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Modelling the Combined Effects of Climate Variables and Land Use Changes on Crop Yields in South-east Nigeria

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Abstract

Despite agriculture playing a pivotal role in South-east Nigeria, the combined effect of climatic variability and change of land-use on crop yield is still poorly quantifiable. This study uses a combined OLS regression framework to quantify the individual and interactive impacts of 7 climate variables including, temperature, rainfall, and wind speed, along with land-use changes on the aggregate yields of maize, cassava, yam and vegetable yields in Anambra, Enugu and Ebonyi states from 1980 to 2024. Utilizing data from Nigeria Meteorological Agency (NiMet), Food and Agricultural Organization (FAO), and National Bureau of Statistics (NBS), three validated models were estimated. They include a combined 8-predictor model; a bivariate land-use change model; and a forest area model. The combined model accounted for 96.5% of the yield variation (R2 = 0.965, $p<0.001$), where the wind speed ($\beta = 7.043$, $p<0.001$) and the area of agricultural land expansion ($\beta = 0.0001$, $p=0.001$) had the dominant significant effects on agricultural output. Most interestingly, the bivariate land-use model found that land-use expansion alone accounts for 90.7% of production variation (R2 = 0.907). Meanwhile, the forest area model demonstrates a near-perfect relationship ($r = -0.979$, $p<0.001$) between forest cover and agricultural production. These results imply that the development of agricultural output in the region follows the paradigm of "horizontal expansion" which is a form of deforestation; a pathway that has reached its functional ecological limits. Transitioning to sustainable intensification and enhanced water management is an empirical necessity for regional food security.

Keywords: climate variability; land use change; crop yield; OLS regression; South-east Nigeria; deforestation; agricultural productivity.

1. Introduction

Agriculture forms the mainstay of livelihood, food security and production output in south-east Nigeria. This area consists of five geopolitical zones including; Abia, Anambra, Ebonyi, Enugu and Imo states. It lies within the tropical rainforest ecology where there are two distinct periods of rainfall pattern each year and is predominantly cultivated by smallholder farmers. It is characterized by intense cultivation of maize, cassava, yam, rice as well as tree crops such as oil palm and rubber. Agriculture is responsible for about 25% of the nation's GDP (NBS, 2020; NAERLS, 2024). However, due to a system dependent almost entirely on rain-fed agriculture, with fewer than 3% of sub-Saharan Africa cropland under irrigation (FAO, 2020), the sector is structurally vulnerable to two inter-related stressors which have become more severe since 1980; increased climate variability specifically more erratic beginning, duration and ending of rainfall and rapid land use change pressures such as increased population density, urbanization and continued conversion of forest land to agriculture. The evidence for climate impacts on agriculture worldwide are now indisputable; climate change has decreased food security across sub-Saharan Africa, as the average maize yields decreases by 5.8% between 1974 and 2008 alone from climate change impact and Africa's agricultural productivity growth has declined by 34% since 1961 more than any other region of the world (IPCC, 2022). Also given the consensus of a shift in earth's climatic status by the end of this century, most of Sub-Saharan African agriculture is vulnerable to climate variations and its extremes owing to 95-97% dependency on rainfall in the short, medium and long runs (IPCC, 2018; Burke et al., 2015). Climate impact assessment indicates a drop in agricultural production by approximately 10-20% by 2050 (Onyango and Nzengya, 2023), whereas majority of smallholder farmers in African lack the access to irrigation and other adaptation technologies needed to mitigate the effects of climate variability (Teshome et al., 2021).

The link between climate change and agriculture production has been clearly established across Nigeria on both the national and sub-national level, particularly with regard to the crops relevant to this study. Maize, cassava, yam and rice yield have been disrupted severely from unreliable rainfall, temperature increases and extreme events at the national level, making Nigeria one of the ten most climate exposed countries globally (Omokaro, 2025). At the crop level, shifts in rainfall pattern disrupts farming activities resulting in crop failure due to severe weather settings like drought. this in turn lead to reduced water availability in the root zone between 54% and 80% (Maiyo et al., 2024). Rainfall, alongside arable land area was found to have been a significant long-term determinants of cassava yield, estimated using an Autoregressive Distributed Lag approach on 1990-2019 FAO data, directly suggesting that climatic and land use variables are to be modeled together for cassava productivity (Anyaegbu et al., 2023). In particular at the South-east Nigeria level, climate variables such as rainfall and temperature have been found to be significant variables that affected maize and yam production across the region (Chikezie et al., 2015), rainfall anomalies were found to reduce cassava yields in Enugu State using NiMet based prediction modeling (Ogbuene et al., 2023) and long-term 30 year analyses shows increasing temperature trends and significantly unstable rainfall patterns across South-east Nigeria, highlighting growing climatic instability in a predominantly rain-fed agricultural system (Chikezie et al., 2016).

Along with climatic variation, large and established land use change have been occurring across South-east Nigeria since 1980, resulting from increasing human population, expansion of agricultural practices, and urban sprawl. At the national scale, transition into cultivated land-cover is the largest land cover change in Nigeria, most predominantly taking place at the expense of forest, shrublands and grassland, based on analysis of GlobeLand30 land-cover data and logistic regression analysis on factors influencing cultivated land expansion (Arowolo and Deng, 2018). Short-term agricultural benefits with the enhanced food provisioning service from this transformation were outweighed by decreased provision of crucial regulating ecosystem services, such as water regulation and local buffering of climatic impact that support agricultural sustainability in the long run (Arowolo et al., 2018). Agricultural land use in Nigeria was estimated to have increased by approximately 8–9 million hectares between 1995 and 2020 expanding from 61.9 million hectares to 70 million hectares, most of which is from conversion of forest and woodland areas to cultivated land cover (FAO, 2018) and deforestation-induced expansion causes increased soil susceptibility to erosion leading to the loss of topsoil that degrades the fertility and productivity of agricultural land (Borrelli et al., 2017; Kehinde et al., 2023). These features, through horizontal expansion, has produced a structural trade-off short-term production enhancement gains, made at the long-term expense of the soil and environmental condition that sustain agriculture. And the extent to which this occurs is yet to be quantified through regression analysis for South-east Nigeria.

In spite of this considerable body of evidence, the combined modelling of climate and land use changes simultaneously as predictors of crop yield variation across South-east Nigeria have not been conducted, and two specific gaps remain unaddressed. The first is that modelling these determinants as distinct analytical components risks misattribution of the explained variance in crop yields, and generating false conclusions about what to invest in most urgently; only a jointly estimated regression can show these components in their entirety. The second gap is wind speed, a variable with documented effects on crop pollination, canopy disease suppression through air circulation, and evaporative cooling, has been entirely absent from agricultural regression analyses for the zone (Chikezie et al., 2015; Maiyo et al., 2024), highlighting an omission with climate-crop models, where several local climate variables such as vapor pressure deficit, rainfall frequency and temperature interactions were poorly represented (Emediegwu et al., 2022). While the regional meteorological background conditions of mean annual rainfall of 183.73mm/month at Owerri, a mean air temperature of 28.06oC at Enugu and mean wind speed varying from 2.65-5.48km/hr in the region has been identified (Ibeje and Ekeleme, 2020), agricultural productivity outcome remain lacking. The current study fills these two gaps by analyzing the role of seven climate variables and land use changes in agricultural yield variation across the region, utilizing three complementary OLS regression models, each tested for full diagnostic validity, with the aim of producing locally specific empirical evidence to support sustainable land management and climate adaptation policy in South-east Nigeria.

