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Environmental Quality and Sectoral Output in Nigeria: Long-Run Elasticity Evidence from Fully Modified and Dynamic Ordinary Least Squares Estimation

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ABSTRACT

This study examines the long-run elasticity effects of environmental quality on agricultural and industrial output in Nigeria for the period 1981-2024, filling a gap in the literature of environmental quality as an outcome of sectors' activity rather than determinant. Eight cointegrated long-run equations are estimated for per capita CO_2 emissions and ecological footprint as environmental quality proxies, precipitation and temperature as climate controls, and primarily using Fully Modified OLS (FMOLS), with Dynamic OLS (DOLS) for robustness. Results show sector specific sensitivity: CO_2 emissions have a positive and significant long-run impact on agriculture (elasticity close to +0.335), possibly due to 'carbon fertilisation effects' on Nigeria's predominant C3 crops. In contrast, none of the environmental quality variables is significant for the models of industrial output under FMOLS. Urbanisation has consistent, high negative impacts on agricultural output (elasticities range between -2.49 and -2.66), accounting for both land use change and rural-urban migration, and GDP per capita is the most powerful determinant in both sectors. The results indicate that environmental quality in the Nigerian economy has a measurable and a double-edged nature in the agricultural sector while it is statistically unmeasurable in the industrial sector, which acts as a source of environmental pressure rather than a recipient. Policy implications include sector-oriented management: agricultural investment for climate-smart agriculture and implementing cleaner production technologies in industry and protecting agricultural land. The study offers long-run elasticity estimates treating environmental quality as explanatory rather than an outcome in Nigerian sectoral output models.

Keywords: Environmental quality, Agricultural output, Industrial output, Ecological footprint, CO_2 emissions

JEL Classification: Q56, Q15, O13

INTRODUCTION

The importance of environmental quality in the development economics of resource-intensive economies is central, but analytically ambiguous. Economic growth, especially in the agricultural and industrial sectors, produces environmental externalities, including emissions, land degradation and resource extraction on the one hand. Conversely, environmental degradation has a negative impact on productive capacity through the degradation of soil fertility, availability of water, variability of climatic conditions, diminished labour productivity due to exposure to pollution, and the degradation of the natural capital on which agricultural systems are based. This feedback mechanism is from environment quality to sectoral output rather than the opposite way round, and it is this neglected direction of causation that motivates the present study, albeit from the different point of view of environment quality.

The Nigerian environmental path offers a good empirical context to investigate this feedback. The CO2 emissions per capita have varied between 0.40 and 0.86 metric tonnes from 1981 to 2024, indicating fossil fuel usage, gas flaring, emissions from industrial processes, urbanisation, etc., while the ecological footprint has

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been moving upwards, with positive momentum maintained in 2024 suggesting continuing loss of biocapacity. Agriculture, the backbone of rural livelihoods and food security, is most vulnerable to fluctuations in soil erosion, deforestation, climate variability and water stress; recent evidence for Nigeria itself supports this, as Obekpa et al. (2025) found that increasing food production activity in Nigeria itself leads to increases in the built-up-land, cropland and forest-product components of the country's ecological footprint, which compounds the country's already constrained biocapacity on which the future food production depends.

By contrast, industry incurs regulatory compliance costs and productivity losses due to pollution exposure, although this structural difference between the sectors, with Nigeria's industry being largely resource extraction and light manufacturing, may make industry less sensitive to environmental feedbacks than are diversified economies, and recent evidence for the Nigeria sectors confirms this asymmetry directly: Gold and Anagun (2026), using a combined ARDL-ECM and DOLS framework for the agricultural and industrial sectors of Nigeria, also find that climate and emissions indicators have significant and asymmetric effects on output in agriculture, while the industrial performance is comparatively robust in the short-term, thus this paper's sectoral asymmetry is anticipated.

The effect of income and sectoral activities on environmental outcomes has been widely discussed in the environmental Kuznets Curve (EKC) literature. But the opposite relationship, that of environmental quality to sectoral productivity in long-run has not been given much consideration, especially in the Nigeria context. Are there any long-term elasticities between CO_2 emissions and agricultural productivity? How is the impact of Nigeria's ecological footprint, a holistic indicator of biocapacity stress, on agricultural and industrial production in the long-run? This is an analytically important question, but one also directly relevant to policy: If environmental quality is statistically significant in the long-run effects on sectoral output, then environmental policy is not only a sustainability imperative, but it is also a productivity imperative. The productivity implications of the question at hand are recent and cross-country and are summarized as follows. AL-Marshadi et al. (2025) provide a systematic analysis of the relationship between ecological footprint pressure and the performance and direction of growth of resource-intensive economies in terms of sustainability, while the method of using VECM and ARDL and FMOLS to Chinese data, as done by Wu et al. (2025), is directly comparable to the dual-estimator strategy followed in this study.

The empirical literature has been reviewed systematically to find that almost all research finds that sectoral output is a determinant of environmental outcomes, but not the other way around. Based on ARDL, Nathaniel and Bekun (2020) demonstrate that the energy consumption, urbanisation and economic growth lead to deforestation in Nigeria, where environmental quality is the dependent variable. Dauda et al. (2023) employ panel DOLS to demonstrate the impact of agricultural production on CO2 emissions in developing countries. Ehigiamusoe et al. (2024) explore the environmental effects of the agricultural and industrial sectors in Malaysia, while Parveen et al. (2023) model environmental degradation as a function of industrial output in newly industrialised countries.

In all these instances, environmental quality is the dependent variable, rather than the other way around. This directionality has even been carried over by the latest studies: Makieu et al. (2026) model agricultural productivity as a determinant of per-capita CO_2 emissions based on Sub-Saharan Africa panel data spanning the period 2000-2024, and Bajja et al. (2026) have applied the Augmented Mean Group (AMG) estimator across six West African economies where CO_2 emissions and climate vulnerability are constraints that shape the agricultural productivity outcomes but where the long-run elasticity of environmental quality is not formally estimated as a regressor in a cointegration output equation.

Directional reversals of the environmental quality regressor in the empirical literature of Nigeria is almost nonexistent in the sectoral output equations. This is an analytical gap: long-run environmental quality elasticities are required to quantify the impact of environmental degradation on agricultural productivity (via soil erosion, climate variations, and water shortage) and industrial productivity (via regulatory costs, resource scarcity, and health-related losses in labour productivity). The present study fills this gap by estimating eight long-run equations, four for agricultural output and four for industrial output, with environmental quality proxies (CO_2, ecological footprint) and climate variability indicators (precipitation, temperature) as

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explanatory variables, estimated using superconsistent FMOLS and DOLS estimators in confirmed cointegrated systems. This dual-estimator approach is also similar to that of Khan and Khan (2026), who use Johansen cointegration, ARDL bounds testing, FMOLS, DOLS and quantile regression to derive robust long-term emissions elasticities for another resource intensive economy, Saudi Arabia, where the impact of environmental pressures is of direct policy relevance.

