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Panel Model Analysis of Impact of Climate Change on Crop Yields in Nigeria: A Fixed Effects Approach

Edokpayi[1]*, A. A., Garba[2], M. K., Ikuenobe[1], C. E. and Edegbe[3], G. N.

[1]Statistics Division, Nigerian Institute for Oil Palm Research, Benin, Nigeria.

[2]Department of Statistics, University of Ilorin, Ilorin, Nigeria.

[3]Edo State Institute of Technology and Management, Usen, Nigeria.

Abstract

The impact of changes in climatic variables (mean temperature and rainfall) and some non-climatic variables on the yields of seven cash crops production in Nigeria was estimated using the fixed effects panel data approach based on a balanced panel of seven crops, for a period of twenty-nine years (1981-2009). The results of the pooled Ordinary Least Square (OLS) show that the impact of climatic factors on crop yields was significant while the fixed effects panel data estimators' shows that changing climatic factors have no significant effects on crops yields. However, the non-climatic factors were generally significant for both the pooled OLS and the fixed effects estimators. But the coefficients of estimates from the pooled Ordinary Least Square (OLS) were generally larger than that of fixed effects model. A comparison of the three fixed effects estimators shows that in terms of efficiency, first difference performed better than the Least Square Dummy variable (LSDV) and within estimation methods as it reported a more smaller value of Standard Error of Estimate (361631, 361631 and 278988) and absence of autocorrelation (2.097). The Least Square Dummy variable (LSDV) estimators performed better in terms of the amount variability in crop yields accounted for by the climatic and non-climatic factors in the model as it reports a higher R^2 values (72 %, 30% and 18%) for LSDV, within and first difference estimators respectively. The intercept values of the seven crops used in the study were statistically significant. From the study, non-significant of the climatic variables suggests that the predicted increase in temperature and precipitation have virtually no effects on yields of the selected crops. For controlling for unobserved heterogeneity and omission variable bias, the study, shows that the fixed effects model is more appropriate than the pooled OLS. Since all the intercepts values of the seven crops were statistically significant, this shows that the impact of climatic factors and the other variables on crop yields are not significantly the same. The study therefore suggest the need for crop specific mitigation or adaptation policies against country level or a national level policy as this may be ineffective.

Keywords: Panel Data Models, Pooled OLS, Fixed Effects Model, Climate Change and Crop Yields

*Corresponding Author: Edokpayi, A. A.
Email: airuoyor@gmail.com

1. Introduction

Climate change and its devastating effects on agricultural productivity have been very well established in the literature. What is receiving attention in the recent time in literature is model for quantifying the economic impacts on agriculture. One of the popularly used models is the Ricardian approach which is an econometric method introduced by Mendelsohn *et al.* (1994). The model uses a multiple regression approach where the farm value/land revenue is regressed on climatic variables, geographical variables and economic variables. The estimated model is then used to predict the effects of future changes in the climatic and geographical variables on farm revenue or land values (ECLAC, 2011). The main strength of this approach is that it captures farmers' adaptation that affects land values as measured by the net revenue or farm income. Consequently, the model has been successfully applied to a wide range of countries.

However, a criticism of this model is that it may fail to include other variables that are also expected to affect the dependent variable but for which data may be scarce. In such cases, the model may be subject to misspecification errors or omitted variable bias. Another concern is the inability of the approach to capture the differences or heterogeneity among subjects (crops in this case). In cross-sectional regression analysis, the uniqueness of subject is ascribed to the disturbance term. Failure to include heterogeneous quantities in the model may introduce bias into the model estimators. These inadequacies have led some researchers to use a panel data approach to take into account the problem of omitted variables and the control individual heterogeneity.

Since Deschenes and Greenstone (2007), original suggestion, the use of panel data set has become reasonably common in climate change impact researches. As suggested by Mossetti *et al.* (2011), the estimation of the impact of climate change on agriculture could be enhanced using panel data as it offers the advantage of controlling unobserved country-specific effects and thus allows accounting for heterogeneity across countries.

Another usefulness of panel data is that it generally more informative and contains more variation and less collinearity among the variables and results in a greater availability of degrees of freedom and hence increases efficiency in the estimation (Elhorst, 2003). Also, panel data can include location specific effects which make it possible to determine if difference exists between locations (Park, 2009).