2.0 Materials and methods

2.1 Study Area

The study was conducted in three of the five states within the South-east region of Nigeria. Anambra and Imo; Ebonyi and Abia having nearly similar features respectively except Enugu being different because of its nature/topography. Anambra, Enugu and Ebonyi states were chosen for this study due to the existence of large scale agricultural production in these states and their reported susceptibility to the effects of climate change. These attributes make them suitable for testing the effects of climatic variables and land use change on crop production. The South-east geopolitical zone extends between longitudes 06°45′E and 08°45′E and latitudes 04°30′N and 07°30′N. It comprises an area of approximately 10,952,400 hectares, and a population exceeding 16.3 million inhabitants (NPC, 2016). Figure 1 displays the location of the study states within the South-east zone.

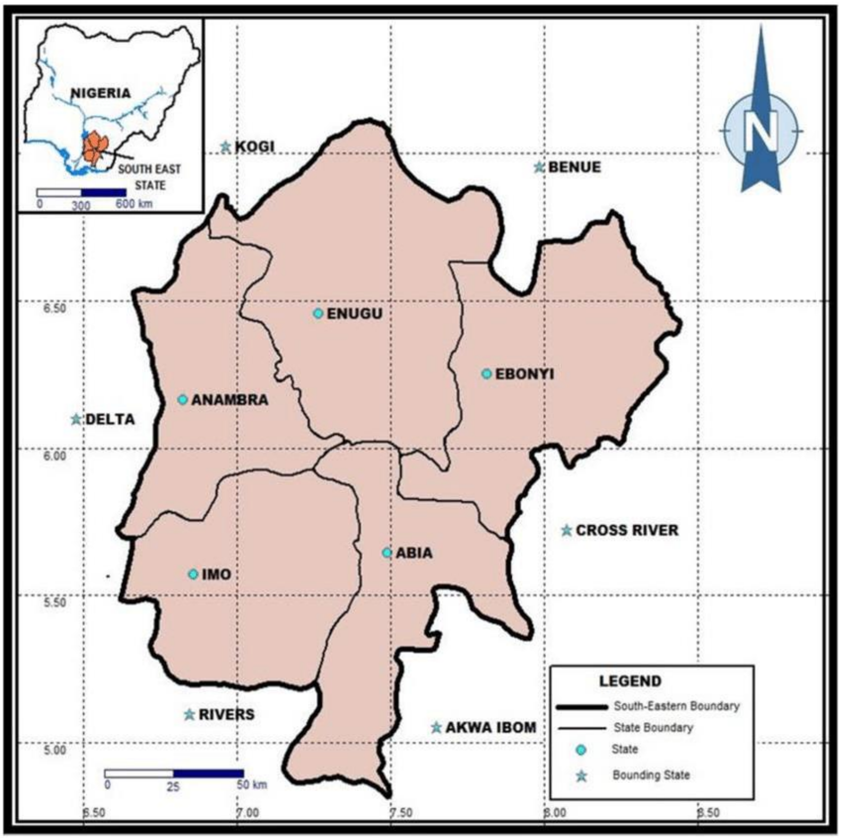

Figure 1. Map of South-east Nigeria showing the three study states (Anambra, Enugu, and Ebonyi). Source: Kayode et al. (2019).

Anambra State is situated at 5°40′N and 6°48′N latitudes and 6°35′E – 7°50′E longitudes and an area of approximately 4,415.54km². The state consists of lowland plain and undulating hills, especially in the northern and central regions. It is bounded on the west by the Niger River, which strongly influences land use and settlement patterns (Agbo et al., 2015).
The soils are predominantly ferrallitic, hydromorphic, and highly permeable, characteristic of the sedimentary Anambra Basin, and generally suitable for agriculture (Ocheli et al., 2021). The state capital is Awka, where the meteorological station for the state is located and records the lowest average annual rainfall in the zone.

Enugu State lies at 5°56′N and 7°06′N, and latitudes at 6°53′E and 7°55′E longitudes with an area of 7,534km². The state is situated on the Udi-Nsukka Plateau and has a tropical wet-and-dry (savanna) climate, with substantial annual sunshine and warm temperatures typical of South-eastern Nigeria. The station at Enugu has the maximum average solar radiation, sunshine hour, air temperature and wind speed among the five zones of South-eastern Nigeria. The dominant soil type is generally well drained, which has suitability for the cultivation of cassava, maize and oil palm and land suitability studies have shown that substantial portions of the state possess soils suitable for these crops under appropriate management practices (Ikagwu et al., 2020; Obumselu et al., 2024).

Ebonyi State is geographically located at latitude 5°56′N and 6°00′N, and longitude 7°61′E and 8°00′E occupying a total area of about 7,465 km² (Ota et al., 2021). The landscape of the state consists of two broad terrain types, including the low lying flood plains and the undulating hilly regions which tend to merge into the river valleys. The water flow patterns in Ebonyi State as well as the farming activities are defined by the presence of Ebonyi and Cross River Basins. The soils in Ebonyi are dominated by alluvial and clay soil which make the state suitable for extensive cultivation of rice. In the same way agriculture, particularly the cultivation of rice, yam, cassava and vegetables constitutes the largest land-use and the state is more rural in nature than both Anambra and Enugu (Onyeneke et al., 2022). Abakaliki, the state capital, serves as the designated meteorological reference point in the state.

All three states are characterized by a tropical climate and a bimodal rainfall pattern. From March to July constitutes the first rainy season, a short dry spell in August; September to November constitutes the second rainy season while the Harmattan dry season is from November to March. Anambra and Ebonyi states are slightly more rainy than Enugu state and these differences in amount of rain impacts the farming system and availability of water within the entire zone. The Harmattan season, common to all three states, results in a drying of the soil surface that limits crop growth (Ibeje and Ekeleme, 2020). Topographically, the differences in topography influences the potential for agricultural productivity as the plateau terrain of Enugu State poses a great threat to soil erosion unlike the low flat terrain of Ebonyi State, a situation which favors extensive farming, especially rice (Onyeneke et al., 2022). Together, these varying agro-ecological conditions across the three states makes them representative study locations for South-east zone.