The main research question is: What is the long-run effect of environment quality on output in the sectors of Nigeria? The specific objective is to assess the long-run impact of environmental quality (measured as CO_2 emission per capita and ecological footprint per capita) on output at the agricultural and industrial sectors in Nigeria using FMOLS and DOLS estimation in cointegrated long-run output equation with Wald tests conducted to provide formal statistical inference on the environmental quality coefficients. This study has three original contributions. First, it offers the first estimate of long-run environmental quality elasticity for Nigerian agriculture and industry based on FMOLS and DOLS, which is the reverse of the conventional analytical flow in which sectoral output is considered as the cause of environmental change. Second, it uses two environmental proxies, CO_2 emissions per capita and ecological footprint per capita, which represent two aspects of environmental pressure, representing atmospheric pollution intensity and comprehensive biocapacity stress, respectively, to avoid inference being reliant on the choice of proxy. Thirdly, it reports on the environmental sensitivity of each sector, including the fact that agriculture is sensitive to CO_2, but industry is not, which offers a more detailed policy foundation for environmental management interventions.

LITERATURE REVIEW

Theoretical Framework

The study is based on three complementary theories: the Environmental Kuznets Curve (EKC) hypothesis, Green Growth Theory and the Neoclassical Production Theory. The EKC hypothesis (Grossman & Krueger 1991; Panayotou 1993) suggests that the relationship between economic growth and environmental degradation is inverted-U and that, after a turning point income, the environment is better off. The EKC, when used in reverse with environmental quality as an input, suggests that the impact on output from environmental deterioration is more severe at lower levels of income and less severe as clean technologies are used. For Nigeria, which is a lower middle income country with high environmental stress, the EKC theory implies that the present environmental degradation has negative productivity impact on agriculture.

The Green Growth Theory (OECD, 2011; UNEP, 2011) explicitly views environmental quality as a productive resource, rather than only a consumer good or a constraint, and as boosting long-run performance of sectors. Better environmental conditions lead to better ecosystem services (soil fertility, water regulation, pollination), better stabilisation of agricultural systems to climate shocks and lower health and regulation costs for industry related to pollution. This framework gives the normative rationale for the empirical specification of the present study, namely using lnENVQ as a regressor in the long-run sectoral-output equations, and expecting that environmental improvement (reduction of emissions, of ecological footprint) leads to a positive long-run productivity dividend.

The analysis is underpinned by neoclassical production theory, which sees natural capital as a productive factor. Natural capital, soil organic matter, water tables, biodiversity, etc., are real inputs in agricultural production that are being lost due to environmental degradation. Moreover, pollution also imposes negative externality in industrial production in the form of regulatory compliance costs, lost productivity from workers' health effects and infrastructure damage. These mechanisms are manifested in long-run relationships between indicators of environmental quality and levels of sectoral outputs that can be estimated in the cointegrated systems framework.

Empirical Review

In all cases, the EKC is estimated using the same methodological approach as the current study, that is FMOLS and panel DOLS, and it is found that income has an inverted-U relationship with ecological footprint, with

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renewable energy exerting a negative impact, and urbanisation exerting a positive impact on biocapacity pressure. (Destek and Sarkodie (2019)). The EF-income elasticities of -0.3 to -0.6 can offer a magnitude reference of the ecological footprint coefficients in the current study. More important, their study uses EF as the dependent variable, not as a regressor in a productivity equation, which is the distinction of the present study.

Dauda et al. (2023) analyse the linkages between agriculture production, renewable energy utilization, governance and CO_2 emissions in developing countries using the panel DOLS approach. They discover that agricultural output has a large impact on emissions, and governance has a moderating effect. The positive relationship between CO_2 and agricultural output observed in the current study (CO_2-agricultural output coefficient = 0.335 in the CO_2-PREC-AGRIO specification) could partly be due to the agricultural-emissions feedback described by Dauda et al. (2023): agriculture in Nigeria may not only be sensitive to CO_2 but may also co-move with CO_2 because agricultural expansion itself contributes to CO_2 emissions. An additional biological mechanism for the positive sign is the carbon fertilisation interpretation, namely, that a moderate increase in CO_2 accelerates photosynthesis in C3 crops. This co-movement is directly supported by recent evidence in Nigeria: Obekpa et al. (2025) demonstrate that food production activity in Nigeria measurably contributes to both the cropland and forest-product components of the national ecological footprint, thus corroborating that the Nigerian agricultural expansion and environmental pressure are jointly determined rather than running unidirectionally.

Sibuea et al. (2021) show that the long-run impact of bioenergy use and renewable energy in general is positive for agricultural sustainability and reducing emissions for ASEAN countries. Zaman et al. (2022) study the situation in Pakistan and conclude that greenhouse gas emissions are considerably reduced by environmentally friendly agricultural production. Neither study is directly an estimate of the effect of environment quality on output in the various sectors; both however confirm the environmental-productivity linkage concept used in this study. More recently, Makieu et al. (2026), based on the panel data for Sub-Saharan Africa for the period 2000-2024, find an elasticity of -2.236 between agricultural productivity and per-capita CO_2 emissions, which means that more productive agriculture systems are correlated with significantly less per-capita CO_2 emissions after accounting for temperature and rainfall and land expansion. In contrast to the other studies reviewed in this paper, their study assumes emissions are the dependent variable, and the elasticity of productivity to emissions that they document is generally in line with the large magnitude of the CO_2-agriculture linkage found in the present study, suggesting that in farming systems in Sub-Saharan Africa, emissions and productivity are closely linked, whether either is treated as the regressant.

Restricting to newly industrialised countries, Parveen et al. (2023) demonstrate using both FMOLS and DOLS methods that it is industrial output that is the main source of CO_2 emissions, not CO_2 that affects industrial output. Their FMOLS approach is directly comparable to the one used in the present study, except for the causal direction. The lack of significance of CO_2 for industrial output in FMOLS ($p > 0.70$) aligns with the study by Parveen et al. (2023), which reported that the industrial-emissions nexus flows from output to emissions and not the other way around, meaning that Nigerian industry is a source of environmental degradation.

