ISSN 1533-9211

DOI 10.17605/OSF.IO/R3Q2Y

SPATIO-TEMPORAL EXPLORATORY ANALYSIS OF THE DETERMINANTS OF CONSUMPTION LEVEL OF RENEWABLE ENERGY IN THE ECOWAS STATES

OLUWAYEMISI OYERONKE ALABA

Department of Statistics, University of Ibadan, Nigeria. Email: oluwayemisioyeronke@yahoo.com, Orcid.org/0000-0002-1376-606X

BERNARD OLAGBOYEGA MUSE

Department of Economics, School of Social and Management Sciences, Bamidele Olumilua University of Education, Science and Technology, Ikere-Ekiti, Ekiti State, Nigeria. Email: bernola2006@yahoo.co.uk, Orcid.org/0000-0003-4029-0519

Abstract

Petroleum, natural gas, and coal are examples of conventional energy sources that have been identified as significant sources of greenhouse gas emissions that contribute to global warming. The ECOWAS states have an abundance of energy resources, including solar, wind, biomass, hydro, and others, which are used to supply domestic energy needs and promote economic growth. This paper estimates the impact of determinants of renewable energy such as access to clean fuel & cooking technology, access to electricity, energy intensity level, total electricity output, and total final energy consumption on the consumption level of renewable energy using spatial panel analysis in 14 ECOWAS states covering the period of 1990 – 2018. The results indicated that access to clean fuel & cooking technology, access to electricity, total electricity output, and carbon (IV) oxide have a negative influence on renewable energy consumption, while energy intensity level and total final energy consumption have a positive effect. As such, reductions in access to clean fuel & cooking technology, access to electricity, total electricity output, and carbon (IV) oxide will increase renewable energy consumption in ECOWAS states. Due to the sustainability of renewable resources and their suitability for installation in communally owned mini-grids, renewable energy technology may offer a feasible solution to ECOWAS states long-standing energy challenges.

Keywords: Spatial Panel, Lagrange Multipliers, Hausman Test, Spatial Weight

JEL Classification: C13, C22, F01, O13

1. INTRODUCTION

Conventional energy sources such as petroleum, natural gas, and coal have been identified as important contributors to greenhouse gas emissions, which contribute to global warming. Energy resources such as solar, wind, biomass, hydro, and others abound in West Africa and are used to meet domestic energy needs and spur economic growth [1]. There are several types of energy resources, including fossil fuels, nuclear energy, and renewable energy. Renewable energy is energy derived from natural sources such as sunshine, tides, biomass, wind, and geothermal energy. Integration of renewable energy into the electrical system, smart grid design, and grid storage preparation are some of the primary concerns in emerging countries [2]. The nature and source of renewable energy used in West Africa, which is primarily wood biomass, slow economic progress [3].

ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

According to some studies, population expansion is reflected in energy consumption, with a large portion of that spent to meet electrical energy demands. Most countries in West Africa use wood biomass, which is frequently dirty and causes pollution. According to Maji et al [3], the utilization of clean energy sources such as wind, hydropower, and solar, which have no negative effects on human or environmental health, is low in West Africa. Several studies, such as [4] – [8] asserted that combustible biomass is the dominant source of energy for residential consumption in most African countries.

The Economic Community of West Africa (ECOWAS) region has a population of over 340 million people and the world's lowest modern electricity usage rates [9]. Electricity access rates range from less than 20% in Liberia to more than 50% in Senegal and 70% in Ghana. In 2018, almost half of Africa's 600 million people lacked access to electricity, and around 80% of sub-Saharan African businesses had regular power outages, resulting in financial losses [10]. According to World Economic Outlook [10], around 900 million individuals, or more than 70% of the population, lack access to clean cooking, which adds to forest depletion due to unsustainable fuelwood gathering as well as places a significant strain and loss of productive time on women. Africa's energy consumption is growing twice as fast as the world average, and the continent's abundant renewable resources and lowering technological costs are driving double-digit growth in utility-scale deployment. Africa is becoming a major player in global oil and gas markets as demand for new and efficient energy sources grows [10]. From insufficient power generation capacity to difficulties in managing energy infrastructure and investments in the sector, to challenges in serving low-income users, sub-Saharan Africa faces multiple dimensions to the problem of energy access, where large segments of the population lack reliable supply of electricity and affordable modern cooking fuels.