2.2 Research Design

This study utilized a quantitative research design. A long-term secondary data of climate variables, land use and crop production from 1980 to 2024 were obtained and examined to determine the temporal trends and statistical relationship between climate variables, change of land use and crop yield. The main objective was to quantify the changes occurring over time and the impact they have on crop yield in the area. Fifteen sampling fields were selected within five Local Government Areas per state - Anambra (Awka South, Awka North, Njikoka, Dunukofia, and Anaocha), Enugu (Enugu North, Enugu South, Enugu East, Nkanu West, and Udi) and Ebonyi (Afikpo South, Ebonyi, Ohaukwu, Izzi and Ikwo) by using both stratified random sampling and purposive sampling methods. This selection criteria was based on the agricultural importance of each state, climate vulnerability, varied types of soil and topographical characteristics as well as suitability of these sites for representing typical agro-ecological zones of the states. Each of the sampling sites was georeferenced with a GPS device (Garmin eTrex 32x, precision 3 meters) as presented in Table 1. While the statistic relies on second-order time-series data, descriptions of sample location and coordinates are necessary in terms of space and illustrating a typical agricultural landscape of South-east Nigeria. In this regard, the location of sampling points is more informative to set the scene for the environmental and land-use characteristics of the study area, rather than to represent primary field-level measurements.

Table 1. GPS coordinates of the 15 field sampling locations in the study area

S/N	State	LGA	Village	Latitude (°N)	Longitude (°E)
1	Enugu	Enugu North	Ihenwuzi	6.34670	7.51070
2	Enugu	Enugu South	Amagu	6.46020	7.54389
3	Enugu	Enugu East	Ako	6.21041	7.41988
4	Enugu	Nkanu West	Amafo	6.14441	7.49848
5	Enugu	Udi	Amabo	6.43413	7.49288
6	Anambra	Awka South	Umueze	6.21000	7.07000
7	Anambra	Awka North	Adama	6.33333	7.07000
8	Anambra	Njikoka	Igbolo	6.21030	7.07001
9	Anambra	Dunukofia	Adagbe	6.21010	7.07005
10	Anambra	Anaocha	Amata	6.21002	7.07004
11	Ebonyi	Afikpo South	Agbogo	6.00000	8.00000

12	Ebonyi	Ebonyi LGA	Uwarem	6.21840	8.12984
13	Ebonyi	Ohaukwu	Eguenyi	6.53285	8.02303
14	Ebonyi	Izzi	Onuoji	6.48653	8.29468
15	Ebonyi	Ikwo	Enyim	6.05316	8.16284

Source: Researcher's Field Work (2025).

These locations defined the geographic representativeness of the research area; the analytic data of climate variables, crop production and land use were obtained through secondary sources as described in Section 2.3.

2.3 Data Sources

Climate data for the period of 1980-2024 were obtained from Nigerian Meteorological Agency (NiMet) for the three selected states of study. Because the study uses long-term regional time-series data, the modelling technique intended to capture large-scale climatic and land-use effects on crop production patterns, rather than field-level experimental relationships. The variables collected included the annual maximum and minimum air temperature (°C), the total annual rainfall (mm), the relative humidity (%), direct solar radiation (cal/cm²/min), the wind speed (km/hr), and wind direction (degrees). These data were sourced from NiMet station; Awka for Anambra, Enugu for Enugu State and Abakaliki for Ebonyi State.

Agricultural production data covering yield of the 4 major staple crops for the region, including maize, cassava, yams and vegetables, were obtained from the FAO database (FAOSTAT), National Agricultural Extension and Research Liaison Services (NAERLS) and the Federal Ministry of Agriculture and Food Security. Land use data specifically, the total agricultural land area in hectares and forest area in km2 was sourced from the World Bank Open Data, FAO Nigeria, and the National Bureau of Statistics (NBS). The climatic data and the crop yield data spans from 1980-2024 with 44 annual observations, agricultural land area spans from 1980-2024 with 50 annual observations, and the forest area spans from 1980-2024 with 44 annual observations, showing the period of which consistent data were available.

2.4 Statistical Analysis

Data were analysed using SPSS, R, and Python (with the Pandas, NumPy, and Statsmodels libraries). Three separate OLS regression models were estimated to address the study objectives.

The first and primary model examined the combined effect of all eight variables; seven climate variables and land use area on crop yield. This Multiple Linear Regression (MLR) model is expressed as Equation (1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon \ldots \quad (1)$$

where Y is the annual aggregate crop yield index; X_1 is annual maximum temperature (°C); X_2 is annual minimum temperature (°C); $X_3$is annual total rainfall (mm); X_4 is annual relative humidity (%); X_5 is annual direct solar radiation (cal/cm²/min); X_6 is annual wind speed (km/hr); $X_7$is annual wind direction (degrees); X_8 is total agricultural land use area (ha); β_0 is the intercept; β_1 to β_8 are the regression coefficients for each variable; and ε is the error term.

The second model examined the independent effect of agricultural land area alone on total agricultural production, using a bivariate regression with 50 annual observations (1980–2024). The third model examined the relationship between forest area and crop production using 44 annual observations (1980–2024).

In addition to the regression models, the Pearson correlation coefficient (r) was calculated to measure the strength and direction of the linear relationship between annual rainfall and crop yield, using Equation (2):

$$r = [n\Sigma xy - \Sigma x\Sigma y]/\sqrt{\{[n\Sigma x^2 - (\Sigma x)^2] \times [n\Sigma y^2 - (\Sigma y)^2]\}} \quad \ldots \ (2)$$

where n is the number of data points; x and y are the values of the two variables being compared; Σxy is the sum of the products of each paired observation; Σx and Σy are the sums of each variable; and Σx^2 and Σy^2 are the sums of the squares of each variable. The resulting r value indicates how strongly the two variables are related and whether the relationship is positive or negative.

To check whether the independent variables in the combined model were too closely correlated with each other, a problem known as multicollinearity, the Variance Inflation Factor (VIF) was calculated for each variable using Equation (3):

$$VIF = 1/\left(1 - R^2{}_i\right) \qquad \text{... (3)}$$

where R^2_i is obtained by regressing each predictor variable against all the others. A VIF value below 10 was used as the acceptable threshold (Hair et al., 2019).

All three models were tested to ensure that the results were reliable and valid. The following checks were carried out: the Breusch-Pagan test was used to check whether the spread of the residuals was consistent across all values of the predictors; the Durbin-Watson statistic was used to detect whether the residuals were correlated with each other across time, with values close to 2.0 indicating no such problem; the Shapiro-Wilk test was used to check whether the residuals followed a normal distribution; and Cook's Distance was used to identify any individual data points that had an unusually large influence on the model results, using a threshold of 1.0. Where the Breusch-Pagan test showed unequal spread in the residuals, corrected standard errors (HC3) were applied to adjust the model accordingly.

To further confirm the reliability of the forest area model, three additional checks were carried out: the model was re-run after converting both variables to their logarithmic form; it was re-run after removing data points identified as influential outliers by Cook's Distance; and it was re-run with a year index added as an additional variable to account for any underlying time trend in the data.

3.0 Result

This section presents the findings from the three OLS regression models estimated to address the study objectives: the combined climate and land use model, the independent land use model, and the forest area model. The results are presented in the order in which the models were estimated, with all relevant diagnostic checks reported alongside each model.

3.1 Combined Effects of Climate Variables and Land Use on Crop Yield

Table 2 presents the results of the full OLS regression model, which examined the combined effect of all seven climate variables and land use area on the aggregate yield of maize, cassava, yam, and vegetables in South-east Nigeria from 1980 to 2024 (n = 44 annual observations).

