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Climate Change Implications on Oil Palm Production Trends in Nigeria

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A R T I C L E I NFO

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ABSTRACT

Climate change had become a focal global environmental concern. Studies on various crops had proved that adverse effects accrue to crop plants from climatic factors variability. This could be in form of increase in temperature, draught, flood or disease epidemics. This study therefore estimated the climate change implications on oil palm production trends in Nigeria from 1981 to 2020 using Johansen cointegration and VECM model. The analysis revealed that ADF shows that at the level all the series data were non-stationary (p-value > 0.05), while at first difference, all variables were all significant at 1% level. AIC and HQC were significant at 5% at an optimal lag three in the model. Johansen cointegration test reveals that Trace test and Lmax test indicates there is only one cointegrating model at the 5% significance level with eigenvalue (0.73); which implies that there is a long-run relationship between Nigeria oil palm production and its climatic factor determinants. The VECM was used to estimates the error correction (EC) which was significant at 1% and 5% respectively in different equations; shows long-run relationships in oil palm production with area of farm, temperature and rainfall. Residuals diagnostics of the estimated VECM using ARCH and autocorrelation indicates that the residuals are homoskedasticity and residuals in the function are not correlated with one another. The study therefore recommended increase in oil palm tree planting; and the trends of climate change and production should be related to stakeholder in oil palm industry.

1.0 Introduction

Agricultural practice globally is the major vulnerable sector to the hazards and effects of international climate change, regardless of the advancements in technology and Green Revolution; weather and climatic factors remain the source and crucial dynamics in determining the level of agricultural productivity in almost regions globally. Temperature and rainfall patterns change with their related effects on availability of water, pests and diseases, and severe weather actions all to a large extent affect the prospective of agricultural production (Sarkar, Begum & Pereira, 2020). Although, the impacts of climate change are not equally experienced globally due to its unpredictability spatial level. The impact of climate change varies in several continents, countries, and regions of the world. Definitely some countries may be prone to more adverse impacts than others, whereas some other countries may likely benefit from the impact of climate change (Environmental Protection Agency EPA, 2016). Hence, climate change can have positive and negative impacts on geographical related area of agricultural production. However, several studies indicated that the negative effects of climate change could be higher than the positive impacts (Intergovernmental panel on Climate Change 2012 as cited in Sarkar *et al,* 2020).

The implications of climate change on agricultural productivity can be difference among crops and regions. The rate of recurrence and gravity of extreme weather events rises because of change in climatic factors, which affect agricultural productivity to a great extent. According to Calzadilla, Rehdanz, Betts, Fallons, Wiltshire and Tol (2013) as cited in Sarkar *et* *al*, (2020) crop production is capable of reducing more or lesser in all regions of the world, excluding Australia and New Zealand because of rise in temperature. Sub-Saharan Africa countries would experience crop production losses (like rice, wheat, fruits, nuts, oil seeds, oil palm etc) of about 10.91% and 25.40% with +2ºC and +4ºC increase in temperature respectively.

Nigeria was the highest oil palm producer globally in early 1960s with about 43% market share globally. Currently, Nigeria is the fifth largest oil palm producer with less than 2% of the aggregate world market production of about 74.08 million metric tonnes MMT (Prince water house Coopers Limited PwC, 2019). Malaysia and Indonesia improved and exceeded Nigeria as the highest global in oil palm production in 1966. Ever since then, Malaysia and Indonesia collectively produce about 80% of the aggregate world oil palm output, with Indonesia alone produced more than 53.3% of world output. According to the Central Bank of Nigeria (CBN) as cited in PwC (2019), if Nigeria had continued and sustained its market largest globally in oil palm production, Nigeria would have been receiving income of about $20 billion per annul from growing and processing of oil palm currently. According to United States Department of Agriculture (USDA) as cited in PwC (2019) Nigeria is presently the fifth highest oil palm producing nation, with about 1.5% that's about 1.03MMT of the global aggregate output. This could be as a result of extreme climatic factors variations.

