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Exploring the effects of Biomass energy consumption and Foreign Direct Investment on Environmental Pollution in West Africa: A Spatial Lag Model Analysis

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ABSTRACT

Energy consumption is known as the catalyst for economic growth. However, the association of CO_2 emissions with energy consumption has prompted policymakers to pursue types of energy that ensure sustainable development. Thus, this paper analyses the marginal impact of Biomass energy consumption and foreign direct investment (FDI) on CO_2 emissions in West Africa by employing spatial econometric models. The robust LM lag and the robust LM error test result implied that the spatial lag model was the best model to explain the spatial effects of the exogenous variables. From the result, the spatial parameter (ρ) revealed that CO_2 emissions have endogenous geographical impacts. Thus, indicating that a rise of CO_2 emissions in a neighboring country results in an increase in a focal country by 0.302%. The results also revealed that biomass energy consumption significantly lessens environmental pollution in a country by 0.048% and that of its neighboring countries by 0.012%. An increase in FDI in a focal country increases CO_2 emissions in its environment and its surrounding countries by 0.076% and 0.042% respectively.Thus, the investment in biomass energy projects in the West African region must increase significantly. This could help fight the environmental problems and these projects could be done by attracting foreign investors through FDI in funding. Overall the study spotlighted some policies suggestions for the West African energy market in achieving a carbon-neutral environment.

Keywords: Biomass energy, Foreign direct investment, CO_2 emissions, Spatial lag model, West Africa

I. INTRODUCTION

As a catalyst for economic development, the world's economies rely so heavily on diverse energy sources, particularly petroleum products (Abban and Hongxing 2021; Ripa et al. 2021). As a result, climate change and the associated emissions of gases (especially CO_2) have triggered major environmental concerns among policymakers and energy stakeholders (Muhammad 2019). Thus, stakeholders in regard to sustainable development are continually making clean energy and energy-efficient appliances a top priority (Wu et al. 2021). This had necessitated the conduct of studies to examine the energy-growth-emissions relationship and the development of an optimization framework for lowering emissions and costs (Acheampong 2018). Energy, labor, Capital are all necessary components for economic growth (Jebli et al. 2019). To achieve sustainable growth, these inputs should be blended in a way that is environmentally benign through the manufacturing process (Tiba 2019). Energy consumption, while beneficial to economic growth, had resulted in the emissions of CO_2 which threatens the survival of humans and their physical environment. Similarly, economic progress can promote investment in a better environment, even if it necessitates more energy use because a clean environment is good for higher productivity, contrary to a polluted environment that can stifle growth (Dyson et al. 2021).

CO_2 emissions from increased energy use to support the rapid growth expansion have become a major issue in Africa, especially West Africa recently (Matthew et al. 2020). Renewable energy sources and technologies are regarded as environmentally friendly. When these renewable energies are employed properly, their environmental impact is minimal and gives out minimal secondary waste. As a result, policymakers and the general public are enthusiastic about renewable energies sources (Qazi et al. 2019). Hydrogen, biofuels, Biomass, ocean wave, wind, solar, and geothermal are all examples of renewable energies sources (Sayed et al. 2021). Among these energy sources, the most weighed one is biomass energy (Tursi 2019). Biomass is seen to be more appealing than other renewable energy sources for some reasons; (1) the percentage share of primary energy demand that is met by biomass sources. Out of the share of the primary energy sources, biomass obtained a 10% share. Additionally, biomass accounts for 76% of the global renewable energy consumption. (2) Out of the world's vast amount of renewable energy (biomass sources), it is estimated that only 7% of it has been explored (Sherwood 2020). Thus, biomass has significant environmental, economic, and political benefits, making it a viable alternative to fossil fuels. Biomass has the potential to save energy-importing countries from politically unstable fossil fuel exporting countries (Wang et al. 2018). Deductively, biomass has the potential to reduce energy dependency while also bolstering national energy security. By replacing fossil fuel with biomass, energy-importing countries can reduce their energy imports, and consequently, their trade imbalance. Furthermore, biomass energy has the potency to regenerate infertile soils by increasing biological diversity, water retention, and soil fertility (Popp et al. 2021). Biomass energy do not only have the potential to generate employment in rural areas but also strengthening the agricultural sector and lower poverty in emerging countries.