Table 2. OLS regression results: combined climate variables and land use on crop yield (n = 44, 1980–2024)

Variable	Coefficient (β)	Std. Error	t-statistic	p-value	95% CI Lower	95% CI Upper
Constant	38.651	23.320	1.656	0.107	−8.063	85.366
Max. Temperature (°C)	−0.022	0.362	−0.062	0.951	−0.749	0.704
Min. Temperature (°C)	−0.158	0.269	−0.589	0.558	−0.703	0.387
Annual Rainfall (mm)	0.018	0.010	1.835	0.074†	−0.001	0.038
Relative Humidity (%)	0.076	0.089	0.855	0.398	−0.105	0.257
Solar Radiation (cal/cm²/min)	−0.083	0.105	−0.794	0.434	−0.300	0.133
Wind Speed (km/hr)	7.043	1.462	4.817	<0.001***	4.095	10.991
Wind Direction (°)	−0.060	0.040	−1.492	0.146	−0.142	0.023
Land Use (ha)	0.0001	0.000	3.732	0.001**	0.000	0.000

$R^2 = 0.965$; Adjusted $R^2 = 0.951$; $F(8,35) = 71.28$; $p = 1.33\times10^{-24}$; Omnibus = 0.304 ($p = 0.858$); Jarque-Bera = 0.338 ($p = 0.844$); Durbin-Watson = 2.024; AIC = 384.50; BIC = 399.46. † $p < 0.10$; ** $p < 0.01$; *** $p < 0.001$. Source: Researcher's Field Computations (2025).

The model accounts for 96.5% of the variation in crop yield ($R^2 = 0.965$) demonstrating a very good fit. The overall model showed statistical significance with F=71.28, and $p = 1.33\times10^{-24}$). The residuals had a normal distribution and verified using the Omnibus test (p = 0.858) and the Jarque-Bera test (p = 0.844), and the Durbin-Watson statistic (2.024) showed that there is no systematic year on year relationship between residuals.

Of the eight explanatory variables, two proved to be significant. Wind speed was found to be the most significant variable and had a positive effect on crop yield ($\beta = 7.043$, $p < 0.001$): that is for every one unit increase in the annual wind speed, crop yield increased by approximately 7.043 units, with all other variables being kept constant. Land area also exhibited a significant positive relationship with crop yield ($\beta = 0.0001$, $p = 0.001$), confirming that increase in the agricultural land area also leads to increase in crop production. This is equivalent to an increase of approximately 1.0 unit in the crop yield index for every additional 10,000 hectares brought under cultivation. Annual rainfall almost achieved significance ($\beta = 0.018$, $p = 0.074$), suggesting a likely positive effect that falls just outside the conventional 5% threshold. All the other variables; max, min temperature, relative humidity, solar radiation and wind direction showed no significant impact on crop yield within the combined model.

Table 3 indicates whether the predictor variables were too interrelated and this would be difficult to isolate the individual effect. Maximum temperature (VIF = 12.06) and minimum temperature (VIF = 11.09) had a high degree of overlap and wind speed (VIF = 10.48) had a borderline level. The individual coefficients of all these three variables must be thus read with some care. The other variables (relative humidity, solar radiation, wind direction, and land use) have quite satisfactory values, which proves that their coefficients are valid estimates.

Table 3. Multicollinearity check: Variance Inflation Factor values

Variable	VIF	Assessment
Maximum Temperature	12.06	High — interpret with caution
Minimum Temperature	11.09	High — interpret with caution
Annual Rainfall	7.34	Moderate
Relative Humidity	1.67	Low — reliable estimate
Solar Radiation	2.15	Low — reliable estimate
Wind Speed	10.48	Borderline — interpret with caution
Wind Direction	1.22	Low — reliable estimate
Land Use	1.15	Low — reliable estimate

Threshold: VIF < 10 (Hair et al., 2019). Source: Researcher's Field Computations (2025).

Figure 2 shows the trends in all climate variables, land use, and crop yield across the study period from 1980 to 2023. Crop yield rose steadily throughout the period. Land use also expanded steadily, before a sharp decline around 2021. Temperatures remained relatively stable, rainfall fluctuated from year to year, and wind speed showed a slight upward trend. Relative humidity and solar radiation were broadly consistent across the period.

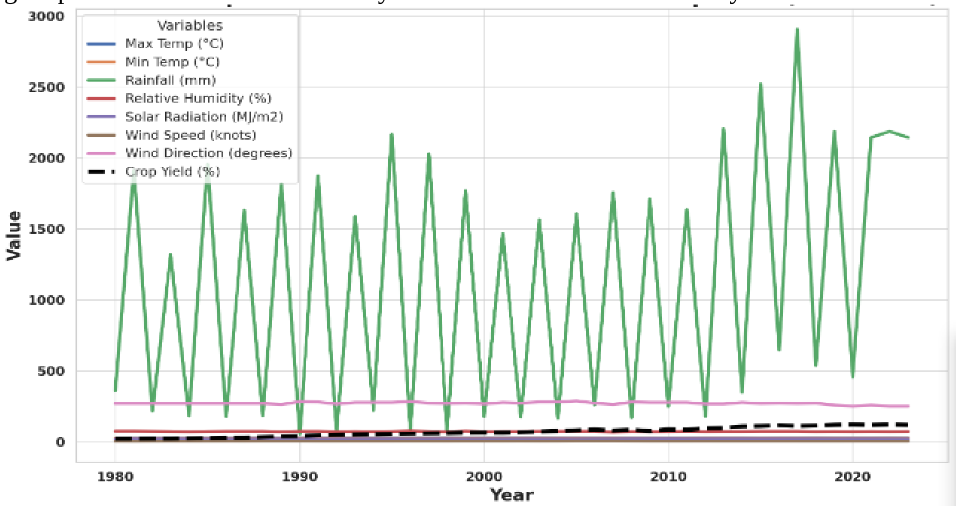

Figure 2. Trends in climate variables, land use, and aggregate crop yield (maize, cassava, yam, and vegetables), South-east Nigeria, 1980–2023. Source: Researcher's Field Work (2025).

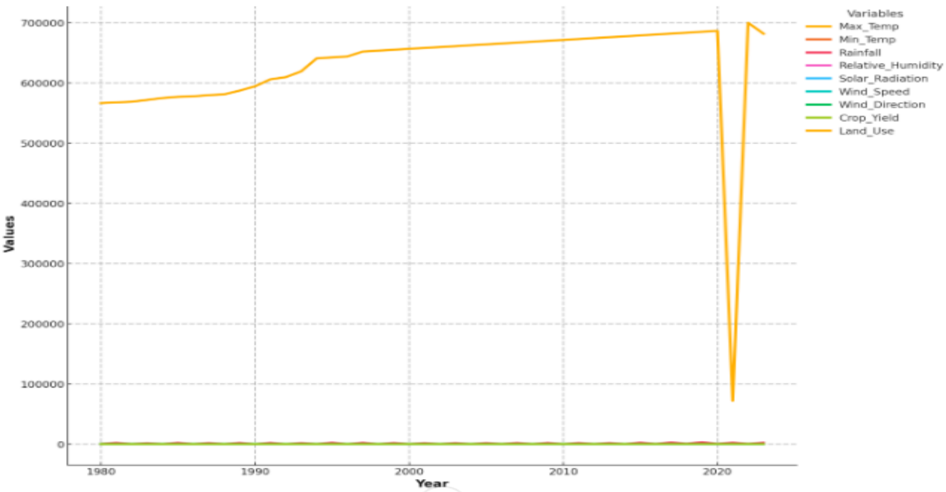

Figure 3. Combined plot of climate variables, land use, and crop yield, South-east Nigeria, 1980–2023. Source: Researcher's Field Work (2025).