The need for energy is rising as a result of rising population, urbanization, and economic development goals [11]. Increased population has resulted in increased energy consumption, which has resulted in increased greenhouse gas emissions, which is the primary driver of global warming, putting the survival of living species in jeopardy. Renewable energy deployment for clean and sustainable power production and consumption, on the other hand, was supposed to reduce reliance on fossil fuel carbon emissions (CO2).

Renewable energy technology may be a viable solution to West Africa's long-standing energy difficulties, as renewable resources are both sustainable and suited for installation in communally owned mini-grids. West African countries could achieve stable power supply and energy efficiency by utilizing renewable resources and embracing alternative technologies. The power sector has been changed by the government in order to encourage private investors to increase renewable energy supplies. However, there are ongoing financial, technical, and regulatory challenges that must be addressed. As a result of the population growth rate, the study aimed at exploring the consumption level of renewable energy in the ECOWAS countries by identifying the spatial influence of access to clean fuel and cooking technology, access to electricity, energy intensity level, total electricity output, and total final energy consumption.

ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

2. METHODOLOGY

2.1 Data Collection

The study areas are the ECOWAS states which are; Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo, and Gambia (Fig. 1). The World Bank database was used to acquire secondary data on variables from the fourteen countries from 1990 to 2018. The database, compiled by the World Bank, collects development indicators from officially recognized international sources, and presents the most accurate and current global development data at national, regional and global levels. We used data on renewable energy consumption (REC), access to clean fuel and cooking technology (ACT), access to electricity (ATE), energy intensity level (EIL), total electricity output (TEO), Carbon(iv)oxide (CO_2), and total final energy consumption (TFE).

2.2 The Model

We considered a spatial panel data model that captures spatial interactions across spatial units and overtime. The general static panel model is presented as;

$$y = \lambda(I_T \otimes W_N)y + X\beta + u \tag{1}$$

where N is the number of observations, T is the time period, y is an $NT \times 1$ vector of observations on the dependent variable, in this case, renewable energy consumption, X is a $NT \times k$ matrix of observations on the non-stochastic exogenous regressors, I_T an identity matrix of dimension T, W_N is the $N \times N$ spatial weights matrix of known constraints whose diagonal elements are set to zero and λ is the corresponding spatial parameters, where the disturbance vector is;

$$u = (\iota_T \otimes I_N)\mu + \varepsilon \tag{2}$$

Where ι_T is a $T \times 1$vector of ones, I_N is an $N \times N$ identity matrix, μ is a vector of time invariant individual specific effects and ε a vector of spatially autocorrelated innovations that follow a spatial autoregressive process of the form;

$$\varepsilon = \rho(I_T \otimes W_N)\varepsilon + v \tag{3}$$

With $|\rho| \prec 1$ as the spatial autoregressive parameters, W_N is the spatial weight matrix, $v_{it} \sim IID(0,\sigma_v^2)$ and $\varepsilon_{it} \sim IID(0,\sigma_v^2)$. Given that the unobserved individual effects are uncorrelated with the other explanatory variables in the model, the error term is written as;

$$\varepsilon = (I_T \otimes B_N^{-1})v \tag{4}$$

Where $B_N = (I_N - \rho W_N)$

Substituting (4) in (2), we have

The Seybold REPORT
ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

$$u = (\iota_T \otimes I_N)\mu + (I_T \otimes B_N^{-1})v \tag{5}$$

The variance-covariance matrix for ε is

$$\Omega_u = \sigma_\mu^2(\iota_T \iota_T' \otimes I_N) + \sigma_v^2[I_T \otimes (B_N' B_N)^{-1}] \tag{6}$$