Ehigiamusoe et al. (2024) discovers that CO_2 emissions in Malaysia are steadily increasing from both agriculture and industry sectors, indicating that the expansion is not sustainable. Like the present study they are sectoral and have ARDL methodology and their result of higher emission intensity in the industrial sector compared to the agriculture sector gives a comparative context to the differential environmental sensitivity found in the results of the present study. Based on the time-series data from Nigeria, Nathaniel and Bekun (2020) show that deforestation is accelerated by energy consumption, urbanisation and economic growth using the ARDL bounds testing technique. The negative and significant urbanisation coefficient in the agricultural output equations in the present study (-2.49 to -2.66) corroborates the ecological land-conversion mechanism reported by Nathaniel and Bekun (2020) but in the opposite direction as urbanisation reduces the agricultural land base, the present study represents as a decrease in agricultural output.

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Two more recent contributions help to clarify this sector-specific picture. Gold and Anagun (2026) model the agriculture and industry sectors together in a unified ARDL-ECM and DOLS framework and obtain a dual-sector asymmetry in that climate indicators are more significant and impactful on agriculture, while the performance of the industry is more resilient to the same climate indicators in the short-term, a pattern that is directly comparable with, and provides independent corroboration of, the differential FMOLS significance obtained in Section 4 of this study. In a similar vein, using FMOLS, DOLS, Canonical Cointegrating Regression and quantile regression, Khan and Khan (2026) examine this question using Saudi Arabia, an equally resource-dependent and oil-exporting economy, and conclude that the impact of environmental and energy factors in terms of productivity is not ubiquitous across sectors or constant across the distribution of outcomes, further reinforcing the methodological rationale behind the sector-disaggregated, multi-estimator approach followed here.

A cross-comparison of methods and results across the studies surveyed shows three important trends. First, the newest contributions to the literature on the long-run energy-environment-output were FMOLS and DOLS, which corroborate the methodological approach of the current study, not only from the earlier literature but also from the newest 2025-2026 contributions (Wu et al., 2025; Khan & Khan, 2026; Gold & Anagun, 2026). Second, the results indicate that agriculture is more environmentally sensitive than industry, which is consistent with the results in previous studies, and is also corroborated by Gold and Anagun's (2026) evidence for the dual sector in Nigeria. Third, the most crucial methodological gap in literature surveyed, including the older and more recent studies (Obekpa et al., 2025; Bajja et al., 2026; Makieu et al., 2026), is the directional assumption as virtually all the studies surveyed have environmental quality as a dependent variable. The present study makes a contribution exactly in this direction by considering environmental quality as a long-run regressor in sectoral output equation in Nigeria. A summary of the comparison of the reviewed studies is presented in Table 1.

Table 1: Cross-Comparison of Selected Empirical Studies on Environmental Quality, Agriculture and Industry

Author(s)/Year	**Country/Region**	**Method**	**Directional Focus**	**Key Finding**
Destek & Sarkodie (2019)	Newly industrialised countries	FMOLS, panel DOLS	EF as dependent variable	Inverted-U income-EF relationship; EF-income elasticity -0.3 to -0.6
Dauda et al. (2023)	Developing countries (panel)	Panel DOLS	Agriculture to CO_2 (reverse of present study)	Agricultural production significantly raises emissions; governance moderates link
Parveen et al. (2023)	Newly industrialised countries	FMOLS, DOLS	Industrial output to CO_2	Industrial output drives emissions, not the reverse
Ehigiamusoe et al. (2024)	Malaysia	ARDL	Sectoral output to CO_2	Both agriculture and industry emissions grew significantly
Obekpa et al. (2025)	Nigeria	KRLS, quantile regression	Food production to ecological footprint components	Food production raises built-up-land, cropland and forest-product footprints
Wu et al. (2025)	China	VECM, ARDL, FMOLS	EF growth and governance to renewable energy/emissions	EF growth drives renewable energy adoption; governance moderates emissions

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AL-Marshadi et al. (2025)	Cross-country	Panel estimation	EF, natural resources, financial development to sustainability	EF pressure systematically linked to resource-dependent growth trajectories
Gold & Anagun (2026)	Nigeria	ARDL-ECM, DOLS	Climate/CO_2 to dual-sector output	Agriculture significantly more climate-sensitive than industry
Khan & Khan (2026)	Saudi Arabia	Johansen, ARDL, FMOLS, DOLS, CCR, quantile regression	Growth/energy/FDI to CO_2	Environmental-productivity effects are sector- and quantile-dependent
Makieu et al. (2026)	Sub-Saharan Africa (panel)	Fixed effects, panel cointegration	Agricultural productivity to CO_2	Elasticity of -2.236 between productivity and per-capita emissions
Bajja et al. (2026)	West Africa (6 countries)	Augmented Mean Group, FMOLS	Emissions/climate vulnerability to agricultural productivity	Carbon reduction and technological innovation shape productivity asymmetrically
This study	Nigeria (1981-2024)	FMOLS (primary), DOLS (robustness)	Environmental quality (CO_2, EF) to sectoral output	Positive, significant CO_2 effect on agriculture; no significant effect on industry

Source: Authors' Compilation (2026).

The literature reviewed offers a rather similar methodological toolkit (FMOLS and DOLS in the context of cointegrated systems) and almost unanimously ranks the directionality opposite (environmental quality is the outcome of interest to be explained, not the explanatory variable). In contrast to the 2025 and 2026 references above, which reiterate the conventional wisdom, the present study's departure from that tradition, along with its explicit cross-sectoral comparison, and dual environmental proxies, addresses a gap that remains in most recent studies.

METHODOLOGY

Model Specification

The functional forms of the long-run sectoral output equations are motivated by Green Growth Theory's introduction of the environment as a productive resource and Neoclassical Production Theory's introduction of nature as a factor of production:

$$lnAGRIO_t = f(lnENVQ_t, lnGDPPC_t, lnCLIV_t, lnENER_t, lnURB_t) \quad (1)$$

$$lnINDUO_t = f(lnENVQ_t, lnGDPPC_t, lnCLIV_t, lnENER_t, lnURB_t) \quad (2)$$

The econometric long-run specifications are:

$$lnAGRIO_t = \alpha_0 + \alpha_1 lnENVQ_t + \alpha_2 lnGDPPC_t + \alpha_3 lnCLIV_t + \alpha_4 lnENER_t + \alpha_5 lnURB_t + \varepsilon_t \quad (3)$$

$$lnINDUO_t = \beta_0 + \beta_1 lnENVQ_t + \beta_2 lnGDPPC_t + \beta_3 lnCLIV_t + \beta_4 lnENER_t + \beta_5 lnURB_t + \mu_t \quad (4)$$

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where $lnENVQ_t$ switches between $lnCO_2$ (log of CO_2 emissions per capita, metric tonnes) and lnEF (log of ecological footprint per capita, global hectares); and $lnCLIV_t$ is a switch between lnPREC (log of precipitation, mm) and lnTEMP (log of temperature, °C), resulting in 4 combinations per dependent variable and 8 equations total. The main parameters of interest are α_1 and β_1, the long-run elasticity of agricultural output and industrial output to environmental quality, respectively. All variables are in natural logs for elasticity interpretation of coefficients and ε_t and μ_t are white-noise disturbance terms.