3.2 Independent Effect of Land Use Change on Agricultural Production

Table 4 presents the results of the bivariate model examining the effect of agricultural land area alone on total agricultural production in South-east Nigeria from 1980 to 2024 (n = 50 annual observations).

Table 4. OLS regression results: land use change on agricultural production (n = 50, 1980–2024)

Variable	Coefficient (β)	Std. Error	t-statistic	p-value	95% CI Lower	95% CI Upper
Constant	−25,856.161	2,758.208	−9.37	<0.001	−31,396.205	−20,316.117
Land Use (ha)	0.0579	0.004	16.39	<0.001	0.050	0.066

$R^2 = 0.907$; Adjusted $R^2 = 0.904$; $F(1,48) = 268.9$; $p = 1.36\times10^{-23}$; Omnibus = 8.251 ($p = 0.016$); Durbin-Watson = 1.964; AIC = 586.94; BIC = 591.45. *** $p < 0.001$. Source: Researcher's Field Computations (2025).

The results show that agricultural land area alone accounts for 90.7% of the variation in agricultural production ($R^2 = 0.907$, $F = 268.9$, $p = 1.36\times10^{-23}$). The coefficient for land use is 0.0579 ($p < 0.001$), which means that for every additional hectare of agricultural land, total production increased by approximately 0.0579 units. The confidence interval for this coefficient [0.050, 0.066] is narrow, confirming the reliability of this estimate. The Durbin-Watson statistic of 1.964 confirms that the residuals do not follow a systematic year-to-year pattern. Since there is only one predictor in this model, no variable correlation check was necessary.

Figure 4 shows the trends in land use and agricultural production from 1980 to 2023. Land use expanded steadily over the first four decades, reaching a peak before a sharp decline around 2021. Agricultural production followed a similar pattern, rising consistently over the decades with some year-to-year variation, before also declining in the most recent years.

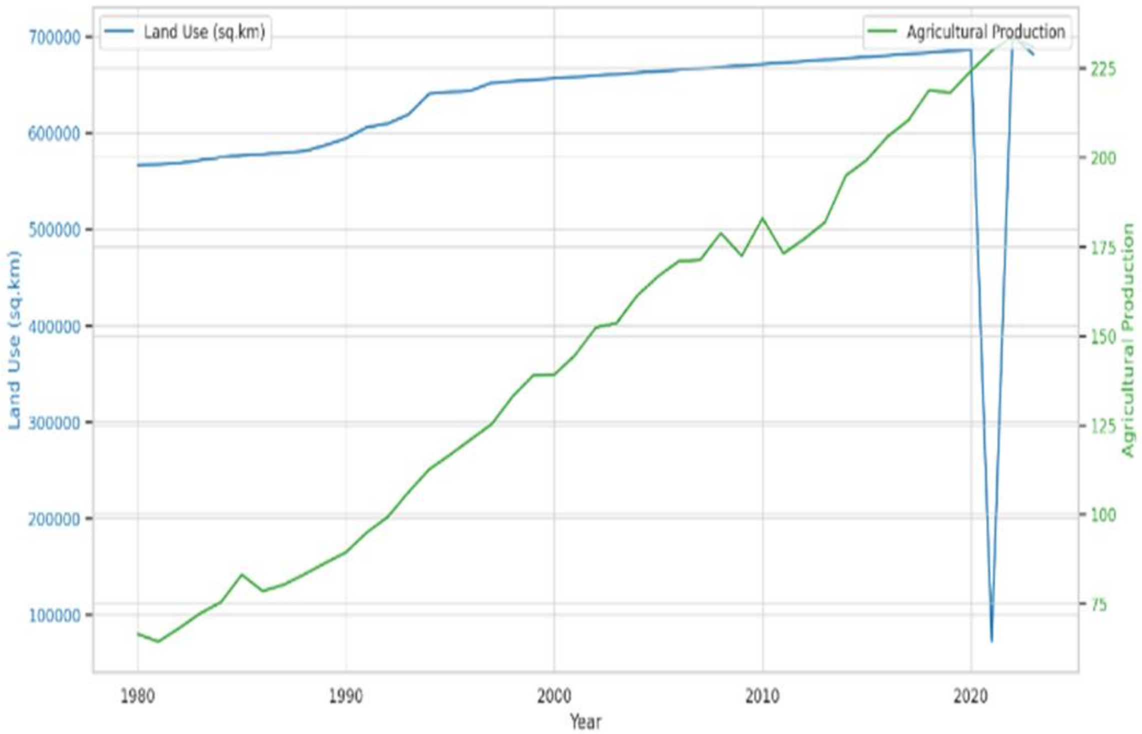

Figure 4. Trends in land use and agricultural production, South-east Nigeria, 1980–2023. Source: Researcher's Field Work (2025).

3.3 Relationship Between Precipitation and Crop Yield

The Pearson correlation coefficient between annual precipitation and crop yield was calculated as $r = 0.844$, using the dataset of 44 paired annual observations. This indicates a strong positive correlation between the two variables, meaning that, in general, years with higher rainfall tended to record higher crop yields. However, when precipitation was modelled alone as a predictor of crop yield in a separate bivariate regression, the result was not statistically significant ($R^2 = 0.027$, $p = 0.286$), indicating that precipitation cannot reliably predict crop yield on its own. This means that while rainfall and yield move together broadly over time, the relationship is moderated by other factors operating simultaneously, which is captured more fully in the combined model.

3.4 Effect of Forest Area Loss on Crop Production

Table 5 presents the results of the OLS regression model examining the relationship between forest area and crop production in South-east Nigeria from 1980 to 2024 (n = 44 annual observations). The Pearson correlation between the two variables is $r = -0.979$, which indicates a very strong inverse relationship.

Table 5. OLS regression results: forest area and crop production (n = 44, 1980–2024)

Variable	Coefficient (β)	Std. Error	t-statistic	p-value	95% CI Lower	95% CI Upper
Constant	422.107	12.751	33.104	<0.001***	396.135	448.080
Forest Area (km²)	−0.0014	5.34×10^{-5}	−26.916	<0.001***	−0.002	−0.001

r (Pearson) = −0.979; $R^2 = 0.958$; Adjusted $R^2 = 0.956$; $F(1,32) = 724.5$; $p = 1.50\times10^{-23}$; Omnibus = 8.855 (p = 0.012); Durbin-Watson = 0.979; AIC = 207.3; BIC = 210.4. *** p < 0.001. Source: Researcher's Field Computations (2025).