2.2.1 Random Effects Model

For model estimate, the study uses the maximum likelihood method, which is written as;

$$\begin{aligned} L(\beta, \sigma_e^2, \phi, \lambda, \rho) = & \frac{-NT}{2} 2\Pi - \frac{NT}{2} \ln \sigma_v^2 + T \ln |A| \\ & - \frac{1}{2} \ln |T\phi I_N + (B'B)^{-1}| \\ & + (T-1)\ln|B| - \frac{1}{2\sigma_v^2} u'\Sigma^{-1}u \end{aligned} \tag{7}$$

Given that β and σ_v^2 are obtained from the first order conditions,

$$\begin{aligned} \beta &= (X'\Sigma^{-1}X)^{-1} X'\Sigma^{-1}Ay \\ \sigma_v^2 &= \frac{(Ay - X\beta)'\Sigma^{-1}(Ay - X\beta)}{NT} \end{aligned} \tag{8}$$

2.2.2 Fixed Effects Model

When N is large, it is impossible to estimate the individual fixed effects consistently. Elhorst [12] proposed that the spatial lag and error models be evaluated individually. The fixed effect spatial lag model is written as follows in stacked form:

$$y = \lambda(I_T \otimes W_N)y + (\iota_T \otimes I_N)\mu + X\beta + \varepsilon \tag{9}$$

Where λ is the spatial autoregressive coefficient, W_N is a non-stochastic spatial weights matrix, ι_T is a column vector of ones of dimension T, I_N an $N \times N$ identity matrix and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$. Transforming the variables in (9) to eliminate the time invariant individual effects to maximize the likelihood function leads to

$$y^* = \lambda(I_T \otimes W_N)y^* + X^*\beta + \varepsilon^* \tag{10}$$

Where $y^* = Q_0 y$, $X^* = Q_0 X$, $\varepsilon^* = Q_0 \varepsilon$, $Q_0 = \left(I_T - \frac{J_T}{T}\right)$, and $J_T = \iota_T \iota_T'$

The log likelihood function of (9) is

The Seybold REPORT
ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

$$L=\frac{NT}{2}\ln(2\Pi\sigma_{\varepsilon}^{2})+T\ln\left|I_N-\lambda W_N\right|-\frac{NT}{2\sigma_{\varepsilon}^{2}}e'e \tag{11}$$

Where $e=y-\lambda(I_T\otimes W_N)y-X\beta$ and $\ln\left|I_N-\lambda W_N\right|$ is the Jacobian of the determinants.

2.2.3 Lagrange Multipliers (LM)

In panel data models, Lagrange multiplier tests are commonly used to test for random effects and serial or cross-sectional correlation. Baltagi et al [13] gave the combined marginal and conditional tests for all combinations of random effects and spatial correlation for model specification. The joint LM test for the hypothesis on no random effects and no spatial autocorrelation is given by;

$$LM_j=\frac{NT}{2(T-1)}G^2+\frac{N^2T}{b}H^2 \tag{12}$$

Where $G=\tilde{u}'(J_T\otimes I_N)\tilde{u}/\tilde{u}'\tilde{u}-1, H=\tilde{u}'(I_T\otimes(W+W')/2)\tilde{u}/\tilde{u}'\tilde{u}$, $b=tr(W+W')^2/2$ and $\tilde{u}$ denotes OLS residuals.

The standardized equation of the marginal LM test of no random effects assuming no spatial correlation is given by;

$$SLM_1=\frac{LM_1-E(LM_1)}{\sqrt{\text{var}(LM_1)}} \tag{13}$$

Where LM_1 is the square root of first term in (12). The standardized equation of (13) is given by

$$SLM_2=\frac{LM_2-E(LM_2)}{\sqrt{\text{var}(LM_2)}} \tag{14}$$

Where LM_2 is the square root of second term in (12).