Dual environmental proxies are methodologically motivated by the different biophysical dimensions they capture. CO_2 emissions per capita is a flow measure of environmental pressure that is directly related to fossil fuel combustion and deforestation, which in turn is a measure of the intensity of atmospheric pollution. Ecological footprint per capita expresses the consumption of all kinds of biocapacity: crop land, grazing land, fishing grounds, forest land, built-up land and carbon sequestration demand. Both proxies are used, as using either could lead to a conclusion about the direction of the relationship between environmental quality and output that is solely based on the choice of proxy (Destek & Sarkodie, 2019; Bekun et al., 2021), and the results of Wu et al. (2025) offer a proof of concept that ecological footprint growth and CO_2 emissions can follow different trends in relation to governance and renewable energy adoption in a large-panel context.

Estimation Technique

The method of estimation used mainly is Fully Modified OLS (FMOLS) introduced by Phillips and Hansen (1990). FMOLS corrects two structural problems that affect the standard OLS in cointegrated systems: (i) endogeneity bias due to the contemporaneous correlation between the I(1) regressors and the error term of the cointegrating equation; and (ii) serial correlation of the residuals which introduces nuisance parameters in the asymptotic distribution of the OLS estimator. FMOLS does so through a semi-parametric kernel-based transformation; it corrects for both through a non-parametric estimate of the long-run endogeneity bias (based on the long-run covariance between the equation error and the first differences of the I(1) regressors), and a serial-correlation correction using the Newey-West long-run variance estimator with the bandwidth automatically selected as in Andrews (1991).

The resulting FMOLS estimator is asymptotically equivalent to the maximum likelihood estimator of the cointegrating vector, is robust to heteroskedasticity and autocorrelation, and has a convergence rate of T (superconsistent) as compared to the standard T^(1/2) (Said et al., 2022). Having this superconsistency is especially useful for the small annual sample size of the present study ($n \leq 44$). The robustness checker used is the Dynamic OLS (DOLS), which is proposed by Stock and Watson (1993) and adds leads and lags of all the I(1) regressors into the static long-run regression to parametrically account for endogeneity and serial correlation. One lead and one lag (DOLS(1,1)) is estimated applying Newey-West HAC standard errors. The consistent results obtained across FMOLS and DOLS provide confidence in the long-run elasticity estimates, a similar approach as Khan and Khan (2026) have recently taken in validating their estimates using five different estimators and Gold and Anagun (2026) have done in cross-checking ARDL and DOLS for Nigeria's real sectors.

The squared t-statistics from the coefficient estimates of the FMOLS are used as formal statistical inferences on the environmental quality coefficients (H0: $\alpha 1 = 0$ for AGRIO equations; H0: $\beta 1 = 0$ for INDUO equations). This gives a precise test of whether environmental quality has a statistically significant long-run impact on the output of the sector, in addition to the usual significance evaluation of each coefficient.

Variable Measurement and Data Sources

Table 2: Variable Measurement and Data Sources

Variable	Description	Measurement	Source
AGRIO	Agricultural output	Constant-price billions of naira	CBN Statistical Bulletin (2024)

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INDUO	Industrial output	Constant-price billions of naira	CBN Statistical Bulletin (2024)
CO_2	CO_2 emissions per capita	Metric tonnes	World Bank WDI
EF	Ecological footprint per capita	Global hectares	Global Footprint Network
GDPPC	Real GDP per capita	Constant USD	World Bank WDI
URB	Urbanisation rate	% of population	World Bank WDI
ENER	Energy intensity	MJ per constant USD of GDP	International Energy Agency (IEA)
PREC	Precipitation	mm	World Bank WDI Climate Change Knowledge Portal
TEMP	Temperature	°C	Climatic Research Unit (CRU) gridded dataset

Note: Sample covers 1981-2024 (44 annual observations). Source: Authors' Compilation (2026).

Pre-Estimation Tests

Unit Root Tests

By ADF test under trend and intercept specification, the following is confirmed: EF is I(1); CO2 is I(1) (ADF determines I(0), but standard practice is to treat as I(1); GDPPC is I(1); PREC is I(1); TEMP is I(0); ENER is I(0); URB is I(1); AGRIO is I(1); INDUO is I(1). It is the mixed I(0)/I(1) integration profile which ARDL bounds testing and FMOLS/DOLS were developed for (Pesaran et al., 2001; Phillips & Hansen, 1990). None of the variables is I(2) and therefore meets the binding requirement for the application of ARDL/FMOLS/DOLS.

Cointegration Tests

There are two cointegration procedures used for each of the eight model specifications. The ARDL bounds F-test (Pesaran et al., 2001) shows that F-statistics in all specifications fall between 0.869 and 2.104, which is below the lower I(0) critical value at 5%, suggesting that ARDL alone does not support any cointegration in any specification. The Johansen (1988) trace test, however, rejects the null of no cointegration at $r=0$ in all eight models: the trace statistics can be observed ranging between 108.91 and 125.43 with the 5% critical value being 95.75. In three of the 8 models, the Johansen trace test also accepts $r \leq 1$, that is, multiple cointegrating vectors exist. Cointegration is confirmed in all eight model systems, which is consistent with the principle: When ARDL (small-sample limitations) and Johansen (a more powerful system procedure) disagree, evidence from Johansen is considered more reliable, so the FMOLS and DOLS are used.

A-Priori Expectations

Table 3: A-Priori Expectations

Variable	**Expected Sign (Agriculture)**	**Expected Sign (Industry)**
CO2 (ENVQ)	Ambiguous (positive at low concentration, negative at high)	Negative

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EF (ENVQ)	Negative	Negative
GDPPC	Positive	Positive
Urbanisation	Negative	Ambiguous

Source: Author's Compilation (2026).

In the EKC framework and Green Growth Theory: α1 (CO_2 coefficient in the AGRIO equation) is probably ambiguous in that it may be positive at low CO_2 levels (carbon fertilisation effect) and negative at high levels, and α1 (EF coefficient) is likely to be negative as biocapacity depletion is likely to have a negative effect on the productivity of agricultural land. In the case of industrial output, β1 is likely to be negative concerning CO_2 and EF, since more emissions and ecological pressure will lead to a rise in regulatory costs and resource scarcity. GDP per capita is predicted to have a positive income effect for both sectors. Urbanisation should have a negative effect on agricultural production (land conversion) and an ambiguous effect on industrial production (agglomeration benefits and congestion costs).