The model explains 95.8% of the variation in crop production ($R^2 = 0.958$, $F = 724.5$, $p = 1.50\times10^{-23}$). The forest area coefficient is −0.0014 ($p < 0.001$), meaning that for every additional square kilometre of forest area, crop production fell by approximately 0.0014 units. Conversely, as forest cover declined, because land was being cleared for farming, crop production went up. This inverse pattern is consistent and strong, confirmed by the very narrow confidence interval (−0.002, −0.001). Three further checks were made in order to ascertain that the result was not a function of the data. The outcome of all 4 model specifications are summarised in Table 6.

Table 6. Robustness checks: forest area and crop production model

Specification	N	R^2	Coefficient	p-value	Finding
Base model (linear)	44	0.958	−0.0014	<0.001	Reference model
Logarithmic transformation	44	0.958	−4.429	<0.001	Relationship stable; result consistent with base model
After removing two outliers (2011, 2013)	42	0.974	−0.0015	<0.001	R^2 improves; inverse relationship becomes even stronger
Time trend added	44	0.958	0.0013	0.751	Forest area loses significance — absorbed by the time trend

Source: Researcher's Field Computations (2025).

The first three checks all confirm the inverse relationship: whether the data are kept in original form, converted to logarithms, or stripped of outlier years, the finding holds. When a year index was added as an additional variable in the fourth check, forest area lost its statistical significance. This is because forest area and crop production both follow strong time trends in opposite directions. As one goes down steadily, the other goes up steadily, and the year index captures that shared time trend, making it difficult to separate forest area's independent contribution. This is a known limitation of regressions involving two variables that both trends strongly over time, and it does not undermine the finding in the base and robustness models.

A companion analysis was also conducted on the direct correlation between the forest cover and the overall area under agricultural production (Table 7). The results show that 83.3% of the variation in agricultural practices area is explained by changes in forest area ($R^2 = 0.833$, $F = 159.4$, $p = 5.68\times10^{-14}$, $n = 44$). The forest area coefficient is found to be -1.5161, implying that as the area of forest increased by one square kilometre, the area of agricultural practices decreased by about 1.52 square kilometres. This proves that growth of agriculture in the zone has been virtually at the expense of forests.

Table 7. OLS regression results: forest area and agricultural practices area (n = 44, 1980–2024)

Variable	Coefficient (β)	Std. Error	t-statistic	p-value	95% CI Lower	95% CI Upper
Constant	1,020,000	28,700	35.546	<0.001***	961,000	1,080,000
Forest Area (km²)	−1.5161	0.120	−12.626	<0.001***	−1.761	−1.271

$R^2 = 0.833$; Adjusted $R^2 = 0.828$; $F(1,32) = 159.4$; $p = 5.68\times10^{-14}$; Durbin-Watson = 0.145. VIF for forest area = 1.00 (no correlation problem). *** $p < 0.001$. Source: Researcher's Field Computations (2025).

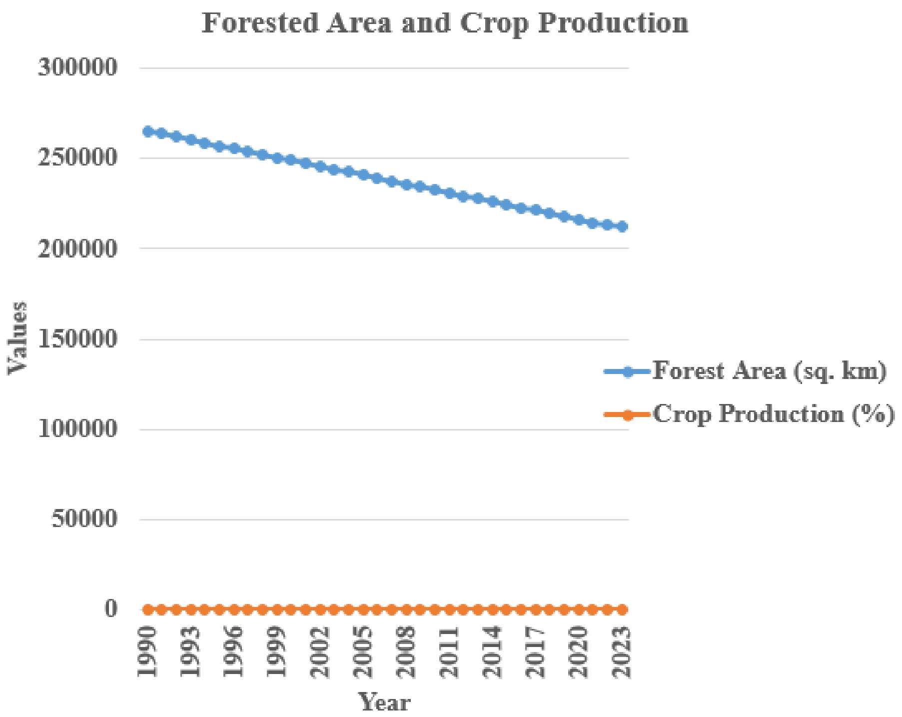

Figure 5. Relationship between forested area and selected crop production (maize, cassava, yam, and vegetables), South-east Nigeria, 1980–2024. Source: Researcher's Field Work (2025).

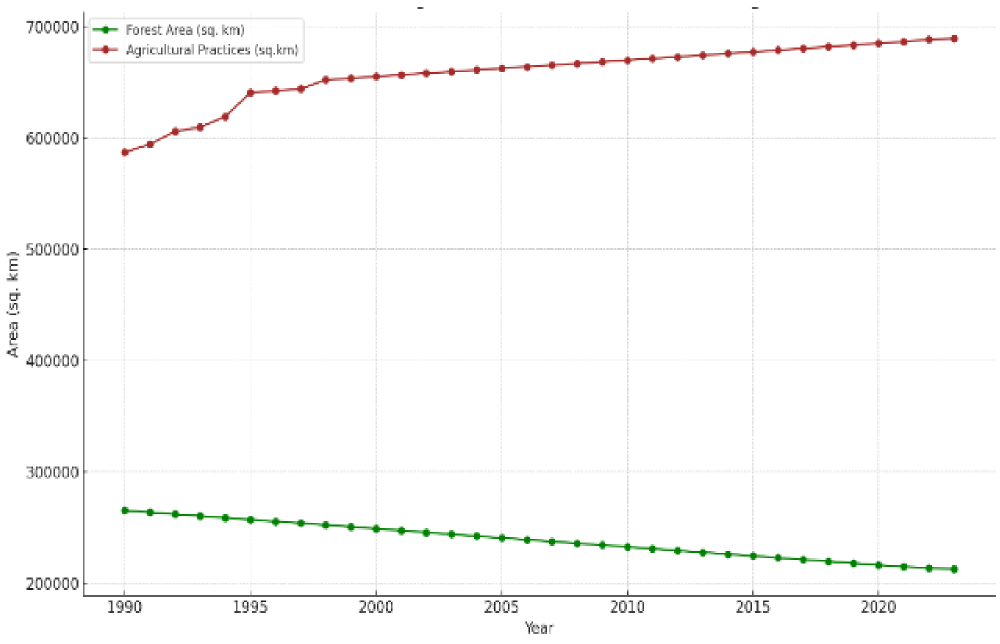

Figure 6. Trends in declining forest area and rising agricultural practices area, South-east Nigeria, 1990–2023. Source: Researcher's Field Work (2025).