2.2.4 Hausman Test

The Hausman test compares random and fixed effects estimators and tests whether or not the random effects assumption is supported by the data. The Hausman test statistic is;

$$H=NT(\hat{\theta}_{FGLS}-\hat{\theta}_W)'(\hat{\Sigma}_W-\hat{\Sigma}_{FGLS})^{-1}(\hat{\theta}_{FGLS}-\hat{\theta}_W) \tag{15}$$

Where $\hat{\theta}_{FGLS}$ and $\hat{\theta}_W$ are respectively the spatial GLS and within estimators and $\hat{\Sigma}_W$ and $\hat{\Sigma}_{FGLS}$ the corresponding estimates of the coefficients' variance-covariance matrix, H is asymptotically distributed χ^2 with k degrees of freedom where k is the number of regressors in the model.

The Seybold REPORT

ISSN 1533-9211

DOI 10.17605/OSF.IO/R3Q2Y

2.2.5 Determination of Spatial Weight

The regional spatial-effect is embodied by the spatial-weight matrix (W_{ij}), created by applying the "Rook" rule, which assumes an adjacency rule where

$$W_{ij} = \begin{cases} 1 & \text{when region i and j are adjacent} \\ 0 & \text{when region i and j are not adjacent} \end{cases}$$

Thus, we obtained an economic weight-matrix based on the binary weight matrix [14], with the following formula:

$$W^* = W * E, E_{ij} = \frac{1}{|\bar{y}_i - \hat{y}_i|} \qquad (16)$$

Where $\bar{y}_i = \frac{1}{t_1 - t_0 + 1} \sum_{t=t_0}^{t_i} y_{it}$

W is the weight-matrix of spatial location; E is the matrix of economic strength.

3. RESULTS PRESENTATION AND DISCUSSION

The average, minimum, and maximum values of the variables of interest in the study are shown in table 1. In the Ecowas countries, the average value of REC and TFEC is 291913, with 352102 having a minimum value of 3344 and 4696 having a maximum

Value of 451991 and 5230433, respectively. Access to clean fuel and cooking technology, ATE, EIL, TEO, and carbon (IV) oxide have minimum values of 0.03899, 0.010, 1.413, 16.0, and 0.04884, respectively, and maximum values of 35.0, 81.930, 57.988, 31426.0, and 0.96192.

Table 1: Descriptive Statistics

Var	Min	1st Quart	Median	Mean	3rd Quarter	Max
REC	3344	34567	55348	291913	101856	4519991
ACFT	0.0389	0.7654	1.4450	5.5430	5.3625	35.000
ATE	0.010	9.757	20.250	25.913	40.156	81.930
EIL	1.413	5.301	7.734	9.660	11.671	57.988
TEO	16.0	171.2	309.5	2926.4	1970.9	31426.0
CO2	0.0488	0.0997	0.1273	0.1578	0.1876	0.9619
TFEC	4696	44908	76920	352102	131702	5230433

The marginal and conditional tests for spatial error correlation test value presented in table 2 is 0.18184, which is not significant at 5%, indicating that there is no spatial autocorrelation. The Hausman test also presented in table 2 is 58.926, significant at 5% shows that one of the models is inconsistent. This implies that the fixed effects model is most appropriate for the study.

ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

Table 2: Diagnostic Test

Test	Statistic	P-value	Remark
LM1	21.912	< 2.2e-16	There is a random effect
LM2	0.1818	0.8557	No spatial autocorrelation
Hausman	58.926	2.472e-10	One model is inconsistent

The result in table 3 shows the spatial autoregressive (SAR) fixed effects model estimation. The result shows that ACFT, ATE, TEO and CO2 are significant at 5% with a negative influence on REC. This indicates that a unit decrease in ACFT, ATE, TEO and CO2 will result to an increase in the REC (Vis-à-vis). Also, EIL and TFEC are significant at 5% with a positive significant