Nigeria utilized (that's both domestic and industrial used) about 6.6 million tonnes MT of oil palm produced from 2014 t0 2018. Out of the aggregate consumption, 75% which was about 4.93MT was locally produced, thus relying on importation for the deficit of about 25% which was about 1.67MT, which amount to about 350,000MT or $223.63 million in 2018. From 2014 to 2018, Nigeria imported palm oil of about 1.7MMT which was about $1.28 billion (PwC, 2019). From being one of the key and foremost oil palm in the 1960s, Nigeria is presently one of the net importers of oil palm produce. In a bid to meet up and closed the gap in knowledge and encourage local oil palm producers this study examined climate change implication on oil palm production and utilisation trends in Nigeria. The remaining part of this article is divided into literature, methodology, results and discussion, and conclusion and policy recommendation. The specific objective of this study was to estimate the temperature and rainfall trends on oil palm production in Nigeria from 1981 to 2020.

1.1 Implications of oil palm farming on climate change

Dislich, Keyel, Salecker, Kisel, Meyer, Auliya, Wiegand (2017) noted that 11 out of 14 ecosystem functions reduced oil palm plantations and green house gasses GHGs contributes to climate change processes. Koh and Wilcove (2008) as cited in Murphy, Goggin and Paterson (2021) stated that expansion of oil palm plantation emerges at the expense of natural forests acting as carbon sinks. The conversion of natural tropical rainforests into oil palm plantations is the main and crucial ecological implication of the oil palm industry (Paterson & Lima, 2018), forested areas are converted for the development and growth of oil palm plantations where the emissions from the used surpassed the possibility of carbon fixing ability of oil palm.

Oil palm production entails deforestation releasing global anthropogenetic emissions of between 6-17% of CO_2 (Murphy *et al*, 2021). Brazil, Indonesia and Malaysia with values of 340, 105 and 41 (Teragrams C/year) respectively are the nations with utmost carbon emissions from there forest shield loss. Indonesia and Malaysia recorded highest carbon emissions due to deforestation as they are the first and second largest country oil palm producers; moreover considerable oil palm production is also carried out in Columbia and Nigeria (Paterson, Kumar, Shabani & Lima, 2017). Huge decreases in GHGs emission and climate guideline adaptation act occur owing to the conversion of natural forest into oil palm plantations. Additional GHGs and volatile organic compounds (VOCs), which occur as antecedents to troposphere zone are produced from oil palm plantations. GHGs released from farm land preparations, burning, and establishment of oil palm plantations are to a greater extent larger than carbon sequestered by oil palm. GHGs, VOCs and aerosol element emissions in the course of burning result directly and indirectly variations in solar irradiation while uninterrupted forests provide lesser air and soil temperature with higher atmosphere humidity microclimates in contrasts to oil palm plantations (Dislich *et al*, 2017).

The prevalent and major compound causal of the GHG from oil palm plantations is CO_2, while nitrous oxide and methane are at abridged intensities, even though with larger consequence per molecule. Greater emissions of CO_2 from land preparation burning operation happen, predominantly on peat. Farm land burning indirectly heightens emissions through increasing peat breakdowns and decomposition. Drainage of peat from farm soil emits substantial concentrations of CO_2 to establish oil palm plantations through oxidation, breakdowns and decomposition; break up and liquefied organic matter is detached from peat farm soils in the course of drainage, which decays, circulates and emits extra CO_2 (Murphy *et al*, 2021). The actual climax oil palm fruit production tolerates higher absorption and acclimatization of CO_2 and generates more biomass than natural forests. This huge level of carbon uptake does not counterbalance for that emitted during forests clearing for oil palm plantations, as natural forests have additional biomass than oil palm plantations except extremely long timelines of about hundreds of years are taken into account deliberately (Paterson *et al*, 2017). Burning adds black carbon, which also increases warming globally and oil palm plantations emit additional nitrous oxide (N_2O) into the air and environment than forests, majorly from fertilizer utilized.

1.2 Implications of climate change on oil palm farming

Generally, climate change is prone to have an effect on continual oil palm productivity as climatic factor appropriateness will reduce, with concurrent rises in economic and social difficulty in oil palm producing regions. According to Paterson *et al*, (2017) oil palm varieties may response differently under climate change to the negative effect on the accuracy and correctness of future climates on oil palm production at global position. Moreover, oil palm production generates climate change as discussed above, and this will have implication on the capacity to grow, maintain and distribution of oil palm. By 2100, higher oil palm plantation mortalities were ascertained globally excluding Paraguay which happened to be almost immune to the impacts of climate change in future. Extreme high oil palm mortality was ascertained for Nigeria and Ghana in Sub-Saharan Africa, while Cameroon will experience low levels, particularly by 2100 (Paterson, 2021). Hence, this forecasting is capable of making oil palm production unsustainable, if accurate measures are not put in place. Therefore, the implications of climate change on oil palm productivity can be colossal owing to the severity, concentration and intensity of climate change: the oil palm plantation land could be dehydrated and degraded; and also the oil palm plantation could be vulnerable to fungus, diseases, and pest infestations because of increase in temperature. Hence, this study attempts to examine the relationship between climate change and oil palm production in Nigeria using time series data.