Figure 6 illustrates the opposite trends clearly. From 1990 to 2023, forest area (green line) declined continuously, while the area under agricultural practices (red line) increased steadily. This visual pattern reflects the statistical finding: forest clearance has been the primary mechanism through which agricultural land has expanded in the zone over the study period.

4.0. Discussion

4.1 Land Use as the Dominant Driver of Agricultural Production

The most policy relevant result of this research is the overwhelming explanatory capacity of land use change as a predictor of aggregate agricultural production. Agricultural area expansion alone accounts for 90.7% of the observed variation in total production ($R^2 = 0.907$, $\beta = 0.0579$, $p < 0.001$, $n = 50$). This puts South-east Nigeria directly at the horizontal expansion model, where production is expanded at the expense of area instead of yield intensification, which defines the smallholder farming systems, where access to yield-enhancing inputs is limited. At the national level, Akinyemi and Ifejika Speranza (2025) found that the expansion of cultivated land has predominated the land-cover change process in Nigeria with cropland increasing in both area and proportion (22% to 37%) of total land area and tree cover decreasing (50% to 31%) between 2000 and 2022, mostly at the expense of forests and shrublands. The temporal pattern at sub-national level for South-eastern zone, as plotted in Figure 4, depicts a consistent land use growth from 1980 - 2020, then a significant decrease and production decline by 2021, raises crucial questions about whether the remaining arable land available in the zone is becoming saturated. This is a situation which deserves critical and immediate study.

4.2 The Deforestation–Production Trade-off

The near inverse correlation between amount of forest and crop production ($r = -0.979$, $R^2 = 0.958$, $p = 1.50\times10^{-23}$) shows one of the key relationships influencing the changes of agricultural development within in the region, that is deforestation, which underlies the increased production over the course of the study. This inversely proportional relation seems to hold significantly well following the log transformation ($R2 = 0.958$, $\beta = -4.429$, $p < 0.001$) and also after removal of the outlier ($R2 = 0.974$, $\beta = -0.0015$, $p < 0.001$), however loses significance when a time trend is added ($p = 0.751$) which is expected outcome when two variables follow strong opposing long-run trends over time. This last finding is the standard result in regressions containing two variables moving in different directions over time. The time trend takes up the common movement between the two variables and does not nullify the substantive relationship recorded in the other three specifications. Despite the increase in food provisioning with agriculture expansion, the capacity of water regulation, erosion control and climate buffering service, that supports the sustainability of agriculture over time, decreases and is gradually eliminated. The environment cost described in Figure 6, showing a monotonic decrease in forest cover with increasing agricultural activity, is therefore not simply an environmental issue; but also a productivity threat to the system that depends on that increase.

Khan et al. (2025) used high resolution satellite images for Nigeria, they discovered that 90% of deforestation area is converted into cultivation area within five years, which directly indicates the forest to cropland conversion effect captured by the coefficient ($\beta = -0.0014$) in this study. This same study noted that although a decrease in forest cover correlated positively with the child's diet diversity, but expansion of cropland alone does not, which supports the notion that converting forestland to farmland is not an optimal solution to food security. The accompanying model in Table 7 ($R2 = 0.833$, $\beta = -1.5161$, $p < 0.001$) enhances this picture by indicating that each extra square kilometre of forest retained corresponds to approximately 1.52 square km reduction in agricultural practice area. This pattern of farming in this zone, has, as such been growing on almost a one-for-one basis at the direct expense of the forest. The reduction in production shown from 2021 on Figure 4 correlates with the depletion of forests cover shown on Figure 6, suggesting that this conversion pathway tends to its limit.

4.3 Wind Speed and Rainfall in the Combined Model

Within the combined eight-predictor model, wind speed is the most statistically significant climate variable ($\beta = 7.043$, $p <.001$). The positive direction of this effect is practically valid at the wind speeds that observed within the zone (2.65 to 5.48 km/hr). The moderate wind enhances dispersal of pollen and the pollination of wind-pollinated crops like maize, helps with air movement through the crop canopy, reduces the accumulation of humidity and resulting fungal diseases, and creates a cooling effect during the hottest period of the growing season. However, one should be explicit in relation to what the coefficient does and does not indicate since the wind speed's borderline VIF is 10.48 (Table 3). A VIF this high indicates that over the 44-year series, wind speed shares statistical overlap with other independent variables in the model, especially in that it has similar a long-run trend as crop yields and land use across the study period. Practically, this implies that while the positive association between wind speed and crop yield is very real and confirmed by the data, the precise size of the coefficient ($\beta = 7.043$) is somewhat exaggerated than what it would have been in a model that has no dependence between the regressors. It is more the direction of the effect that is definitely established rather than the magnitude. The statistically significant effect at $p < 0.001$, along with an upper 95% confidence interval of (4.095, 10.991), which clearly does not cross zero, confirms the fact that wind speed has a genuine and distinct positive effect on variation in crop yield. Both the researcher and policymakers can therefore regard the direction of the finding as being credible. When a more precise estimate of the magnitude is required (e.g. For use in cost benefit analysis), the coefficient should only be taken as a provisional estimate of upper limit until a model with less confounding variables can be produced. This finding is consistent with Affoh et al. (2023) which reported positive and negative relationships between wind speed and maize/sorghum yield in different growth stages in Togo, an agro-ecological context that shares similarity with South-east Nigeria. Other research work done in the zone used rainfall and temperature only as climate predictors. This paper is the first study to measure the contribution of wind speed under combined climate-land use regression models in South-east Nigeria.

Annual rainfall falls short of significance of 5% in the combined model, (β = 0.018, p = 0.074, VIF = 7.34). The marginal result doesn't imply that rainfall is not relevant for the production of crops in the zone, instead its partial variance is now sharing with co-trending predictor variables in the joint model which now makes its individual contribution difficult to isolate. The agro-climatic (crop specific and geographically different) rainfall–yield relationship in the rainforest zone in Nigeria explains why the aggregate effect on 4 crop types in an annual model does not reach the typical levels of significance. Obahoundje et al (2025) has shown across West Africa that rainfall increases lead to yield increases by 40-50% in certain areas and decreased yields by 20-50% in other parts of the same country for maize and rice respectively, confirming that the impact of rainfall varies greatly by crop type and location. A similar point emerges from Aberji et al. (2025) whose Nigeria-wide analysis of cassava (1988–2023), and showed a negative correlation between cassava yield and rainfall (β = -73,133.9, $p < 0.001$) while it found a positive and significant interaction effect between rainfall and sunshine duration. This shows that sunshine duration can somewhat alleviate the negative impacts of excessive rainfall, an interaction that a single rainfall model cannot capture, and that the integrated approach presented herein is better suited to handle. The insignificance of maximum and minimum temperatures, relative humidity, solar radiation and wind direction in the integrated model should be evaluated in the context of annual aggregation scale used here. It is well known that temperature impacts on crop yields act through specific crop development phases (e.g., heat stress on maize during tasselling or moisture stress on cassava during bulking) that are poorly captured by annual averages over a multi-decade series