With panel data, one can either use the random effects (RE) or the fixed effects (FE) approaches (Todd, 2007), but the fixed effects model has been most extensively used in estimating the impact of climate change on agriculture. The appealing feature of the fixed effects model is that it provides estimates of the effects of weather on crop yields that are purged of bias due to determinants of agricultural output that are beyond farmers control (e.g., soil quality). That is, fixed effects models are mostly useful when we suspect that the outcome variable (crop yields) depends on explanatory variables which are not observable but correlated with the explanatory variables. Since in most cases, climatic variables correlates with soil type/ quality, because climate influences soil formation. These soil types are constant over time, and are not usually measurable or observable so not usually included in the regression equation. So with such omitted variables that are constant over time, fixed effects remove the effects of these time-invariant characteristics from the predictor variable so that we can assess the predictors' net effects.

The fixed effects panel data methods have been extensively used in climate impact research. For instance, Guiteras (2007) applied the fixed effects panel data approach to agriculture in India using a panel of over 200 districts covering 1960 – 1999. Ahmed and Schmitz (2011), also use a fixed effects panel framework to study how climate change affects the agricultural productivity in Pakistan. He defined the dependent variable as average food crop yield (wheat, rice and maize) variable against fertilizer, used credits, irrigation, labour force, tractors and climate as independent variables Uzma *et al.* (2011) used one way fixed effects panel model for eleven districts and a time horizon 1970 – 2009. Precipitation, mean minimum and maximum temperature, population density and per capita income were used as the independent variables why the model was estimated with the feasible generalized least square regression technique. Sarker *et al. (*2011) employed the three-step feasible generalized least square (FGLS) to estimate a form of fixed effects panel data model for climate change and agriculture. Others include Amiraslany (2010), Mossetti *et al.* (2011), Mobolaji *et al.* (2011), Menya (2011), Blanc (2012), Odusola and Abidoye (2012), Garba et al. (2013) among others.

Presently, there is a strong debate whether warming will be a net gain or loss for agriculture especially in developing countries (Schlenken and Roberts, 2008). In Nigeria, the risk of climate change is particularly high, due to its low lying coastline that is highly populated with heavy concentration of industries and infrastructure. In addition, the north of the country which form part of the Sahel region is at risk of further desertification and drought (see Akor, 2012). Since, agriculture is an important sector that contributes to the economic development of Nigeria, providing livelihood for more than 70% of the population and contributing about 40% to country's Gross Domestic Product (GDP), there is the need for concern to any threat in output (Akintude, 2013). Nigeria agriculture just like elsewhere depends highly on climate and considering the frequency and the intensity of climate related events such as flooding in the country in recent times, agriculture is most likely to be affected by climate. If the nation is to sustain is current efforts of agricultural transformation and boost food production, there is the need to properly evaluate or quantify this impact so that appropriate adaptation and mitigation policy recommendation can be formulated.

Although some attempts have been made in the past to estimate the impact of climate change on Nigerian agriculture, (See Oluyole, 2010; Ayinde *et al.*, 2011; Apata, 2012; and Bello *et al.* 2012). These studies have been restricted to the use of either cross-sectional or time series approach. No known study has applied the panel data methodology to evaluate the effects of changing climate on crop yields in Nigeria. Unlike in previous studies, our departure from existing works centre on the sophistication of our modeling approach which is the panel data methodology. This approach takes into account the problem of omitted variables, control individual heterogeneity and give more reliable estimates.

In this paper, we developed a fixed effects panel data model to estimate the link between weather and yields for some major cash crops in Nigeria. These cash crops are very important to the Nigerian economy, apart from being a source of revenue, it is also a major source of foreign exchange, row materials to the industries, and employment. Hence, estimating the correct relationship between weather and these major crops is critical to developing appropriate measures because if the underlying relationship is modeled incorrectly, it will give biased results leading to wrong implications on Nigerian economy.

2. Materials and Methods

Data used for the study

The empirical analysis for this study is based on data consisting of balanced panel for seven crops/zones (Groundnut, Cotton, Coconut, Shea nut, Oil palm, Cocoa, and Rubber) for twenty-nine years in Nigeria. State level annual mean rainfall and temperature data were collected from the Nigerian Meteorological Agency (NMA) for the periods of 1981 to 2009. Data on crop yields measured in kilograms per acre (kg/acre) were drawn from 2011 statistical bulletin of the Central Bank of Nigeria (CBN). The climatic data were aggregated in such a way that the mean values of the weather data from states within the country where each crops are grown were taken and used for the study.