Post-Estimation Diagnostics

The following tests are used to check the post-estimation validity: ADF tests on FMOLS residuals for stationarity (as a confirmation of the validity of the cointegrating relationships); Durbin-Watson statistics for first-order serial correlation; Jarque-Bera tests for normality of the residuals; and CUSUM tests for parameter stability over the full sample period (Brown et al., 1975).

RESULTS AND DISCUSSION

Pre-Estimation Results

Descriptive Statistics

Table 4: Descriptive Statistics: Environmental Quality and Control Variables (1981-2024)

Variable	N	Mean	Std. Dev.	Min	Max	Skewness	JB p-val
EF (gha/cap)	44	0.9147	0.1376	0.6867	1.2527	0.4805	0.424
CO2 (t/cap)	44	0.6541	0.1277	0.4000	0.8600	-0.2177	0.469
GDPPC (USD)	44	1867.88	431.58	1387.92	2585.73	0.2895	0.082
ENER (MJ/USD)	44	6.4749	4.1100	0.8712	19.2685	0.9493	0.026
URB (%)	44	4.5010	0.6023	3.3629	5.8233	-0.2310	0.764
PREC (mm)	44	1163.74	84.71	887.82	1296.63	-0.7877	0.053
TEMP (°C)	44	27.2648	0.3299	26.3600	27.9100	-0.4310	0.503

The descriptive statistics of the environmental quality and control variables are presented in Table 4. The average ecological footprint was 0.9147 global hectares per capita (std = 0.1376), with a minimum of 0.687 and a maximum of 1.253, and a slight positive skew, which means that during certain periods, biocapacity was consumed faster. The average CO_2 emission per capita was 0.654 metric tonnes (std = 0.128) with relatively low variability and some extreme variations including a growth rate of +72% in 1994 in the context of oil-related production shocks. A moderate level of standard deviation was observed on these values of GDP per

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capita averaging USD 1,867.88, thereby reflecting the uneven income growth path for Nigeria over the sample. Urbanisation averaged 4.501 in log terms, indicating that Nigeria is rapidly urbanising, now being at about 56% of the population in urban areas compared to 28% at the beginning of the period, and with the attendant pressures on agricultural land.

Note: gha/cap = global hectares per capita; t/cap = metric tonnes per capita; MJ/USD = megajoules per constant USD of GDP. JB = Jarque-Bera normality test p-value. Source: Author's computation (2026).

Cointegration Results

Table 5: Johansen Cointegration Test: Trace Statistics (All Eight Model Specifications)

Model	Trace (r=0)	CV 5%	Trace (r≤1)	CV 5%	Decision
CO2-PREC-AGRIO	121.23	95.75	75.84	69.82	Cointegrated (r≥1)
CO2-PREC-INDUO	108.91	95.75	59.22	69.82	Cointegrated (r=1)
CO2-TEMP-AGRIO	125.43	95.75	81.38	69.82	Cointegrated (r≥2)
CO2-TEMP-INDUO	119.24	95.75	75.54	69.82	Cointegrated (r≥1)
EF-PREC-AGRIO	113.93	95.75	73.51	69.82	Cointegrated (r≥1)
EF-PREC-INDUO	113.21	95.75	60.80	69.82	Cointegrated (r=1)
EF-TEMP-AGRIO	112.89	95.75	73.86	69.82	Cointegrated (r≥1)
EF-TEMP-INDUO	119.73	95.75	62.65	69.82	Cointegrated (r=1)

Note: Critical values from Osterwald-Lenum (1992). All models show Trace(r=0) > CV5%, confirming cointegration. ARDL bounds F-statistics (all below the I(0) lower bound) are superseded by the Johansen system-wide evidence. FMOLS and DOLS are the appropriate estimators. Source: Author's computation (2026).

FMOLS Long-Run Estimates: Agricultural Output

Estimates of the long-run coefficients in the four model specifications for agricultural output are reported in Table 6. The most important result is that the coefficient of lnCO_2 in the CO_2-PREC specification is positive and statistically significant ($\alpha_1 = 0.335, std.error = 0.162, p = 0.045$). The same is true for the corresponding coefficient for CO_2-TEMP, but the level of significance is only 10% (p = 0.061). The ecological footprint coefficients are positive and statistically insignificant for both EF specifications, indicating that at the annual aggregate level, the biocapacity pressure is not significant and does not lead to a long-run agricultural output effect.

Table 6: FMOLS Long-Run Estimates, Dependent Variable: lnAGRIO (Agricultural Output)

Variable	CO_2-PREC	Sig.	CO_2-TEMP	Sig.	EF-PREC	Sig.	EF-TEMP	Sig.
Constant	-2.749	n.s.	-5.654	n.s.	-1.850	n.s.	-9.612	n.s.
lnENVQ (CO_2 or EF)	0.335	**	0.309	*	0.132	n.s.	0.177	n.s.

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lnGDPPC	1.668	***	1.647	***	1.566	***	1.549	***
lnENER	-0.037	n.s.	0.000	n.s.	-0.084	n.s.	-0.036	n.s.
lnURB	-2.538	***	-2.658	***	-2.495	***	-2.579	***
lnCLIV (PREC/TEMP)	0.436	n.s.	1.890	n.s.	0.401	n.s.	3.257	n.s.
R^2	0.939	-	0.949	-	0.935	-	0.950	-
Adj. R^2	0.929	-	0.940	-	0.924	-	0.942	-
n	43	-	43	-	43	-	43	-

*Note: ***, **, * = 1%, 5%, 10% significance. n.s. = not significant. All variables in natural logarithms. lnENVQ = $lnCO_2$ or lnEF; lnCLIV = lnPREC or lnTEMP. FMOLS with Bartlett kernel and Andrews automatic bandwidth. Coefficients are long-run elasticities. Source: Author's computation (2026).*

FMOLS Long-Run Estimates: Industrial Output

Table 7 shows the long-run estimates of FMOLS of industrial output. All environmental quality coefficients are statistically insignificant in all four industrial output specifications, in contrast to the agricultural results. CO2 coefficients range from 0.011 to 0.029 (all $p > 0.70$), and ecological footprint coefficients range from 0.010 to 0.021 (all $p > 0.88$). GDP per capita is the strongest predictor in all of the industrial equations (coefficients between 0.694 and 0.711, all $p < 0.01$), which is in line with demand-driven industrial growth.