2.0 Methodology

To examine the implication relationship between climate change and oil palm production and utilization, this study used secondary data related to oil palm production area, oil palm production, annual mean temperature and annual mean rainfall in Nigeria. Oil palm production (area harvested) in thousand hectares (ha), oil palm production and consumption in thousand metric tonnes (MT) are extracted from United States Department of Agriculture USDA from 1981 to 2020, while population, annual mean temperature in (^oC) and annual mean rainfall in (mm) from Nigerian Meteorological Agency and World Development Indicator (WDI) the primary World Bank collection of development indicators from 1981 to 2020.

According to Engle and Granger (1987 as cited in Songsiengchai, Sidique, Djama and Azman-Saini, 2018), two or more sequences of non-stationary data possibly will be present as a stationary linear model combination, if they are cointegrated. Thus, the linear model combination can be expressed as:

$$\mu_t = y_t - \beta_0 - \alpha_i x_i \qquad (1)$$

Where;

μ_t = Stationary

y_t and x_i = set of non-stationary data

This model combination represents the relation of long-run stability in the midst of variables. In order to estimate the long-run relationship of the equation (1), Hoffman and Rasche (1996 as cited in Songsiengchai *et al*, 2018) recommended vector error correction model (VECM) that proffers a long-run relationship and efficient coefficient estimation. The processes of estimating VECM are; first, assess the unit root tests. The unit root test is required before proceeding to analyse cointegration; to check the stationary and integration properties of the data. Augmented Dickey-Fuller (ADF) which is widely in testing unit root tests is applied in this study. Secondly, identify and estimate a vector autoregressive (VAR) model of the integrated series. Then, use suitable lag order of VAR model criteria like Sequential Likelihood Ratio (LR), Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQC) and Schwarz Information Criterion (SIC). Lastly, utilize Johansen (1988 as used and cited in Songsiengchai *et al*, 2018). The VECM model can be expressed as:

$$\Delta y_t = \pi y_{t-1} + \sum_{i=1}^{k-1} \tau_i \Delta y_{t-i} + \mu + \epsilon_t \qquad (2)$$

Where;

y_t = (n x 1) vector of the n variables

Δ = First difference operator

π = (n x n) coefficient matrix

τ = (n x (k-1)) matrix of short-run coefficients

μ = error term

ϵ_t = (n x 1) vector of white noise disturbances

The production model as the following will be estimated:

$$Prod_t = f(ProdAr_t, Temp_t, Rain_t) \qquad (3)$$

Where;

$Prod_t$ = oil palm production (in 1000 MT)
$ProdAr_t$ = oil palm production area (in 1000ha)
$Temp_t$ = annual mean temperature (in °C)
$Rain_t$ = annual mean rainfall (in mm)

3.0 Results and Discussion

Table 1: Summary statistics of Nigeria oil palm production and its determinants

	Prod (1000 MT)	ProdAr (1000 ha)	Temp (°C)	Rain (mm)
Mean	767.52	2226.9	27.17	1137.1
Median	760	2500	27.19	1139
Minimum	500	1.00	26.32	872.04
Maximum	1275	2800	27.81	1269.2
Std. Dev.	191.4	636.71	0.32	82.15
Skewness	0.66	-2.50	-0.32	-0.79
Kurtosis	-0.24	5.64	0.16	0.92
Jarque-Bera	3.03	94.82***	0.72	5.56*
Doornik-Hansen	5.12*	100.21***	1.44	4.67*