4.4 Policy Implications

The regression coefficients from this analysis offer a direct, quantitative policy implications rather than general sustainability claims. The coefficient on land use change, in a bivariate regression analysis, (β = 0.0579, $p < 0.001$), suggests that for every additional hectare placed into cultivation, the index on crop production increases by 0.0579 units. In essence, if further agricultural expansion was halted, consistent with the stated goals of sustainability and conservation, and an offsetting intensification did not occur in existing agricultural area, a measurable deficit of 0.0579 production units per hectare withheld from cultivation would be occurring. Concurrently, the forest area coefficient (β = -0.0014, $p < 0.001$) implies that for each sq km of forest converted, crop production rises by 0.0014 units, representing that the expansion of production has been driven almost entirely by conversion of forests and at ever higher ecological costs. Taken together, these two coefficients represent the balance that must be made by farmers and policy makers. Each hectare of forest that becomes farmland results in short term production benefits but simultaneously degrades the water regulation, erosion control, and buffering service that supports the long-term productivity of all the land that does not become farmland. The drastic turn in both area and production around 2021 as represented in Figure 4 indicate that the balance is no longer productive. There may be a fundamental scarcity of land suitable for farming while accumulated soil degradation from many years of deforestation induced expansion begins to undermine the very productivity gains that expansion was hoped to provide.

The quantitative evidence suggests three evidence-based priorities for policy intervention. Firstly, sustainable intensification-achieving increased output per unit of land, as opposed to additional land use-by increasing yield on existing farmlands via improved seed technology, soil fertility management, and precision agriculture, offers the sole route by which the production deficit, arising from the cease of forest clearing, can be met without forever losing the ecosystem services necessary for its production. Onoja (2017) showed that in Nigeria further land use increase must be coupled with increased input use for yields to be sustainable and Kamara et al. (2023) found that Nigerian farmers that used sustainable intensification technology increased yields and net revenues. Secondly, even within the land-use focused models the marginal effect of annual rainfall remains a relevant constraint, approaching but not reaching conventional significance (β = 0.018, p = 0.074), confirming it to be a constraint on agricultural output even when linked to land use changes. Investments in small-scale irrigation infrastructure and water harvesting technology will therefore serve as a complement to agricultural intensification and will also alleviate production risk associated with annual precipitation variation without increasing pressure to clear further land. Thirdly, the positive effect of wind speed on output (β = 7.043, $p < 0.001$) justifies, particularly in Enugu where wind speeds are highest and expansion highest, agro-forestry windbreak systems to improve microclimate favorable for pollination and crop development, and thus contribute to stopping forest conversion. Farmers are already adopting these systems in Kaduna State (Sirajo et al., 2025). Delivery of these intensified irrigation and sustainable land use technologies can be built upon existing policy platforms that have strengthened specific value chains, such as the FADAMA III Additional Finance Project in Anambra and Enugu for rice and cassava and for all three states through the overall FADAMA III programme (The Guardian, 2016).

4.5 Limitations

There are several limitations noted in this study. First, the use of annual aggregated data for climate variables does not incorporate the intra-season timing, which is sometimes critical in the determination of crop production. Seasonal or monthly climate data may allow for a clearer picture of how weather affects crop production within the zone. Second, the presence of high multicollinearity between the temperature variables (see table 3) and wind speed indicates that a simpler model may provide more stable parameter estimates (perhaps using principle component analysis or ridge regression). Third, the study looks at average yields of all four crops and more narrowly focused individual crop studies may find unique crop production response mechanisms to climate and land use change. Fourth, aggregation of the yield of the four crops in a composite index might mask the difference of their responses to climate factors. This simply implies that while temperature and solar radiation are important for yam production in South-east Nigeria (Ogbonna et al., 2024), it is more of timely rain falls for vegetables (Amujil, 2021). Future research on crops should be disaggregated, in order to capture the differences between the crops. Finally, the time-trend issue identified in the forest area model (Table 6) points to the need for panel data methods (such as fixed-effects or first-difference models) that can better isolate the independent contribution of forest cover change from shared temporal trends. Future work should use monthly or dekadal climate data, disaggregate by crop, and apply ARDL or panel methods.

5.0 Conclusion

This study represents the first integrated analysis using OLS regression methods to examine climate and land use effects on crop yields across Anambra, Enugu and Ebonyi states in South-east Nigeria from 1980 to 2024. This produced a single body of reliable evidence based on three corroborating models which are all fully diagnosed. Using the combined model ($R2 = 0.965$, $F = 71.28$, $p = 1.33\times10^{-2}$) only two variables became statistically significant (wind speed ($\beta = 7.043$, $p < 0.001$) and land use expansion ($\beta = 0.0001$, $p = 0.001$) with a nearly significant annual rainfall effect ($p = 0.074$). This is the first evidence for wind speed being a statistically significant predictor within a combined climate and land use regression for South-east Nigeria and adds to the literature the absence of which has previously been noted in studies concentrating solely on rainfall and temperature. In isolation, over the same time span, the bivariate land use model ($R2 = 0.907$, $\beta = 0.0579$, $p < 0.001$, $n = 50$) demonstrates that agricultural area alone explains over 90% of variation in production. The forest area model ($r = -0.979$, $R2 = 0.958$, $p = 1.50\times10^{-23}$, $n = 44$) with validation on log transformed data and exclusion of the outlier established a near-perfect inverse correlation between the remaining forest cover and agricultural production. A further analysis demonstrated that every km2 of forest retained corresponds to an approximate 1.52 square kilometers loss of cultivated land ($R2 = 0.833$, $\beta = -1.5161$, $p < 0.001$) showing that the area dedicated to farming in the zone has expanded on an almost one-for-one basis as an inverse function of retained forest cover.

The main driver of increased agricultural output in the south-east of Nigeria for the last forty years has been through expanding land horizontally, at the expense of forest cover, a method that is not ecologically sustainable and appears to be hitting functional limits. The decline in the size of agricultural land as well as agricultural output in the south east after 2021 shown in Figure 4 supports conclusion that available arable land in the region may be nearing exhaustion. Three calculable policy objectives can be seen clearly from these findings; the land-use coefficient ($\beta = 0.0579$) clearly shows why sustained intensification is a necessity; where each hectare of land spared from further deforestation should be offset by increasing the output from land under production.; The near significant effect of rainfall ($\beta = 0.018$, $p = 0.074$) gives direct evidence that investment in small scale irrigation and rainwater harvesting should complement intensification to alleviate risks arising from seasonal rainfall variation; and the significant impact of wind speed ($\beta = 7.043$, $p <0.001$) can be used to justify investment in windbreak systems through agro-forestry practices to preserve existing forest areas while promoting stable and favorable conditions for crops in the context of pollination.

Future research should utilize monthly or seasonal climatic data to address growth stage-specific susceptibilities undetectable by annual averages, extend this analysis to include all five of the South-eastern state, and utilize panel data methods to distinguish the individual long-run effects from the common time trends. It is also recommended to incorporate remotely sensed land cover data, which can be useful in improving the accuracy of the estimate of deforestation rates for the zone.

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