Fixed Effects Model

The general framework of the fixed effects panel data analysis is a regression model of the form;

$$Y_{it} = \alpha_i + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + \mu_{it}. \quad 1a$$

The equation (1a) could be compactly written in matrix form as

$$Y_{it} = \alpha_i + X'_{it}\beta + \mu_{it} \ , \quad 1b$$

for $i = 1,2, \dots, n \ and \ t = 1,2, \dots, T$,

where $\boldsymbol{Y_{it}}$ is the response for unit $\boldsymbol{i}$ at time $\boldsymbol{t}$, $\boldsymbol{\alpha_i}$ is the individual-specific intercept, vector $\boldsymbol{X'_{it}}$ contains k regressors for unit $\boldsymbol{i}$ at time $\boldsymbol{t}$, vector $\boldsymbol{\beta}$ contains k regression coefficients to be estimated and $\boldsymbol{\mu_{it}}$ is the error component for unit $\boldsymbol{i}$ at time $\boldsymbol{t}$.

This model is suitable for explanatory variables that vary among subjects but is constant over time for a given subjects (time-invariant). The model examines group differences in intercept, assuming the same slope and constant variance across entities or subjects. Since a group (individual specific) effects is time invariant and considers a part of the intercept, the unobserved effects (α_i) is allowed to be correlated to other regressors.

Model Estimation:

There are several methods of estimating linear panel regression models, namely, pooled estimators; fixed effects model an estimator which includes Least Squares Dummy Variable (LSDV), within-group regression and the First Differences (FD) methods.

In the pooled estimator, we neglect the cross-section and time series nature of the data and pool all observation together and estimate a 'grand' regression using Ordinary Least Square (OLS).

$$Y_{it} = \beta_1 + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + \mu_{it}. \quad 2$$

Applying OLS, this equation gives the pooled OLS estimator

$$\hat{\beta}_{OLS} = \sum_{i=1}^{N} \sum_{t=1}^{1} (X^1X)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{L} (X^1Y). \quad 3$$

The pooled OLS assumes that the intercept and slope coefficients are constant across time and individuals (Oyeniyi, 2012).

In the least square dummy variable (LSDV), we pool all observations together, but allow each cross-section unit to have its own (intercept) dummy variable. Symbolically, equation (1a) can be restated capturing the dummy variables as

$$y_{it} = \alpha_i + \alpha_2 D_{2i} + \cdots + \alpha_k D_k + \beta_2 X_{2it} + \cdots \ \beta_K X_{kit} + \mu_{it}, \quad 4$$

where $\boldsymbol{\alpha_1}$ is intercept for crop1 (Groundnut) which is the benchmark and $\boldsymbol{\alpha_2}$, $\boldsymbol{\alpha_3}$, $\boldsymbol{\alpha_4}$, $\boldsymbol{\alpha_5}$, $\boldsymbol{\alpha_6}$ and $\boldsymbol{\alpha_7}$ are the differential intercepts for the remaining six crops. In this case, all the heterogeneity is subsumed in the intercept values and the estimated intercepts for each subject or crop in this case represent the subject-specific characteristics. The parameters $\alpha_i, for\ i = 1,2,3, \dots N$ and β can be estimated by OLS. The implied estimator for β is referred to as the Least Square Dummy Variable (LSDV) estimator (Park, 2011).

Fixed Effects Within- Group

In fixed effects within-group, we also pool, but for each cross-section, we express each variable as a deviation from its mean value and then estimate an OLS regression on such mean-corrected or "demeaned" values. Recalling equation (1a),

$$Y_{it} = \alpha_i + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + \mu_{it}.$$

Then averaging the equation overtime for each ***i*** yields

$$y_{it} - \bar{y}_i = \beta_I (x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \ . \quad 5$$

Applying OLS, this equation gives the fixed effects within group estimator

$$\hat{\beta}_{FE} = \left(\sum_{i=I}^{N} \sum_{t=I}^{I} (X_{it} - \bar{X}_i)^{-I} \sum_{i=1}^{N} \sum_{t=1}^{I} (X_{It} - \bar{X}_i)(y_{it} - \bar{y}_i) \right). \quad 6$$

For the First-Difference (FD) approach, for each subject (crop/zone), we take successive difference of the variables and regress the first difference values of the dependent variable on the first difference of the explanatory variables using OLS. It is an alternative way to eliminate αi from equation (1a), then taking the first-difference

$$Y_{it} = \alpha_i + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + \mu_{it},$$

$$y_{it} - y_{l,t-I} = \left(X_{it} - X_{i,t-I}\right)^{'} \beta + \left(u_{it} - u_{i,t-I}\right), \qquad 7$$

this becomes $\Delta y_{it} = \Delta X'_{it}\beta + \Delta u_{it}.$ 8

Applying OLS, this equation gives the First Difference (FD) estimator

$$\hat{\beta}_{FD} \left(\underset{i\,=\,I}{\overset{N}{\sum}} \underset{T\,=\,I}{\overset{T}{\sum}} \Delta X_{It} \Delta X_{It}^{'} \right)^{-I} \underset{i\,=\,I}{\overset{N}{\sum}} \underset{t\,=\,I}{\overset{T}{\sum}} \Delta X_{It} \Delta y_{It}. \qquad 9$$

