics and Management*, *11*(S3), 573–590.

Basso, B., & Antle, J. (2020). Digital agriculture to design sustainable agricultural systems. *Nature Sustainability*, *3*(April), 254–256. https://doi.org/10.1038/s41893-020-0510-0

Boye, J. I., & Arcand, Y. (2013). Current trends in green technologies in food production and processing. *Food Engneering Review*, *5*, 1–17. https://doi.org/10.1007/s12393-012

Chand, R. (2010). Understanding the nature and causes of food inflation. *Economic and Political Weekly*, (9), 10–13.

Chavas, J. (2008). On the economics of agricultural production. *Australian Journal of Agricultural and Resource Economics*, *52*, 365–380. https://doi.org/10.1111/j.1467-8489.2008.00442.x

Chavula, H. K. (2014). The role of ICTs in agricultural production in Africa. *Journal of Development and Agricultural Economics*, *6*(7), 279–289. https://doi.org/10.5897/JDAE2013.0517

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66.

Ervin, D., & López-Carr, D. (2017). Linkages among population, food production, and the environment at multiple scales. *Journal of International and Global Studies*, *9*(1), 1–17.

Fasanya, I. O., & Odudu, T. F. (2020). Modeling return and volatility spillovers among food prices in Nigeria. *Journal of Agriculture and Food Research*, *2*(December 2019), 100029. https://doi.org/10.1016/j.jafr.2020.100029

Geffersa, A. G., Agbola, F. W., & Mahmood, A. (2019). Technology adoption and technical efficiency in maize production in rural Ethiopia. *African Journal of Agricultural and Resource Economics*, *14*(3), 184–201.

Herrendorf, B., Rogerson, R., & Valentinyi, A. (2014). Growth and structural transformation. *Handbook of Economic Growth*, *2*, 855–941.

Hopfenberg, R., & Pimentel, D. (2001). Human population numbers as a function of food supply. *Environment, Development and Sustainability*, *3*, 1–15.

Idemudia, U. (2012). The resource curse and the decentralization of oil revenue: the case of Nigeria. *Journal of Cleaner Production*, *35*, 183–193. https://doi.org/10.1016/j.jclepro.2012.05.046

Johansen, S. (1988). Statistical analysis of cointegrating vectors. *Journal of Economic Dynamics and Control*, *12*(2–3), 231–254.

Julian, L. S. (1976). Population growth may be good for LDCs in the long run: A richer simulation model. *Economic Development and Cultural Change*, *24*(2), 309–337.

Malley, A. L., Bronson, K., Burg, S. Van Der, & Klerkx, L. (2020). The future(s) of digital agriculture and sustainable food systems: An analysis of high-level policy documents. *Ecosystem Services*, *45*, 1–12.

Mekuria, W. (2018). The link between agricultural production and population dynamics in Ethiopia: a review. *Advances in Plants & Agriculture Research*, *8*(2), 349–353. https://doi.org/10.15406/apar.2018.08.00336

Michael, A. O., Prince, S. N., & Bekun, V. F. (2018). Revisiting population growth and food production nexus in Nigeria: an ARDL approach to cointegration. *Agricultural & Applied Economics Digital Library*, *4*(4), 41–51.

Molotoks, A., Smith, P., & Dawson, T. P. (2021). Impacts of land use, population, and climate change on global food security. *Food and Energy Security*, *10*, 1–20. https://doi.org/10.1002/fes3.261

Moses, E. (2011). Oil and nonoil FDI and economic growth in Nigeria. *Journal of Emerging Trends in Economics and Management Sciences*, *2*(4), 333–343. Retrieved from http://jetems.scholarlinkresearch.org/articles/Oil and Nonoil FDI and Economic Growth in Nigeria.pdf

Nazlioglu, S. (2011). World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy*, *39*(5), 2935–2943. https://doi.org/10.1016/j.enpol.2011.03.001

Orji, A., Abubakar, M., & Ogbuabor, J. E. (2021). Non-oil export and exchange rate nexus in Nigeria: Another empirical verification. *Growth*, *8*(1), 39–47. https://doi.org/10.20448/journal.511.2021.81.39.47

Pala, A. (2013). Structural breaks, cointegration, and causality by VECM analysis of crude oil and food price. *International Journal of Energy Economics and Policy*, *3*(3).

Pawlak, K., & Kolodziejczak, M. (2020). The role of agriculture in ensuring food security in developing countries: considerations in the context of the problem of sustainable food production. *Sustainability*, *12*, 1–20.

Schneider, U. A., Havlík, P., Schmid, E., Valin, H., Mosnier, A., Obersteiner, M., … Skalsky, R. (2011). Impacts of population growth, economic development, and technical change on global food production and consumption. *Agricultural Systems*, *104*, 204–215. https://doi.org/10.1016/j.agsy.2010.11.003

Sennuga, O. S., Conway, J. S., & Sennuga, M. A. (2020). Impact of information and communication technologies (ICTS) on agricultural productivity among smallholder farmers: evidence from sub-Saharan African communities. *International Journal of Agricultural Extension and Rural Development Studies*, *7*(1), 27–43.

Suri, T., & Udry, C. (2022). Agricultural technology in Africa. *Journal of Economic Perspectives*, *36*(1), 33–56.

Tsiboe, F., Asravor, J., & Osei, E. (2019). Vegetable production technical efficiency and technology gaps in Ghana. *African Journal of Agricultural and Resource Economics*, *14*(4), 255–278.

Uddin, M. F., & Zahurul, K. (1992). Population and agricultural land use: towards a sustainable food production system in Bangladesh. *Population, Natural Resources and Development*, *21*(1), 50–55.

Wang, X. (2022). Managing land carrying capacity: key to achieving sustainable production systems for food security. *Land*, *11*, 484. https://doi.org/https://doi.org/10.3390/ land11040484