Source: Authors computation, 2022

Table 1 illustrates the summary statistics for the Nigeria oil palm production and its determinants. During the period of 1981 to 2020, mean oil palm output was 767.52 thousand MT at about 2226.9 thousand MT ha at 27.17 °C temperature and rainfall at 1137.1 mm. production area (size of farm), temperature and rainfall were negatively skewed, while production output was positively skewed. Jarque-Bera test statistics result affirmed oil palm production area of land covered was not normally distributed. Doornik-Hansen test was used to test the normality of the residuals (Ali, 2015), oil palm production (5.12) and climatic factors that's temperature (1.44) and rainfall (4.67) supported the null hypothesis of the normality of residuals. Several studies have reported similar trends. For instance, Bindoff *et al* (2013) noted that global weather trends and water levels are gradually altering because of elevated temperatures caused by human activities releasing greenhouse gases into the atmosphere. One major cause of global warming is Carbon-dioxide., mainly released into the atmosphere from burning and consumption of fossil fuels as well as variation in land use patterns such as deforestation, although other greenhouse gases such as methane are also key contributors (IPCC 2013). Greenhouse gas emissions and temperatures will continue to increase throughout the 21st century. This will cause a higher frequency and intensity of extreme weather events such as heat waves, drought, and sudden heavy rainfall. Sea levels are also continually rising with temperature increase.

Table 2: ADF unit tests results of oil palm production

Variables	Level		First Difference	
	t-value	*p*-value	*t*-value	*p*-value
Intercept:				
LProd	1.6870	0.9997	-5.4019	0.0000
LProdAr	-2.9021	0.0551	-23.1879	0.0000
LTemp	-1.4205	0.5739	-8.6122	0.0000
LRain	-2.4984	0.1158	-8.8805	0.0000
Intercept and trend:				
LProd	-1.1971	0.8972	-5.4858	0.0000
LProdAr	-1.9578	0.6237	-21.1167	0.0000
LTemp	-4.8779	0.9998	-8.4828	0.0000
LRain	-3.0657	0.1146	-8.7739	0.0000

Source: Authors computation, 2022

Table2 above shows the unit root test at a level and first difference. Augmented Dickey-Fuller (ADF) unit root tests were conducted for stationary test. The ADF shows that at the level all the series data were non-stationary (p-value > 0.05). This means that all the variables are not *I(0)*. At first difference, all variables were all significant at 1% level (P-value < 0.01). This signifies that all the variables considered are integrated of order *I(1)*. This finding agrees with Songsiengchai *et al*, (2018) in their study of crude palm oil price in Thailand. The trend of oil palm production and climate factors in Nigeria is provided in Appendix.

Table 3: VAR lag order selection criteria

Lag	LogL	LR	AIC	BIC	HQC
1	257.72856	NA	-12.5405	-11.1329*	-12.0492
2	284.0765	0.00001	-13.1154	-11.0040	-12.3784
3	310.1977	0.00001	-13.6776*	-10.8625	-12.6951*

Source: Authors computation, 2022

Table 3 above shows the assessment results of the VAR model for decisive optimal lag orders. The asterisks (*) above indicate the best values of the respective information criteria at 5% level significance. Akaike Information Criterion (AIC) and Hannan-Quinn Criterion (HQC) called for three (3) lags, excluding Bayesian Information Criterion (BIC) that called for one lag. Hence, this study decisively chooses three lags as an optimal lag in the model.

Table 4: Johansen cointegration test of oil palm production

H_0: rank = r	Eigen value	Trace test	*P-value*	Lmax test	*P-value*
r = 0*	0.7265	82.974	0.0000	49.260	0.0000
r ≤ 1*	0.3575	33.713	0.0404	16.812	0.2538
r ≤ 2	0.2299	16.902	0.1378	9.9261	0.3527
r ≤ 3	0.1677	6.975	0.1311	6.9754	0.1310

Note: * implies rejection of the hypothesis at 5% level
Source: Authors computation, 2022

Table 4 shows that both trace and Lmax tests accept the null hypothesis that the smallest eigenvalues is zero (0) as seen in the last row of the table. This implies that the series are in fact non-stationary. However, some linear combination may be *I(0)*. Since, all the variables in the model were integrated of order one, the Johansen cointegration test was chosen to discover long-run relationships. Supposing there is no deterministic trend in the data, no constant or trend in the cointegration model, the finding of Trace test and Lmax test indicates there is only one cointegrating model at the 5% significance level. This implies that there is a long-run relationship between Nigeria oil palm production and its climatic factor determinants. According to Baiyewu-Teru (2017), Oil palm crop production is confronted with many past, present and future setbacks, including emerging threats from climate change and pests and diseases. In a similar view, Merem (2020), noted that the inevitability of climate change requires more effective international synergy for its reduction as it has brought much greater negative effects on oil palm production and utilization efforts. Amidst rising environmental impacts made up of deforestation, biodiversity loss, land grabbing standoff, rural urban migration as well as dislocation and resettlement of rural dwellers due to rising communal conflicts and general insecurity.