Hypotheses

To assess the validity of the fixed effects method, there is the need to apply tests to determine whether fixed effects (differences in the intercepts for each group or crop) should be included in the model. To do this, the standard F-test can be used to check fixed effects against the simple common constant method (pooled model).

The hypothesis to be tested is

H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7$ ***versus*** **H_1:** $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \neq \alpha_7$,

where $\boldsymbol{H_0}$ is that cross-sectional heterogeneity does not exist while $\boldsymbol{H_1}$ is that there is presence of cross-sectional heterogeneity. In other words climatic factors are the same across locations associated with each crops while the alternative is otherwise.

The test statistic is given as

$$\boldsymbol{F(n-1, nt-n-k)} = \frac{\left(\boldsymbol{e'e_{OLS} - e'e_{FE}} \big/ \boldsymbol{(n-1)}\right)}{\left(\boldsymbol{e'e_{FE}} \big/ \boldsymbol{(nT-n-k)}\right)}. \qquad 10a$$

The test statistic given as equation 10a above can be equivalently stated as

$$\boldsymbol{F(n-1, nt-n-k)} = \frac{\left(\boldsymbol{R^2_{FE}} - \boldsymbol{R^2_{OLS}} \big/ _{(\boldsymbol{n}-\mathbf{1})}\right)}{\left(\mathbf{1} - \boldsymbol{R^2_{FE}} \big/ _{(\boldsymbol{nT}-\boldsymbol{n}-\boldsymbol{k})}\right)} \quad , \qquad \text{10b}$$

where $\boldsymbol{R^2_{FE}}$ denotes the coefficient of determination of the fixed effects model and $\boldsymbol{R^2_{OLS}}$ stands for the coefficients of determination of the pooled OLS model. If the observed F-statistic is greater than the critical F-value, then we reject the null hypothesis. If the null hypothesis is not rejected, the pooled OLS regression is favoured. But if the null hypothesis is rejected, one may conclude that there is a significant fixed effect. Therefore, the fixed effect model is better than the pooled OLS.

Another very important test in panel data analysis is the Hausman's Specification Test**:** This test is the classical test of whether the fixed or random effect models should be used in panel data analysis. The hypotheses are to test if there is significant correlation between unobserved individual specific $(\boldsymbol{\alpha_i})$ random effects and the regressors ($\boldsymbol{X_{it}}$) and this is defined as;

H0: $\mathrm{Cov}(X_{it}, \alpha_i) = 0$ ***versus*** **H1**: $\mathrm{Cov}(X_{it}, \alpha_i) \neq 0$.

The hypotheses can be modified as follows;

H0: $(\beta_{FE} - \beta_{RE}) = 0$ ***versus*** **H1**: $(\beta_{FE} - \beta_{RE}) \neq 0$.

Therefore, under the null hypotheses, there should be no systematic differences between $\boldsymbol{\beta_{FE}}$ and $\boldsymbol{\beta_{RE}}$. As an intuition, compare the estimates under random effects and fixed effects, if the estimates are close random effects model is appropriate. But if otherwise, use fixed effects model (see Lloyd, *et al*, 2001).

The Hausman's statistic is defined as;

$$\boldsymbol{H} = \left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{FE}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{RE}}\right)^{\mathbf{1}}\left[\widehat{\boldsymbol{V}}\left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{FE}}\right) - \widehat{\boldsymbol{V}}\left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{RE}}\right)\right]^{-\mathbf{1}}\left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{FE}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{RE}}\right), \qquad 11$$

where $\hat{V}_S$ denotes estimates of the true covariance metrics.

The Hausman's test is a kind of Ward χ^2test with k-1 degrees of freedom, where k = number of regressors (Yaffe, 2003). Use random effects unless test rejects orthogonality conditions between α_i and $\boldsymbol{X_{it}}$. Rejection means that the random effects assumption fails and fixed effects should be used.