Table 7: FMOLS Long-Run Estimates, Dependent Variable: lnINDUO (Industrial Output)

Variable	**CO_2-PREC**	**Sig.**	**CO_2-TEMP**	**Sig.**	**EF-PREC**	**Sig.**	**EF-TEMP**	**Sig.**
Constant	3.672	n.s.	7.603	n.s.	3.738	n.s.	6.910	n.s.
lnENVQ (CO_2 or EF)	0.011	n.s.	0.029	n.s.	0.010	n.s.	0.021	n.s.
lnGDPPC	0.694	***	0.711	***	0.694	***	0.707	***
lnENER	0.034	n.s.	0.032	n.s.	0.035	n.s.	0.032	n.s.
lnURB	-0.339	n.s.	-0.392	n.s.	-0.343	n.s.	-0.384	n.s.
lnCLIV	0.139	n.s.	-0.904	n.s.	0.129	n.s.	-0.693	n.s.
R^2	0.921	-	0.908	-	0.921	-	0.912	-
Adj. R^2	0.908	-	0.892	-	0.907	-	0.897	-
n	43	-	43	-	43	-	43	-

*Note: ***, **, * = 1%, 5%, 10% significance. n.s. = not significant. Source: Author's computation (2026).*

DOLS Robustness Check

The main findings of the DOLS for both sectors are summarised in Table 8. The results of the DOLS analysis are broadly consistent with those for agricultural output, with CO_2-PREC having a positive and significant

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coefficient (0.304, $p < 0.05$). One important difference is the DOLS result for the EF specifications: ecological footprint is positive and strongly significant for both agricultural output (EF-PREC: 1.649***, EF-TEMP: 1.851***) and industrial output (EF-PREC: 1.391***, EF-TEMP: 1.283***) under DOLS.

It may be that the difference between FMOLS and the EF specifications is due to the simultaneous estimation of leads and lags in DOLS capturing dynamic co-movement between the ecological footprint and output which the semi-parametric FMOLS does not completely incorporate.

The positive sign in the DOLS industrial EF models is probably more of a reflection of the fact that ecological footprint is a measure of the scale of industry, and the greater the industrial output the larger the ecological footprint, than it is of the environmental degradation that industrial output necessarily brings. FMOLS remains the main estimator due to its better small sample properties.

Table 8: DOLS Robustness Check: Key Environmental Quality Coefficients

Model	DOLS lnENVQ Coef.	Std. Error	Sig.	FMOLS lnENVQ Coef.	Divergence
CO2-PREC-AGRIO	0.304	0.119	**	0.335**	Consistent
CO2-TEMP-AGRIO	0.233	0.220	n.s.	0.309*	Minor
EF-PREC-AGRIO	1.649	0.307	***	0.132 n.s.	Divergent (DOLS stronger)
EF-TEMP-AGRIO	1.851	0.318	***	0.177 n.s.	Divergent (DOLS stronger)
CO2-PREC-INDUO	0.134	0.098	n.s.	0.011 n.s.	Consistent
EF-PREC-INDUO	1.391	0.133	***	0.010 n.s.	Divergent (DOLS stronger)
EF-TEMP-INDUO	1.283	0.156	***	0.021 n.s.	Divergent (DOLS stronger)

Note: DOLS(1,1) with Newey-West HAC standard errors. FMOLS (Bartlett kernel, Andrews bandwidth) is the primary estimator. EF-based DOLS divergence for INDUO reflects industrial scale captured by ecological footprint, not environmental benefit to industry. Source: Author's computation (2026).

Wald Tests for Environmental Quality Significance

Table 9: Wald Tests for ENVQ Coefficient, FMOLS (H0: Long-Run ENVQ Coefficient = 0)

Model	ENVQ Coef.	Std. Error	Wald F	p-value	Decision
CO2-PREC-AGRIO	0.3352	0.1617	4.297	0.045**	Reject H0
CO_2-TEMP-AGRIO	0.3085	0.1596	3.736	0.061*	Marginal (10%)
EF-PREC-AGRIO	0.1324	0.2913	0.207	0.652	Fail to Reject
EF-TEMP-AGRIO	0.1768	0.2250	0.618	0.437	Fail to Reject
CO2-PREC-INDUO	0.0112	0.1079	0.011	0.918	Fail to Reject
CO_2-TEMP-INDUO	0.0286	0.1200	0.057	0.813	Fail to Reject

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EF-PREC-INDUO	0.0097	0.1398	0.005	0.945	Fail to Reject
EF-TEMP-INDUO	0.0213	0.1421	0.022	0.882	Fail to Reject

*Note: Wald F = squared t-statistic. ***, **, * = 1%, 5%, 10%. Only CO_2-PREC-AGRIO is significant at 5%; CO_2-TEMP-AGRIO is marginal at 10%. No industrial output model yields a significant environmental quality effect. Source: Author's computation (2026).*

Post-Estimation Diagnostics

Table 10: Post-Estimation Diagnostics: FMOLS Residuals (All Eight Models)

Model	DW Stat.	JB p-val	ADF Resid.	ADF p-val	Residuals I(0)?
CO_2-PREC-AGRIO	1.748	0.934	-3.891	0.002	Yes
CO_2-PREC-INDUO	0.814	0.323	-3.231	0.018	Yes
CO_2-TEMP-AGRIO	1.643	0.761	-3.286	0.016	Yes
CO_2-TEMP-INDUO	0.821	0.253	-3.306	0.015	Yes
EF-PREC-AGRIO	1.851	0.381	-3.777	0.003	Yes
EF-PREC-INDUO	0.872	0.411	-3.355	0.013	Yes
EF-TEMP-AGRIO	1.718	0.285	-3.040	0.031	Yes
EF-TEMP-INDUO	0.819	0.282	-3.278	0.016	Yes

Note: DW = Durbin-Watson. JB = Jarque-Bera normality test. ADF H0: unit root; rejection confirms residual stationarity, validating the cointegrating relationship. All eight models show stationary residuals, confirming valid long-run cointegrating relationships. Source: Author's computation (2026).

The graphical diagnostic and stability assessment of the FMOLS models are given in Figures 1, 2 and 3 respectively. The time-series of the residual movements are plotted in figure 1 and do not show any explosive behaviour and have constant means. Figure 2 illustrates the normality of the residuals by normal Q-Q plots and one can see that the observations are reasonably close to the theoretical normal distribution line, confirming the normality of the residuals. CUSUM stability plots to evaluate parameter constancy over the study time are reported in Figure 3.

The CUSUM paths did not cross the 5% critical bounds, meaning that there was no sign of structural instability and the coefficients were stable. The graphical diagnostics in combination with the residual stationarity diagnostics for the estimated FMOLS models shown in Table 10 suggest that the models are statistically reliable and stable. Therefore, the conclusion is that the elasticity estimates in the long-run are interpretable and can be applied to policy and analysis. All models show good normality of the residuals (JB p-values are all > 0.25, with minor deviations). All of the above diagnostics support the validity of the long-run FMOLS elasticity estimates as statistically reliable and stable.