Table 5: Cointegrating Beta and Adjustment Alpha Vectors

Variables	Coefficient *β Matrix*				*α Matrix*			
	1st equation	2nd equation	3rd equation	4th equation				
***β* cointegrating vectors**					***α* adjustment vectors**			
Prod	-0.0038	-0.0075	-0.0006	0.0002	-4.2438	-4.8292	-23.032	0.2219
ProdAr	0.0024	-0.0003	-0.0002	-0.0001	-411.29	-35.400	41.493	-21.008
Temp	0.3198	5.2622	-0.5597	-3.1677	0.0002	-0.0923	-0.0345	0.0778
Rain	-0.0003	0.0127	-0.0090	0.0123	26.935	-25.594	0.7398	-21.744
Const	-11.186	-151.32	25.361	71.968				
Renormalized *β*					**Renormalized *α***			
Prod	1.0000	24.369	0.0010	0.0191	0.0163	0.0015	12.891	0.0027
ProdAr	-0.6256	1.0000	0.0004	-0.0076	1.5819	0.0109	-23.224	-0.2562
Temp	-83.153	-17132	1.0000	-259.70	-8.7e-7	2.8e-5	0.0193	0.0009
Rain	0.0667	-41.472	0.0160	1.0000	-0.1036	0.0079	-0.4141	-0.2652
Const	2908.4	4.9e+5	-45.310	5900.3				
Long Run *π (αβ')* Matrix								
Equation	Prod	ProdAr	Temp	Rain	const			
Prod	0.0652	-0.0041	-14.581	0.1486	210.10			
ProdAr	1.8190	-0.9851	-274.50	-0.9734	9498.0			
Temp	0.0007	2.8e-5	-0.7128	8.2e-5	18.689			
Rain	0.0824	0.0745	-57.601	-0.6048	2025.5			
Eigenvalue	0.7265	0.3575	0.2299	0.1677				

Source: Authors computation, 2022

The Johansen cointegrating beta (β) and adjustment alpha (α) vectors test presented in Table 5 above. It shows that one (0.73) of the eigenvalues is larger in comparison to other eigenvalues. This indicates that there is at least one cointegrating long-run relationship. Therefore, the succeeding column vector to this eigenvalue (0.73) (oil palm production) consequently form the constructive and useful relationship. The coefficient of Temp (0.32) in the first equation is close to one in the eigenvector matching to the highest eigenvalue. This indicates that Temp as variable may likely be in the last order of influence in that vector. Hence, Temp equation signifies a very vital long term functional and useful relationship.

Table 5 above also shows the model output, where beta signifies the long-term implications, while alpha signifies the degree and dimension of the adjustment of the cointegration vector when the correlation is diverging from the long-term relationship procedure. The ith column of the beta matrix represents the coefficients of each of the variables under consideration in the ith variable equation (that's ith cointegration relationship). Whereas, the ith row signifies the influence of the ith variable to each of the dealings. In the same way, the ith vector of alpha matrix indicates the rate of adjustment of each relationship to be volatile and unstable in ith relation, whereas the row vector indicates the adjustment rates of the ith relation to each of the unstable in relationships.

3.1 Vector Error Correction Model (VECM) Output

VECM is the short-run deviations development of the functional model. It is used to determine the extent of the error correction coefficient. Hence, the VECM analyses the socks in the model, at the same time estimating the functional model of the time series data. Error correction term (EC) is to correct (in percentage) the error in the next period in uniting to the long-run relationship (Ali, 2015). Johansen test specified two rank order of the impact matrix; this study used this order for the VECM estimation.