Model Specification

A fixed effects panel data model specification was used to relate crop yields to standard weather variables such as temperature and precipitation and other control variables (credit and prices). The relationship between crop yields and the climatic variables follows the standard Ricardian model which relies on quadratic formulation of climatic variables. Accordingly, our fixed effects panel model was specified as follows;

$$Y_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 R_{it}^2 + \beta_3 T_{it} + \beta_4 T_{it}^2 + \beta_5 R_{it} x T_{it} + \beta_6 C_{it} + \beta_7 P_{it} + \alpha_i + \varepsilon_{it}\ , \qquad 12$$

$\boldsymbol{Y_{it}}$ is the crop yield, the $\boldsymbol{i}$ represent a particular crop and the $\boldsymbol{t}$ a particular time, $\boldsymbol{R_{it}}$ is rainfall attributable to particular crop and at a given time period while $\boldsymbol{T_{it}}$ is temperature attributable to particular crop and at a given time period, $\boldsymbol{\beta_0}$ is the intercept which explains the change in crop yield before the influence of the climatic factors begin to be noticed, $\boldsymbol{\beta_i}$ is the slope coefficients or parameter estimates for all independent variables and this tells us the change in crop yield as a result of a unit change in the climatic factors. The quadratic terms for weather variables are included in the specification to account for non-linear weather effects on crop yields. Interaction terms between weather variables are used to determine the potential effects of one weather variable given the effect of the other variable. The $\boldsymbol{C_{it}}$ and $\boldsymbol{P_{it}}$ are the agricultural loans to farmers and prices of the various crops respectively while $\boldsymbol{\alpha_i}$ is added to the equation to capture the unobserved or heterogeneity effects. This accounts for other variables which contribute to crop yields and are constant over time, but not directly observable or measurable such as soil type, fertilizer use, crop management, seed types etc. The $\boldsymbol{\mathcal{E}_{it}}$ denotes idiosyncratic error term or time varying error and represents unobserved factors that change over time and affects crop yields.

The linear terms in the above model represent the marginal value of climate at the mean while the squared terms are representing the shape of the relationship between climate and crop yields. According to Mendelsohn (2001), a positive coefficient indicates a U-shape and the negative coefficient reflects a hill shape relationship. A hill shape relationship between climate variables and crop yields indicates that as the climate variables increases, crop yields increases to a certain point (maximum), increasing climate variable beyond this points reduces crop yields. On the other a U-shape relationship shows that crop yields will decrease as climate variable rise to reach a certain point (minimum) and then both crop yields and climate variables will increase.

3. Results and Discussion

The fixed effects model was applied to the data collected for this study and necessary hypotheses tests were carried out, the following results were obtained.

Table 1: Summary Statistics of Variables used in the Study

Variable	Mean	Standard Deviation	Variance	Minimum	Maximum
Output	508066	666142	4.437E11	12000.00	3.9786
Rainfall	1132	1589.308	2.526E6	28.40	19482.00
Rainfall^2	1860808	3133460	9.819E12	3380.25	3.35E7
Temp	28.5655	3.56601	12.716	22.90	41.70
Temp^2	828.5	222.4	49462.2	524.41	1738.89
Loans	2954	4691	22001791	3.70	25017.00
Prices	3727	4596	21120566	37.00	22886.90

Table 1 reports the summary statistics of all variables used in the study for the period 1981-2009. The results show that the average crop yields for the period was 5080700 kg/acre. While the average crop yields for the respective crops were 1724857, 152718, 319686, 283650, 640829, 218936 and 215786 for Groundnut, Cotton, Coconut, Sheanut, Oilpalm, Cocoa and Rubber respectively with Groundnut and oilpalm contributing more to the total yearly average and cotton contribute the least. The mean yearly rainfall and temperature recorded during the periods were 1132 mm and 28.56 ^{0}C while the standard deviations 1589 mm and 3.5^{0}C respectively indicating some level of climatic variability within the period under study. Total average Credit to farmers and prices for the study periods were 2954 and 3727 with deviations of 4691 and 4596 respectively. The average loans and prices for Groundnuts, Cottons, Coconuts, Sheanut, Oilpalm Cocoa and Rubber for the period were 4396, 7237, 1964, 2444, 2963, 1455, 217.1 and 523.3, 3075, 5990, 5414, 5267, 3434, 2388.