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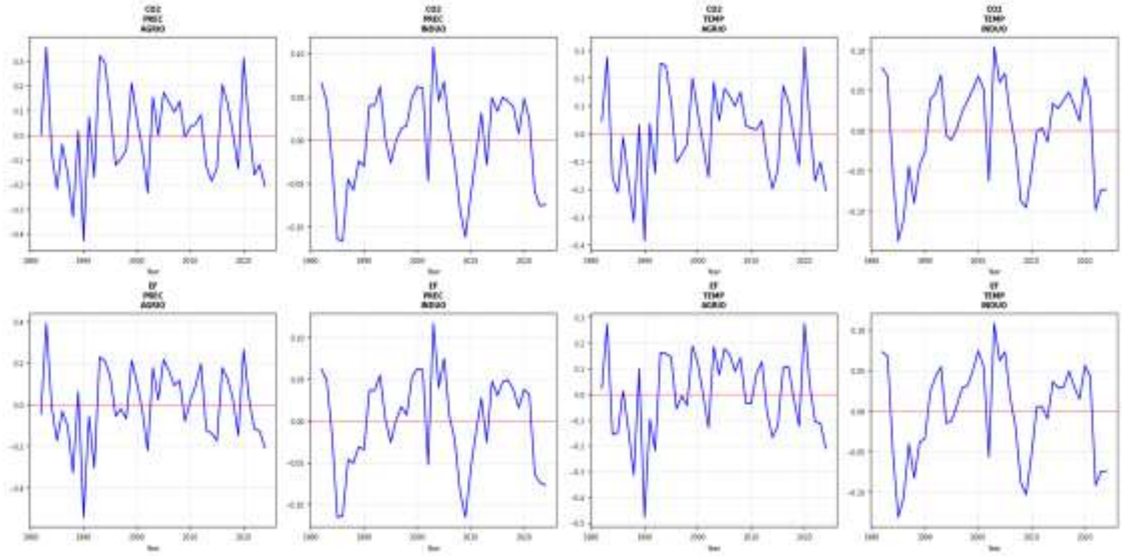

Figure 1: FMOLS Residuals over Time, All Eight Model Equations

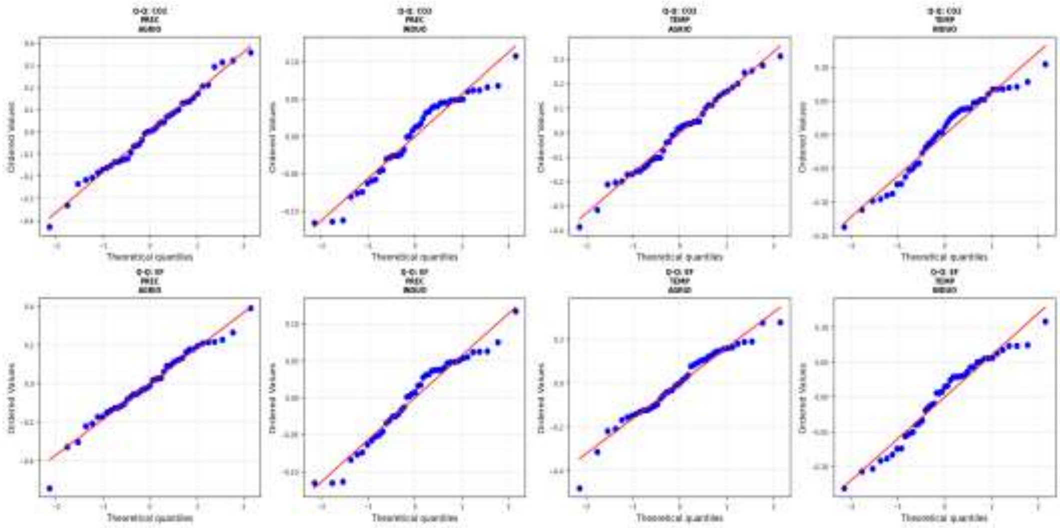

Figure 2: Normal Q-Q Plots of FMOLS Residuals - All Eight Models

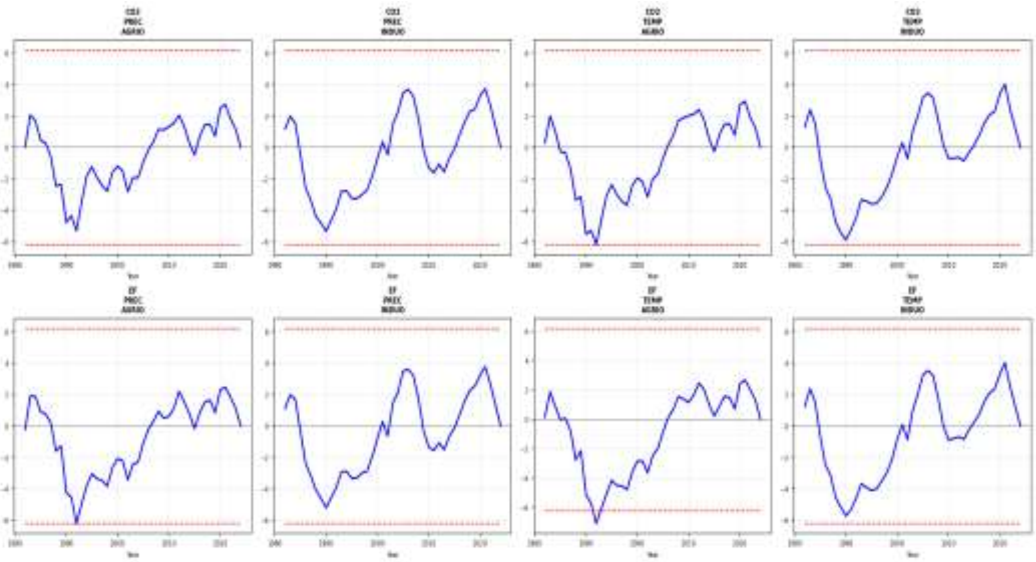

Figure 3: CUSUM Stability Tests, FMOLS Residuals, All Eight Models

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DISCUSSION OF FINDINGS

The FMOLS results show a clear pattern of sector-specific environmental sensitivity, with agriculture being sensitive to the environmental proxies in the expected direction – that is, positive sensitivity to CO_2 under carbon fertilisation – while industry is unresponsive to both environmental proxies. This differential pattern is explained in two complementary ways. First, at the outset, it is noted that this pattern is independently corroborated by the evidence of Gold and Anagun (2026) arising from a dual-sector study in Nigeria, which also shows that while the climate and emission variables have significant impacts on the agriculture sector, impacts on the industrial sector are comparatively muted.