Table 6: Equation 1: d_Prod1000MT

Variable	**Coefficient**	**Std. Error**	***t-ratio***	***p-value***	**Indicator of low p-value**
Const	−80.0433	3985.09	−0.02009	0.9841	
d_Prod1000MT_1	−0.0196	0.2409	−0.0813	0.9358	
d_ProdAr1000ha_1	−0.0271	0.0169	−1.603	0.1197	
d_Temp_1	25.3878	32.8137	0.7737	0.4454	
d_Rain_1	−0.0504	0.1136	−0.4441	0.6603	
EC1	−0.0028	0.0605	−0.0464	0.9633	
EC2	0.0005	0.0195	0.0247	0.9805	
R^2	0.1289		Adjusted R^2	-0.1122	
Rho	0.0886		Durbin-Watson	1.65	
Production vector		*B*			*A*
d_Prod1000MT_1	1.0000	0.0000		-0.0028	0.0005
d_ProdAr1000ha_1	1.0000	0.0000		2.5267	-0.9724
d_Temp_1	1365.7	325.40		-0.0005	0.0000
d_Rain_1	3.8185	1.0897		-0.2512	0.0618
Trend	21.763	9.9e+7			

Note: d is used to specify a differenced variable, such as d_Prod1000MT, while d_Prod1000MT_1, d_ProdAr1000ha_1, d_Temp_1, and d_Rain_1 indicate lagged differenced variables. The greater the number of asterisks (*), the smaller the *p-value* to indicate the significance level of the variable. ***, **, and *are significant at 1%, 5% and 10% respectively.
Source: Authors computation, 2022

From Table 6 only d_Temp_1 coefficient is positive all other variables were negative. This implies that Temp is directly related to Prod while other variables were inversely related to the differenced Prod. The sign of EC1 is negative though not significant, which is logical, whereas EC2 is statistically zero. The Rho (0.1) coefficient is small; denote weaker relationships in the function. Durbin-Watson (1.7) is within acceptable region of the model, this implies that there is positive correlation. These realities were further established in Okolo *et al*, (2019) survey which found a significant relationship between annual average temperature and oil palm production in Nigeria.

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Table 7: Equation 2: d_ProdAr1000ha

Variable	**Coefficient**	**Std. Error**	***t-ratio***	***p-value***	**Indicator of low p-value**
Const	−94684.3	24209.5	−3.911	0.0005	***
d_Prod1000MT_1	−2.45054	1.4633	−1.675	0.1047	
d_ProdAr1000ha_1	0.2505	0.1025	2.443	0.0209	**
d_Temp_1	−0.0544	199.344	2.174	0.0380	**
d_Rain_1	−0.0544	0.6900	−0.0788	0.9377	
EC1	2.5267	0.3678	6.870	0.0000	***
EC2	-0.9724	0.1188	-8.188	0.0000	***
R^2	0.7297		Adjusted R^2	0.6552	
Rho	0.0526		Durbin-Watson	1.87	

Note: d is used to specify a differenced variable, such as d_Prod1000MT, while d_Prod1000MT_1, d_ProdAr1000ha_1, d_Temp_1, and d_Rain_1 indicate lagged differenced variables. The greater the number of asterisks (*), the smaller the *p-value* to indicate the significance level of the variable. ***, **, and *are significant at 1%, 5% and 10% respectively.
Source: Authors computation, 2022

From Table 7, the production area (1000 ha) equation, constant and coefficients of lagged differenced of ProdAr and Temp were found to be significantly affecting oil palm production in Nigeria. The EC1 and EC2 was both significant. EC2 is negative, which is logical. This implies that 97 percent of the error will be corrected in the next period concerning the long-run relationship, as well as inversely related to differenced production of oil palm in Nigeria. Rho (0.1) was also weak and Durbin-Watson (1.9) is positively autocorrelated, with high determinant R^2 of 73%, which implies that the model is a good fit.

Table 8: Equation 3: d_Temp

Variable	**Coefficient**	**Std. Error**	***t-ratio***	***p-value***	**Indicator of low p-value**
Const	−48.3884	19.7286	-2.453	0.0204	**
d_Prod1000MT_1	0.0003	0.0012	0.2516	0.8031	
d_ProdAr1000ha_1	-0.0001	8.3e-5	-1.793	0.0834	*
d_Temp_1	−0.0882	0.1624	-0.5432	0.5911	
d_Rain_1	0.0001	0.0006	0.2094	0.8356	
EC1	-0.0005	0.0003	-1.756	0.0897	*
EC2	5.9e-6	9.6e-5	0.0611	0.9517	
R^2	0.4654		Adjusted R^2	0.3179	
Rho	-0.0325		Durbin-Watson	2.04	