Table 2: Pattern of Temperature in areas under the cultivation of crops used in the study

Variable	Mean	Standard Deviation	Variance	Minimum	Maximum
Groundnut	29.97	3.22155	10.378	25.70	35.80

Cotton	25.93	1.96529	3.862	22.90	28.40
Coconut	30.33	3.05809	9.352	26.90	36.10
Shea nut	32.12	5.69204	32.399	25.10	41.70
Oilpalm	27.86	1.06237	1.129	26.20	30.45
Cocoa	26.51	1.14741	1.317	24.45	28.65
Rubber	27.22	1.05387	1.111	25.30	29.30

The average temperature during the study periods is as shown in Table 2. In some cropping areas, the average temperature was as high as 32.11^{0}C while the lowest average was 25.93^{0}C. Temperature movement could not be said to be the same across locations were the different crops are cultivated. While most of the cropping areas experienced temperature rise in the early 80s, there was up and down move between 1985 about the year 2000. But in almost all the cropping areas covered in this study, there were rise in temperature from 2000 to 2009. Overall, all the cropping areas experienced unsteady trend suggesting variation in temperature variables for the years covered in this study.

Table 3: Pattern of Rainfall in areas suitable for the cultivation of crops used in the study

Variable	Mean	Standard Deviation	Variance	Minimum	Maximum
Groundnut	439.51	341.70695	1.168E5	60.70	1073.30
Cotton	1170.60	1339.51755	1.794E6	28.40	5787.20
Coconut	581.58	459.50948	2.111E5	58.14	1370.00
Shea nut	442.83	291.44049	8.494E4	68.99	864.60
Oilpalm	1096.00	806.74540	6.508E5	181.81	2566.20
Cocoa	1789.40	310.49115	9.640E5	1071.00	2464.50
Rubber	2407.50	3441.80589	1.185E7	170.17	19842.00

There is occurrence of rainfall variability (inter – annual) and unreliability in the country across the cropping areas under study (Table 3). The average rainfall was particularly high in areas were Rubber is cultivated followed by areas were Cocoa, Cotton and Oilpalm. Areas were Groundnut is cultivated experienced the lowest rainfall with an annual average of 439.51 while the 1981 average was 1073. In most of the cropping areas investigated, the average rainfall for 1981 (base year) was higher than the average rainfall for the periods covered in the study. This decrease in rainfall is an evidence of climate change.

Table 4: Means difference showing Cross-sectional heterogeneity

Variable	G/Nut	Coconut	Shea tree	Cotton	Oil palm	Cocoa	Rubber	P-Val
Crops	1.7249E6	1.52721E5	3.1969E5	2.8365E5	6.4083E5	2.1894E5	2.1579E5	<0.0001
Rain	4.3951E2	1.1706E3	5.8158E2	4.4283E3	1.0960E3	1.7894E3	2.4075E3	<0.0001
Rain2	3.0568E3	3.1531E6	5.4023E5	2.7800E5	1.8289E6	3.2578E6	3.6620E5	<0.0001
Temp	29.9714	25.9357	30.3321	32.1179	27.8636	26.5107	27.2268	<0.0001
Temp2	9.1021E2	6.7639E2	9.2665E2	1.0628E3	7.7751E2	7.0376E2	7.4237E2	<0.0001
RXT	1.3985E4	2.8752E4	1.8501E4	1.5381E4	3.0735E4	4.7403E4	6.5187E4	<0.0001
Loans	4.3962E3	7.2369E3	1.9639E3	2.4436E3	2.9626E3	1.4549E3	2.1712E2	<0.0001
Price	5.2392E2	3.0754E3	5.9900E3	5.4143E3	5.2674E3	3.4340E3	2.3877E3	<0.0001

The F- test conducted to determine the application of fixed-effects model versus the total pooled model is reported in Table 4. The results of this test show that the F statistics is 55.36 with a p-value < 0.0001. Thus pooled model did not fit the data implying that there are individual or group effects suggesting that panel data analysis should be used for model estimation.

Table 5: Results of Hausman's Test

Variable	Fixed Coefficient	Random Coefficient	Difference
Rain	-521.847	-363.3438	-158.5032
Rain2	-0.0045361	-0.0422437	0.0377076
Temp	-113780.6	300766.7	-414,547.3
Temp2	872.8444	-5186.586	6,059.4304
RXT	19.15582	12.60898	7.14684
Loan	39.60702	50.68623	-11.07921
Price	-0.4043697	-27.9519	27.5475

The Hausman's fixed effects test is performed to ensure the appropriateness of employing the fixed effects model. The obtained results presented in Table 5 shows coefficients of the fixed effects for the climatic and other variables and the corresponding random effects estimates are considerably higher or not the same inviting the suspicion that they may be inflated by unobserved heterogeneity. The Wald $\chi 2_{(7)}$ is 53.93 with a p-value < 0.0001 indicating a rejection of the null hypothesis. This shows that the coefficients of the Fixed Effects Model (FEM) are efficient and therefore concluded that the use of fixed effects estimation is justified.