Figure 1: ECOWAS States Boundaries

(Source: **http://ecowax.atspace.com)**

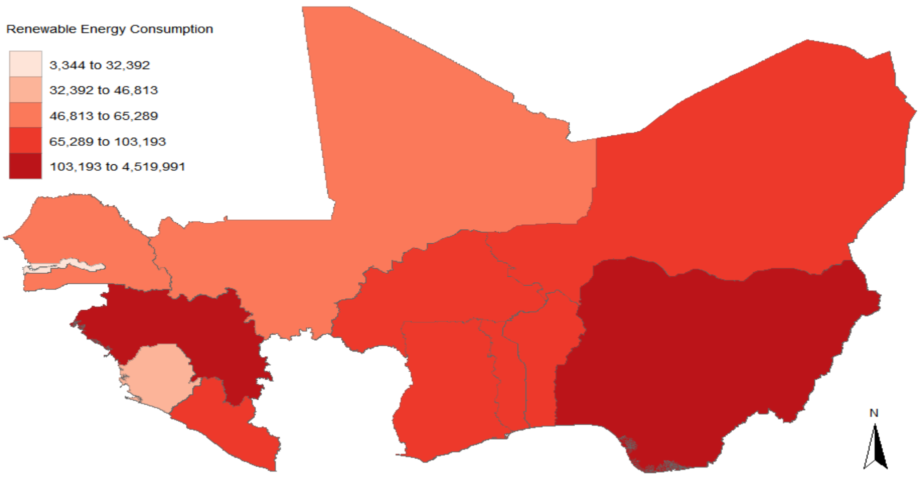

Figure 2: Spatial Average Distribution of Renewable Energy Consumption in ECOWAS

ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

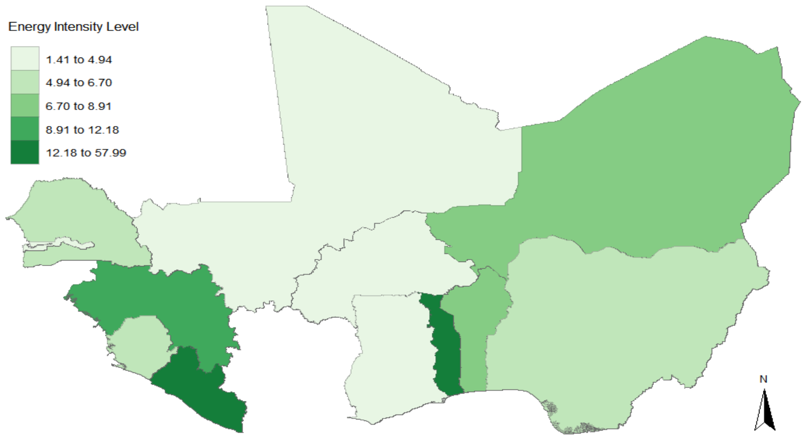

Figure 3: Spatial Percentage Distribution of Energy Intensity Level in ECOWAS

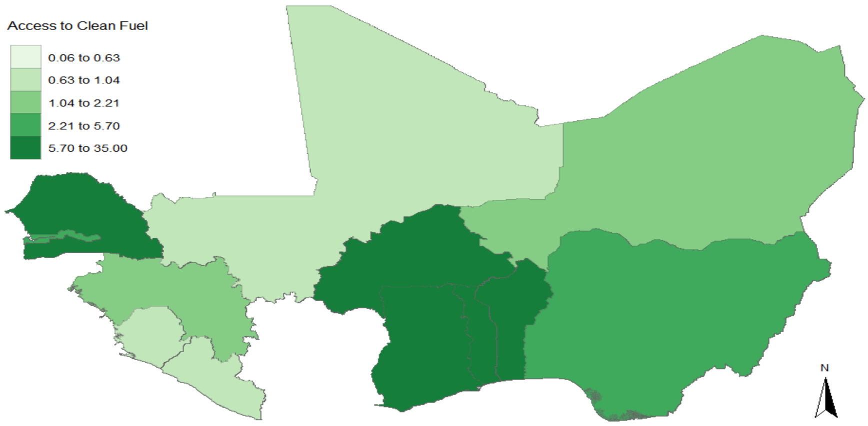

Figure 4: Spatial Percentage Distribution of Access to Clean Fuel and Technologies for Cooking in ECOWAS