Another determining factor of CO_2 emissions is foreign direct investment (FDI). As a result of the opening of the world economies, more outsourcing, and shifting international economic policies, FDI had increased dramatically since early 1990 (Huang et al. 2019). The transfer of modern technology and the influence of FDI inflows on job creation, and the standard of living of people has greatly improved (Zhang and Zhou 2016). Even though Asia and BRICS countries had received the majority of the world FDI, the West African economies have been successful in obtaining more FDI in their efforts to close the savings-investment gap and correct balance of payment imbalances (Yusuf et al. 2020). Inflows of FDI in West Africa have surpassed the Sub-Saharan African average in the recent two decades (Batrancea et al. 2021). For example, FDI inflows to West Africa increased from 5.97% in 2010 to 7.59% in 2011, and the area got 23.7% of Africa's FDI inflows in 2014, rising to 26% in 2017 (Halliru et al. 2021). The increased influx of FDI in recent years could be attributed to political stability and new oil discoveries in some West African countries. Also increased trade openness and improved infrastructure could also be the influencing factor, as these are important elements in attracting FDI to countries. Studies such as (Ali et al. 2021; Khan et al. 2021) believe that FDI has a negative influence on the environment, while studies such as (Chishti et al. 2021; Essandoh et al. 2020; Zmami and Ben-Salha 2020) posit the opposite influence of FDI in their studies.

The majority of the studies cited above focused on the causal relationship between CO_2 emissions, FDI, and energy use. As a result, this research adds to the body of knowledge in three ways: first, unlike prior West African studies, this study investigates the effects of biomass energy consumption and FDI on CO_2 emissions in the presence of trade openness, urbanization, and economic growth. Secondly, this study unveiled the spatial effect of CO_2 emissions in the West Africa region. It is general knowledge that sovereign nations with land border constraints can nonetheless interact spatially freely.Validating the spatial dependence of CO_2 emissions informs critical policy decisions in international organizations focused on CO_2 emissions, hence this research is vital. Finally, the study uses spatial econometric models to evaluate CO_2 emissions and its determinant effects, which eliminates the bias associated with typical panel estimate methods such as random effect and fixed effect estimations. As a result, this research provides valuable insight into CO_2 emissions that could be utilized to develop policies to reduce CO_2 emissions in the region.

II. METHODOLOGY

1.1 Model specification

To disclose the objectives of the study; we followed studies done by such as (Balado-Naves et al. 2018; Zeng et al. 2021) to model our econometric equation, thus, the multivariate framework for the study to unveil the spatial effect of CO_2 emissions and its influencing factors in West Africa was given as;

$$\mathrm{LnCEM}_{2i,t} = f(\mathrm{GDP}_{i,t}, \mathrm{BIO}_{i,t}, \mathrm{TOP}_{i,t}, \mathrm{URB}_{i,t}, \mathrm{FDI}_{i,t}) \quad (1)$$

Where $\mathrm{CEM}_{i,t}\mathrm{GDP}_{i,t}, \mathrm{BIO}_{i,t}, \mathrm{TOP}_{i,t}, \mathrm{URB}_{i,t}, \mathrm{FDI}_{i,t}$ represent CO_2 emissions, economic growth, biomass energy, trade openness, urbanization, and foreign direct investment of country iin year t, respectively. The study enforced a spatial panel model to divulge the spatial effects, which may allow us to accredit the disequilibrium shocks the factors (GDP, BIO, FDI, TOP, URB) to CEM. Thus, the spatial panel model for the study is as followed;

$$\begin{aligned}\mathrm{LnCEM}_{2i,t} = \alpha_i + \rho \sum_{j=1}^{N} W_{ij}\,\mathrm{LnCEM}_{i,t} + \beta_1 \mathrm{LnGDP}_{i,t} \\ + \beta_2 \mathrm{LnBIO}_{i,t} + \beta_3 \mathrm{LnTOP}_{i,t} \\ + \beta_4 \mathrm{LnURB}_{i,t} + \beta_5 \mathrm{LnFDI}_{i,t} \\ + \gamma_1 \sum_{j=1}^{N} W_{ij}\,\mathrm{LnGDP}_{i,t} \\ + \gamma_2 \sum_{j=1}^{N} W_{ij}\,\mathrm{LnBIO}_{i,t} \\ + \gamma_3 \sum_{j=1}^{N} W_{ij}\,\mathrm{LnTOP}_{i,t} \\ + \gamma_4 \sum_{j=1}^{N} W_{ij}\,\mathrm{LnTOP}_{i,t} \\ + \gamma_5 \sum_{j=1}^{N} W_{ij}\,\mathrm{LnFDI}_{i,t} + \pi_{it}\end{aligned} \quad (2)$$

$$\pi_{it} = \vartheta \sum_{j=1}^{N} W_{ij}\,\pi_{it} + e_{it}$$

Thus, the model in Eq. 2 comprises three spatial impacts characteristics;