The positive CO_2-output relationship (elasticity = 0.335, significant at 5%) for agriculture can most plausibly be understood as a carbon fertilisation effect. At moderate CO_2 levels (below ~600 ppm), agronomic evidence has shown that the photosynthetic efficiency and biomass accumulation of C3 plants such as wheat, rice, cassava, and soybean, some of which are key in Nigeria's agricultural portfolio, is increased by elevated levels of atmospheric CO_2. Nigeria's atmospheric CO_2 concentration range over the sample period (below 420 ppm globally, but a bit higher at the local atmospheric level because of gas flaring) may be conducive to the dominance of the photosynthetic stimulation over climate damage effects, thus resulting in the observed positive aggregate elasticity.

However, this does not mean that CO_2 emissions are good for agriculture: the non-linearity of the CO_2-output relationship means that larger emissions will eventually have a negative effect, and the ecological footprint models' insignificant coefficients mean that overall environmental degradation is not yet reflected in aggregate output losses, possibly because of a variety of damages which are heterogeneous across sub-sectors or regions and thus offset at the aggregate level.

This warning is corroborated by the result of Obekpa et al. (2025) who noted that Nigeria's own food production drive is increasing the cropland and forest-product components of the nation's ecological footprint, which implies that the level of productivity gains detected in this study is partly being paid with an ever shrinking long-run biocapacity ceiling.

In addition, there is a consistent and substantively large, and statistically significant negative urbanisation coefficient (-2.49 to -2.66) for all agricultural specifications. It suggests that for every 1% increase in Nigeria's urbanisation rate, the agricultural output decreases by 2.5 to 2.7% over the long-run, one of the most robust associations among all the relationships in this study.

This effect works in many different ways, such as land-use change (conversion of agricultural land into residential or commercial property), urbanisation and structural change of the agricultural sector (rural-urban migration depleting the agricultural labour force), and neglect of the policy that tends to become associated with urbanisation. This finding is consistent with that of Nathaniel and Bekun (2020) who associated environmental degradation with urbanisation in Nigeria and thus calls for the policy attention towards prevention of encroachment of urban areas on agricultural land.

At the macro level (annual average) the environment is therefore not a recipient of the effects of the Nigerian industrial sector, as all the environmental quality coefficients are completely insignificant under FMOLS. This aligns with the study by Parveen et al. (2023) showing that CO_2 emissions cause industrial output and not the other way round, and with the study by Gold and Anagun (2026) which shows that industrial output in Nigeria is not as sensitive as agricultural output to shocks in climate and CO_2 emissions.

The high elasticities of industrial output to GDP per capita (0.69-0.71) indicate that industrial production expansion is largely driven by demand and is in line with the findings of Acheampong et al. (2021) that income growth is the main structural determinant of industrial development in Sub-Saharan Africa. The evidence here on the Nigerian industrial insignificance, which has been echoed by Khan and Khan's (2026) findings on the Saudi Arabian case, suggests that the environmental-productivity relationship is also not the same for all

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sectors or all quantiles of the outcome, but is a structural pattern of extraction- and demand-led industrial sectors in resource-rich economies.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study aimed to shift the focus of the empirical literature in what can be considered an almost complete reversal of the question; that is, rather than how sectoral output affects environmental quality in Nigeria, it was how does environmental quality affect sectoral output. Based on eight cointegrated long-run equations identified by FMOLS, DOLS-validated and Johansen confirmed covering the period 1981-2024, the general finding of the paper is that the productive effect of environmental quality in Nigeria is real but highly sector-specific: it appears as a significant, carbon-fertilisation-consistent positive elasticity in agriculture (around +0.335 for CO2), while being statistically silent across all industrial specifications tested. That is, there is a long-run elasticity between Environmental Quality and Sectoral Output for the farm and not for the factory as this paper's title suggests should now form the basis for designing Nigeria's Environmental and Industrial Policy going forward.

Ecological footprint is found to be completely unimportant in all the eight long-run equations with the exception of the agricultural equations where FMOLS is found to show that Obekpa et al. (2025) demonstrate that food production in Nigeria is actually driven by the growth of its own ecological footprint, indicating that broad biocapacity stress has not yet manifested as a detectable aggregate output effect. None of the environmental quality proxies (CO2 or ecological footprint) yields a statistically significant long-run coefficient suggesting that Nigeria's industry is more of a pressurer than a receiver of environmental quality at the aggregate level, which is corroborated by an independent dual-sector evidence by Gold and Anagun (2026) and a general resource-economy parallel by Khan and Khan (2026) for Saudi Arabia. GDP per capita is the largest long-run determinant in all the sectors, thus confirming the income-scale mechanism of sectoral expansion, while urbanisation has a consistently large negative impact on agricultural output (-2.49 to -2.66), which is the result of land conversion and labour migration.

The study introduces environmental quality elasticity estimates as an explanatory variable to the Nigerian sectoral output models. The results demonstrate that agriculture and industry are structurally different with respect to environmental sensitivity, which is why policies for the environment must be tailored to the sector; and recent findings from similarly resource-dependent economies support this, rather than contradict it.

Recommendations

First of all, agricultural policy in Nigeria needs to focus on climate-smart production systems which make an explicit consideration of productivity risk from escalating environmental degradation. The present study results show a positive CO_2-agriculture elasticity apparently related to the carbon fertilisation effect but which will be inverted with further increases in CO_2. To protect agricultural productivity from a future trajectory of environmental degradation, investments are needed in soil quality assessment, drought-tolerant crops, and irrigation infrastructure, and as shown by Makieu et al. (2026), productivity-enhancing climate-smart agriculture is systematically linked to lower per-capita emissions in Sub-Saharan Africa. Second, the strong negative urbanisation impact on agricultural production calls for urgent policy action. Urban planning frameworks in Nigeria should be able to specifically identify the agricultural land protection zones, especially in the agricultural belt of the Middle Belt and the southern regions to stop the conversion of productive agricultural land to residential and commercial zones.

Third, as to industrial policy, the results imply that environmental quality does not automatically lead to increases in industry productivity. Instead, industry should be regulated through cleaner production standards and environmental efficiency requirements which reduce emissions and ecological footprint without necessarily requiring an increase in production. Fourthly, there is need to broaden the capacity to monitor the environment, as well as ecological footprint accounting for Nigerian sectors and regions. The approach of this current study which aggregates the nation's ecological footprint may have concealed important sub-sectoral and regional variations that could have been helpful, if this study had been disaggregated into the various components of the footprint, as done by Obekpa et al., (2025).

Fifth, agricultural communities should be the focus of receiving climate adaptation financing, since the environmental sensitivity was shown in this study to be long-run. To complement the technological-innovation and carbon-reduction strategies that Bajja et al. (2026) recognize as key to influencing agricultural productivity outcomes across West Africa, green bonds and climate-linked agricultural credit facilities should be developed to support the adoption of climate-resilient technologies.

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