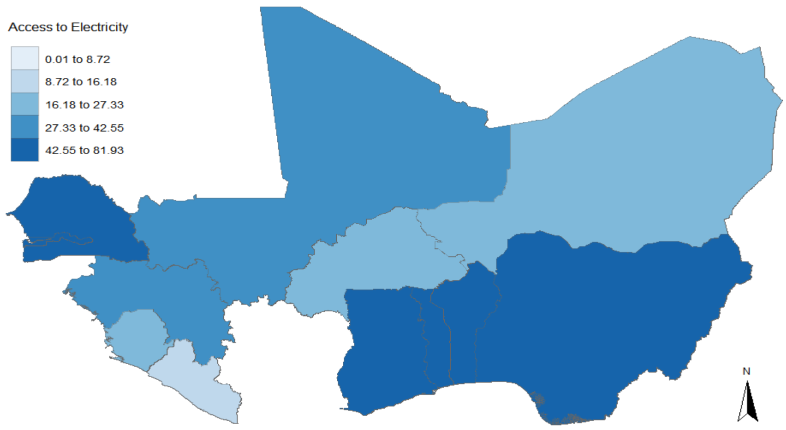

Figure 5: Spatial Percentage Distribution of Access to Electricity in ECOWAS

ISSN 1533-9211

DOI 10.17605/OSF.IO/R3Q2Y

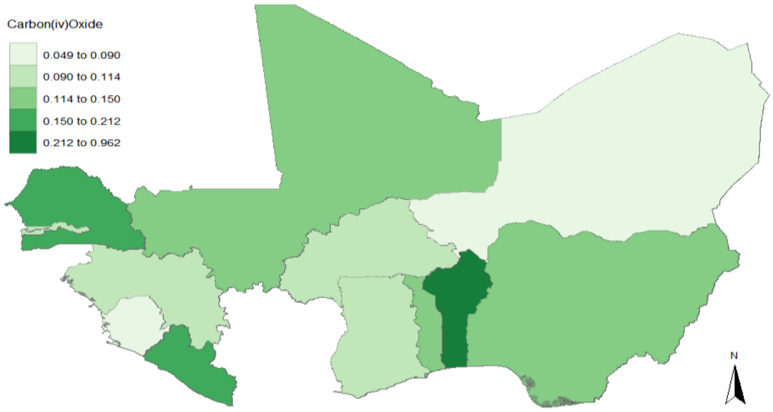

Figure 6: Spatial Percentage Distribution of Carbon (IV) Oxide in ECOWAS

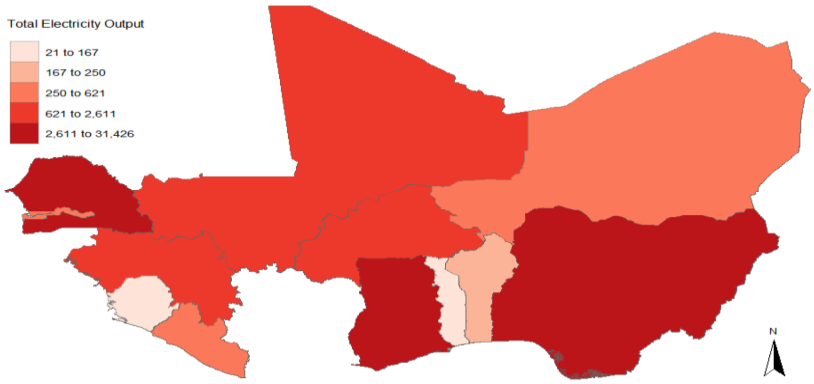

Figure 7: Spatial Percentage Distribution of Total Electricity Output in ECOWAS

Influence on REC. This implies that a unit increase in the EIL and TFEC will leads to an increase in the REC.