Note: d is used to specify a differenced variable, such as d_Prod1000MT, while d_Prod1000MT_1, d_ProdAr1000ha_1, d_Temp_1, and d_Rain_1 indicate lagged differenced variables. The greater the number of asterisks (*), the smaller the *p-value* to indicate the significance level of the variable. ***, **, and *are significant at 1%, 5% and 10% respectively.
Source: Authors computation, 2022

Table 8 shows the temperature (°C) equation, constant and coefficient of lagged differenced of ProdAr were found to be significant affecting oil palm production in Nigeria. The EC1 was also significance. EC2 and temperature are not found to significant to differenced Prod equation, the coefficient determinant (R^2) was 47%, which indicates that the model is a good fit, with adjusted R^2 of 0.3, for production of oil palm equation. Rho (-0.03) shows weak relationships and Durbin-Watson (2.0) within acceptable region of autocorrelation.

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Table 9: Equation 4: d_Rain

Variable	**Coefficient**	**Std. Error**	***t-ratio***	***p-value***	**Indicator of low p-value**
Const	−2657.99	5937.74	-0.4476	0.6577	
d_Prod1000MT_1	0.2713	0.3589	0.7560	0.4557	
d_ProdAr1000ha_1	0.0101	0.0251	0.4036	0.6894	
d_Temp_1	129.242	48.8920	2.643	0.0131	**
d_Rain_1	-0.4456	0.1692	-2.633	0.0134	**
EC1	-0.2512	0.0902	-2.785	0.0093	***
EC2	0.0618	0.0291	2.122	0.0425	**
R^2	0.564		Adjusted R^2	0.4440	
Rho	-0.1647		Durbin-Watson	2.27	

Note: d is used to specify a differenced variable, such as d_Prod1000MT, while d_Prod1000MT_1, d_ProdAr1000ha_1, d_Temp_1, and d_Rain_1 indicate lagged differenced variables. The greater the number of asterisks (*), the smaller the *p-value* to indicate the significance level of the variable. ***, **, and *are significant at 1%, 5% and 10% respectively.
Source: Authors computation, 2022

Table 9 shows the rainfall (mm) equation, the coefficient of lagged differenced of Temp and Rain were found to be significantly affecting oil palm production in Nigeria. The EC1 (-0.25) was negatively significance at 1%, this implies that 25 percent of the error will be corrected in the next period concerning the long-run relationship, as well as inversely related to differenced production of oil palm in Nigeria. This indicates that the relationship is corrected when inversely related to differenced Prod. Oil palm yield is limited by the length of annual dry season, so areas with consistently high rainfall throughout the year have particularly high yields (Munévar, 2003). In a similar view, Noojipady *et al*, (2017) noted that the most important factor determining oil palm yield is the availability of water in the soil, which largely depends on rainfall, but is also affected by temperature and other factors such as soil type. When there is less rainfall, there is also greater risk of fire, as seen during recent events in Nigeria, which is a hazard for workers, in terms of air quality, and causes loss of yield.

EC2 was also significance at 5% level, with Durbin-Watson of 2.3, which is within the range of acceptance, and with high determinant R^2 of about 73%, which implies that the model is a good fit.

Table 10: Residuals diagnostics of the estimated error correction model

Diagnostic tests	**Oil palm production**	
	Statistics-value	***p*-value**
ARCH	115.01	0.14
Autocorrelation	1.26	0.24
Doornik-Hansen test	18.06	0.02**

** Significant at 5%
Source: Authors computation, 2022

This study confirmed the robustness of the error correction model in Nigeria oil palm production using Doornik-Hansen test, autocorrelation and ARCH. The result is in Table 10 above. The result shows that the single error correction model of oil palm production in Nigeria is serially correlated since statistic-value of autocorrelation test cannot reject the null hypothesis of the serial correlation. This implies that the residuals in the function are not correlated with one another. Using ARCH chi-square test, heteroskedasticity was not significant, which indicates that the residuals are homoskedasticity.

4.0 Conclusion and Recommendation

The study established that the time series on Prod, ProdAr, Temp, and Rain were cointegrated using time series data from 1981 to 2020. Augmented Dickey-Fuller (ADF) unit root tests were conducted for stationary test. The ADF shows that at the level all the series data were non-stationary (p-value > 0.05). Johansen's cointegration method presents the long-run relationships and the extent of adjustment assuming there is deviation in the long-run relationship. Also, VECM was used to estimates the error correction (EC); which presents the relationships on the differenced variables in the presence of level variables. The robustness of the error correction model in Nigeria on oil palm production using Doornik-Hansen test, autocorrelation and ARCH was also examined in the study. The study, therefore recommended;

i. There is need to increase the population of oil palm in Nigeria in order to increase oil palm production;
ii. There is need to invest in research and development (R & D) activities; and
iii. Climate factor trends should be related to stakeholder in oil palm industry.