Table 6: Coefficients Estimates from Pooled Regression Model

Variable	Coefficient	SE	t-value	p-value
Constant	-3719007	30098146	-1.20	0.231
Rainfall	-363.3438	845.0628	-0.43	0.668
Squared Rain	-0.0422437	0.0161233	-2.62	0.010***
Temperature	300766.7	189936.7	1.58	0.115
Squared Temp	-5186.586	2816.859	-.1.84	0.067*
Rain X Temp	12.00898	31.87238	0.38	0.707
Loan	50.68623	10.25284	4.94	<0.0001***
Price	-27.9519	9.830025	-2.84	0.005***
F-value = 7.70; **R-square =** 0.2229; **Adjusted-R^2 =** 0.1940; **RMSE** = 0.000060				

Table 6 shows the results of pooled model. The coefficients of the model show that rainfall was not significant in linear terms, but was highly significant in its squared term at the 1% level of significance. Also statistical evidence does not support the impact of temperature on crop yield in linear form, but was significant at 10% for its quadratic terms. The two control variables (loan and price) were highly significant. The significance of the quadratic terms suggests that the relationship between climate factors and crop yield is non-linear. These findings tally with the findings Deressa *et al.* (2005) that climate change has significant non – linear relationship with net revenue (crop yield). The signs for rainfall were negative for both the linear and quadratic terms; indicate that rainfall impacted negatively on crop yield. But the negative squared terms indicates that crop yield will decrease as rainfall increases, after a certain point (minimum) both crop yields and rainfall will increase. On the other hand, temperature in linear terms shows a positive impact, but its quadratic terms show a negative impact indicating a decrease in crop yield as temperature increases, after a certain point (minimum) both crop yields and temperature will increase.

A statistical evaluation of the model shows the R^2 value is 0.2229 meaning that the model accounts for just 22 percent of total variance in crop yields. In addition, the table clearly shows that the pooled OLS model fits the data well at .05 significant level ($F = 7.70$ and $p < 0.0001$) while the RMSE and SEE values were 0.000060 and 598061.00 respectively.

Table 7: Coefficients Estimates from Fixed Effects Panel Regression Models

Variable	LSDV Estimates		Within Estimates		FD Estimates	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Constant	4129486	2050776	2917149	2034952	3439.86	79353.37
Rain	-521.847	547.79	-521.847	547.79	-1.800753	177.0256
Rain2	-0045361	0.0100808	-0045361	0.000808	0.0006157	0.0060466
Temp	-113780.6	1252858	-11380.6	125285.8	49950.7	89.65782
Temp2	872.8444	1870.22	872.8444	1870.215	-728.8163	4.6535*
RXT	19.15582	20.71	19.15582	20.71471	-20.1885	0.25856
Loan	39.60702	6.58267*	39.60702	6.58267*	25.46109	4.2690*
Price	-4043697	6.66981*	-4043697	6.66981*	-1.179194	4.3612
D2	-1827142	110917.7*				
D3	-1291236	106040.5*				
D4	-1275978	111150.1*				
D5	-1120681	108007.9*				
D6	-1524117	113217.7*				
D7	-1447203	116697.7*				
	F = 36.90		**F** = 11.04		**F** = 5.80	
	$\mathbf{R^2}$ = 0.7249		$\mathbf{R^2}$ = 0.30		$\mathbf{R^2}$ = 0.1785	
	Adj-$\mathbf{R^2}$ = 0.7053				**Adj-**$\mathbf{R^2}$ = 0.1477	
	RMSE = 0.000636				**RMSE** = 0.000028	

From the estimated fixed effects models presented in Table 7, the coefficients for the Within and the least square dummy variable (LSDV) estimation were the similar, the climatic variables were not statistically significant, the coefficients for rainfall and temperature have negative signs indicating that rainfall impacted negatively on crop yields while rainfall in quadratic terms also have negative signs meaning that as the climate variables increase, crop yields increase to a certain point (maximum), increasing climate variable beyond this points will reduce crop yields. But the quadratic terms for temperature have positive signs indicating that crop yields will decrease as climate variables rise to reach a certain point (minimum), and then both crop yields and climate variables will increase.

However, for the first difference (FD), the coefficients are smaller in magnitude than the other two estimation methods. Also, the sign for rainfall in linear term was negative while a squared term for temperature was negative and also significant. Unlike the other two estimation methods, the squared rainfall and linear temperature have positive signs.