Table 3: Fixed Effects of SAR Coefficients of Estimation

	Estimate	Std.Error	t – value	Pr (>
Coefficients				
log(ACFT)	-0.0409	0.0067	-6.0946	1.097e-
log(ATE)	-0.0087	0.0043	-2.0410	0.04125*
log(EIL)	0.1622	0.0217	7.4602	8.636e-
log(TEO)	-0.0589	0.0125	-4.7197	2.362e-
log(CO2)	-0.1273	0.0164	-7.7379	1.010e-
log(TFEC)	0.9822	0.0117	84.0630	< 2.2e-
Spatial Error Parameter				
Rho	0.0346	0.0653	0.5296	0.5964
Spatial Autoregressive Coefficient				
Lambda	0.0051	0.0158	0.324	0.7459

The Seybold REPORT

ISSN 1533-9211

DOI 10.17605/OSF.IO/R3Q2Y

The results in table 4 shows the spatial individual effects for the selected countries. The spatial effects of Ghana and Senegal are significant. This indicated that there is a spatial significant relationship between the REC of Ghana and Senegal.

Table 4: Spatial Individual Fixed Effects

	Estimate	Std.Error	t – value	Pr (> |t|)
Intercept	-0.2676	0.1356	-1.9737	0.04842*
Benin	-0.2464	0.1308	-1.8835	0.0596
Burkina Faso	0.0852	0.1385	0.6150	0.5386
Cote d' Ivoire	0.2261	0.1486	1.5213	0.1282
Ghana	-0.2819	0.1087	-2.5921	0.0095**
Guinea	0.1082	0.1503	0.7202	0.4714
Guinea	-0.1310	0.1217	-1.0771	0.2814
Liberia	0.0593	0.1440	0.4115	0.6807
Mali	-0.0750	0.1426	-0.5263	0.5987
Niger	0.1020	0.1357	0.7517	0.4522
Nigeria	-0.0224	0.1295	-0.1732	0.8625
Senegal	0.4684	0.1799	2.6034	0.0092**
Sierra Leone	-0.1370	0.1322	-1.0357	0.3003
Togo	-0.0781	0.1316	-0.5940	0.5525
Gambia	-0.0772	0.1307	-0.5910	0.5545

Table 5 presents the spatial time effects error model. The result shows that ACFT, ATE, and CO2 have a significant negative effect on REC. This implies a unit decrease in the ACFT, ATE and CO2 will lead to an increase in REC over the spatial time. However, EIL and TFEC have a positive influence on REC, which implies that a unit increase in the EIL and TFEC will result to an increase in REC. Also, the result shows that TEO does not have a significant effect on REC over the spatial time. Figures (2- 7) depict the spatial pattern of ACT, ATE, EIL, TEO, CO2, and TFE, respectively.

Table 5: Spatial Panel Time Fixed Effects Error Model

	Estimate	Std.Error	t – value	Pr (> |t|)
Coefficients				
log(ACFT)	-0.0683	0.0050	-13.7358	< 2.2e-16***
log(ATE)	-0.0125	0.0039	-3.2112	0.0013**
log(EIL)	0.1960	0.0148	13.2241	< 2.2e-16***
log(TEO)	0.0110	0.0059	1.8533	0.0638
log(CO2)	-0.2227	0.0129	-17.3332	< 2.2e-16***
log(TFEC)	1.0450	0.0072	144.5047	< 2.2e-16***
Spatial Error Parameter				
Rho	-0.3104	0.0668	-4.6466	3.374e-06***

The Seybold Report
ISSN 1533-9211
DOI 10.17605/OSF.IO/R3Q2Y

4. CONCLUSION

This study estimated the spatio-temporal relationship of access to clean fuel & cooking technology, access to electricity, energy intensity level, total electricity output, and total final energy consumption on the consumption level of renewable energy in the West African countries using spatial panel analysis by employing a sample of 14 countries covering the 1990–2018 period.