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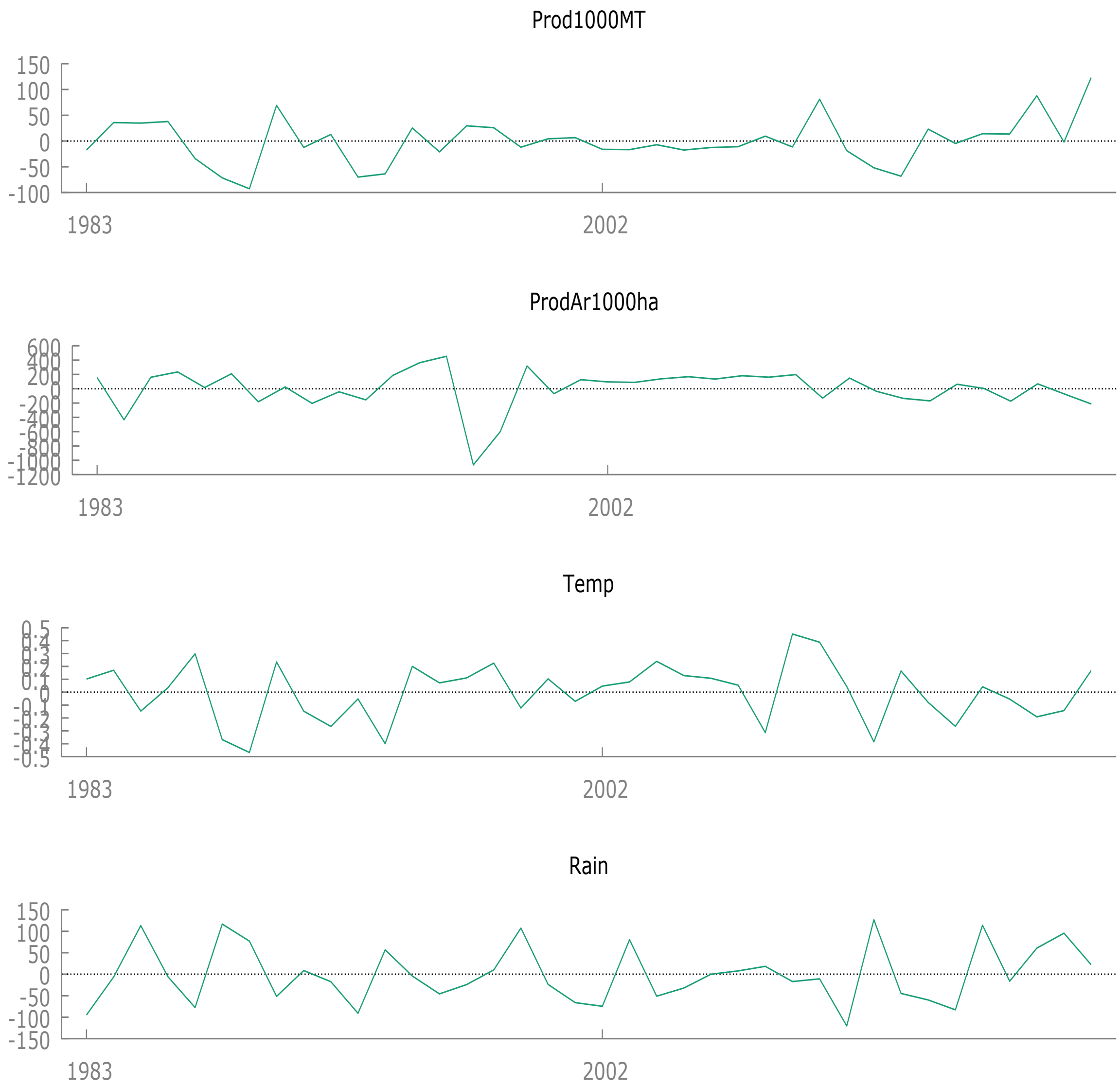
Appendix: Trend of oil palm production and climate factors in Nigeria



Source: Authors computation, 2022