The other control variables (credit and price) were significant for the LSDV and Within effects approaches. Only the loan or credit variable was significant across the three methods. The signs and magnitude were generally not the same for all methods. The calculated intercepts for each crop is as follows (Groundnut = 4,129,486, Cotton = 4,018,568.3, Coconut = 4,023,445.5, Sheanut = 4,018335.9, Oilpalm = 4,021,478.1, Cocoa =4,016,268.3, Rubber = 4,012,788.3). All the intercepts values of the seven crops were statistically significant indicating that the impact of climatic factors and the other variables on crop yields are not significantly the same across crops.

Given the behaviours of the three fixed effects estimators, the choice of estimator for this data will depend on the relative efficiency of the estimator. As noted above, the least square dummy variable estimators and fixed effects within estimators have similar values. But the within estimation produces incorrect statistics, since no dummy is used, the within estimation will have larger degrees of freedom for errors, accordingly reporting small mean squared errors (MSE), standard error of estimates (SEE) and incorrect standard error of parameter estimates. The R^2 is also not correct because the intercept term is suppressed, and finally it does not report individual dummy coefficients, as the least square dummy variable model (Park, 2011). Thus, the dummy variable approach enables us to estimate the impact of climate change across the different crops. The standard errors of estimate (SEE) values were 361631, 361631 and 278988 while the R^2 values were 72 %, 30% and 18% for the LSDV, Within and FD respectively. However, the dummy variable approach produces a high R^2 which helps to measures the goodness-of-fit, indicate a better fit of the model. But the SEE of the FD is smaller than that of the dummy variable approach.

The choice between fixed effects and FD hinges on the relative efficiency of the estimators as both are unbiased and consistent under the same assumptions (Gujarati, 2009 and Garba *et al*., 2013). From the results, the Durbin Watson (D-W) statistic which measures the serial correlation of the idiosyncratic errors gave the values of 0.407 and 2.097 for fixed effects and the FD respectively. The D-W of LSDV is close to zero indicating an evidence of positive serial correlation while the value for that of the first difference is closer to 2, which mean that there is no serial correlation either positive or negative which may make the FD more efficient than other fixed effects estimation. But on account of the special feature of the LSDV which enables one to determine the significance of the cross-sectional units, the three approaches can complements one another for a more robust analysis.

4. Summary and Conclusion

This paper has attempted an efficient estimation of the economic impact of climate change on the some crop yields in Nigeria using a fixed effects panel data model methodology. The results from study show that there was variability in rainfall and temperature pattern during the study periods and across major areas where these crops are been cultivated. The results of the utilized model framework indicated significant effects of climate change on crop yields when cross-sectional units were ignored, but when the difference in cross-sectional units where considered, the climatic variables were not significant. All the dummy variables were statistically significant suggesting that different crops are impacted differently by climate change. The non-climatic variables (loans and prices) were both significant for the pooled OLS and fixed effects estimation respectively, but the coefficients reported by the pooled OLS were generally higher than those of the fixed effects estimation.

The study has shown that the use of pooled OLS for the empirical analysis of the impact of climate change on crop yields in Nigeria is inappropriate and the results misleading as it does not distinguish between the various crops and does not also tell us whether the response of crop yields to climatic factors over time are the same for all crops. On the performance of the three fixed effects estimators applied to the data, the results provided varied conclusions. On account of R^2 which is a measure of variation in crop yields explained by the independent variables in the model, LSDV approach performed better than the other two methods as it reported a higher R^2 value. With LSDV, it was also possible to determine the significance of the cross-sectional units hence determine if the seven crops are statistically different from one another. But on account of efficiency using means square error criterion, FD method is better because it has a lower MSE value.

Based on our findings from this study, the following conclusions could be drawn: the climatic variables were not significant suggesting that the predicted increase in temperature and precipitation have virtually no effects on yields of the selected crops. Secondly, the study revealed that the fixed effects model is more appropriate than the pooled OLS as it controls for unobserved heterogeneity and omission variable bias resulting from the correlation between climatic factors and soil type which was omitted from the regression equation due to limitations of the data utilized for this study. Thirdly, all the intercepts values of the seven crops were statistically significant indicating that the impact of climatic factors and the other variables on crop yields are not significantly the same across crops. Finally, the different fixed effects estimators could be used to complement one another for more robust analysis.

The study therefore suggests the need for crop specific mitigation or adaptation policies against national level policy as this may be ineffective. This suggestion will help the development of local or micro-level policies peculiar to each crop in other to reduce yield variability and ensure food security that will alleviate rural poverty in the presence of changing climatic factors.

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