The results indicated that access to clean fuels & cooking technology, access to electricity, total electricity output, and carbon (iv) oxide have a negative influence on renewable energy consumption. The findings showed that the kind of cooking technology, electricity and carbon (iv) oxide used in West Africa reduced the consumption level of renewable energy. However, the energy intensity level and total final energy consumption have a positive influence on renewable energy consumption. Also, the result showed that, out of the fourteen countries considered, the renewable energy consumption of Ghana and Senegal have a spatial relationship.

References

1. UNEP. Financing Renewable Energy in Developing Countries. 2012. https://unepfi.org/fileadmin/documents/Financing_Renewable_Energyin_subSaharan_Africa.
2. Pasari S., V.S.S.K. Nandigama. "Statistical Modeling of Solar Energy. Enhancing Future Skills and Entrepreneurship", Sustainable Production, Life Cycle Engineering and Management, 2015. https://doi.org/10.1007/978-3-030-44248-4_16
3. Maji I.K., Sulaiman C., A. S. Abdul-Rahim. "Renewable Energy Consumption and Economic Growth Nexus: A Fresh Evidence from West Africa". Energy Report, vol. 5, pp. 384 – 392, 2019.
4. Adewuyi A.O., O. B. Awodumi. "Biomass Energy Consumption, Economic Growth and Carbon Emissions: Fresh Evidence from West Africa using a Simultaneous Equation Model". Energy vol.119, pp. 453 – 471, 2017.
5. Sulaiman C., Abdul-Rahim A.S., Mohd-Shahwahid H.O., L. Chin. "Wood Fuel Consumption, Institutional Quality, and Forest Degradation in Sub-Saharan Africa: Evidence from a Dynamic Panel Framework". Ecol. Indic. vol. 74, pp 414 – 419, 2017.
6. Amoo O.M., R. Fagbenle. "Renewable Municipal Solid Waste Pathways for Energy Generation and Sustainable Development in the Nigerian context". Int. J. Energy Environ. Eng. Vol.4, no. 1, pp 42, 2013.
7. Ajoku K.B. "Modern Use of Solid Biomass in Africa: Prospects for Utilization of Agro-Waste Resources in Nigeria, Bio-Energy for Sustainable Development in Africa" pp. 131–146, 2012.
8. Mbah P.O., T. C. Nzeadibe. Inclusive Municipal Solid Waste Management Policy in Nigeria: Engaging the Informal Economy in Post Development Agenda. 2016. http://doi.org/10.1080/13549839.2016.1188062.
9. Vilar (ed). "Renewable Energy in Western Africa: Situation, Experiences and Trends ECREEE and Casa Africa" 2012. www.ecreee.org/sites/default/files/renewable_energy_in_west_africa
10. International Energy Agency. "Africa Energy Outlook. A Focus on Energy Prospects in Sub-Saharan Africa, 2019". (World Energy Outlook Special Report).
11. Hafner M., Tagliapietra S., L. Strasser. "Energy in Africa", Springer Briefs in Energy, 2020. https://doi.org/10.1007/978-3-319-92219-5_1

ISSN 1533-9211

DOI 10.17605/OSF.IO/R3Q2Y

12. Elhorst J.P. "Specification and Estimation of Spatial Panel Data Models". International Regional Sciences Review. Vol.26. no. 3, pp. 244 – 268, 2003.

13. Baltagi B.H., Song S.H., W. Koh W. "Testing Panel Data Regression Models with Spatial Error Correlation". Journal of Econometrics, vol. 117, pp. 123 – 150, 2003.

14. Lin G., Long, Z., M. Wu. "A Spatial Analysis of Regional Economic Convergence in China". China Econ, Vol.1, 67 – 82, 2005.