(a) endogenous spatial impacts;

$$\sum_{j=1}^{N} W_{ij}\,\mathrm{LnCEM}_{2i,t}$$

(b) exogenous spatial impacts;

$$\sum_{j=1}^{N} W_{ij}\,\mathrm{LnGDP}_{i,t}, \sum_{j=1}^{N} W_{ij}\,\mathrm{LnBIO}_{i,t}, \sum_{j=1}^{N} W_{ij}\,\mathrm{LnTOP}_{i,t}, \sum_{j=1}^{N} W_{ij}\,\mathrm{LnTOP}_{i,t}, \sum_{j=1}^{N} W_{ij}\,\mathrm{LnFDI}_{i,t}$$

and,

(c) residual spatial impacts;

$$\vartheta \sum_{j=1}^{N} W_{ij}\,\pi_{it}$$

1.2 Spatial correlation tests

1.2.1 Global spatial autocorrelation

The Moran I's index was used to determine the global spatial autocorrelation along West African countries. The index is a regularly used metric for determining the degree of geographical clustering of the attributes of the employed variables. As stated by Moran (1950), the indicator can be calculated as;

$$\text{Moran's I} = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}^{A} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}^{A}\right) \times \sum_{i}^{n} (x_i - \bar{x})^2} \quad (3)$$

Where n represent the number of spatial units indicated by i and j. x is the variable of interest, the average of x is given by $\bar{x}$, the $(n \times n)$ weight matrix indicating the interrelation between a variable and its surrounding is given by W_{ij}^{A}. Generally, the Moran I's index is evaluated by the Z-score, which is calculated as;

$$Z = \frac{I - E(I)}{\sqrt{var(I)}} \quad (4)$$

Where the expectation if the index is given by $E(I)$; the variance of the index is given by $var(I)$. It is expected that $1.96 \leq |Z| < 2.54$ to designate the significance of spatial autocorrelation with a significance level of 0.05 or 0.01 respectively. In effect, the Moran's I index varies from $-1\ to + 1$ indicating negatively or positively spatial autocorrelation. Furthermore, the Local indicators of spatial association (LISA) which are also used to assess the degree of association between a country and its surroundings is calculated by the expression;

$$I_i = Z_i' = \sum_{i}^{n} W_{ij} Z_j' \quad (5)$$

Where Z_i is the standardized form of the variable x_i and spatial weight matrix is given by W_{ij}. A negative or positive LISA coefficient, on the other hand, suggests surrounding features with differing or similar attribute values. The LISA coefficients (Spatial distribution) could be visualized in illustrating the clusters of low-low values (L-L), high-high values (H-H), and outliers such as low-high (L-H) and high-low (H-L). The queen contiguity was used to define the relationship among a country and its neighbors as a spatial unit that shares a common vertex.

1.2.2 Spatial regression models

In working with spatial interaction and spillover effects among spatial units, the spatial regression model (SRM) outperforms the ordinary least square (OLS) regression in terms of providing in-depth information on spatial correlations between the variables while explicitly accounting for geographical impacts. The SRM includes three basic models; the spatial Durbin model (SDM), the spatial lag model (SLM), and the spatial error model (SEM). The spatial autoregressive process which incorporates in both explanatory and response variables in the SDM model can be constructed as (Elhorst 2014a; Elhorst 2014b; Wang et al. 2019)

$$\begin{Bmatrix} Y_{it} = \beta X_{it} + \rho W Y_{it} + \delta W X_{it} + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \rho W Y_{it} + \delta W X_{it} + u_i + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \rho W Y_{it} + \delta W X_{it} + v_i + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \rho W Y_{it} + \delta W X_{it} + u_i + v_i + \varepsilon_{it} \end{Bmatrix} \quad (6)$$

Whereas the spatially autoregressive process (W) which is incorporated into the explanatory variables in the spatial lag models (SLM) (Elhorst 2014a; Elhorst 2014b). Thus, the SLM models can be defined as;

$$\begin{Bmatrix} Y_{it} = \beta X_{it} + \rho W Y_{it} + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \rho W Y_{it} + u_i + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \rho W Y_{it} + v_i + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \rho W Y_{it} + u_i + v_i + \varepsilon_{it} \end{Bmatrix} \quad (7)$$

Lastly, the spatial autoregression process error term denoted by $\emptyset$,whereas the autocorrelation error term's spatial influence is given by λ are incorporated into the SEM models as noted by (Elhorst 2014a; Elhorst 2014b; Zhu et al. 2020), thus, it was constructed as;

$$\begin{Bmatrix} Y_{it} = \beta X_{it} + \lambda W \emptyset + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \lambda W \emptyset + u_i + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \lambda W \emptyset + v_i + \varepsilon_{it} \\ Y_{it} = \beta X_{it} + \lambda W \emptyset + u_i + v_i + \varepsilon_{it} \end{Bmatrix} \quad (8)$$

To select the appropriate model for the study, the Lagrange multiplier (LM) diagnostic tests would be employed. The LM diagnostics provides four (4) statistic tests; that is LM error, robust LM error, LM lag, and robust LM lag. Furthermore, the log-likelihood approach, Schwartz criterion (SC), and the Akaike information criterion (AIC) would be used to compare the models to aid in selecting the best model. To reduce the numerical magnitude disparities in the original data, the Z-score approach was used to standardize it. This ensures that the spatial regression estimates are robust.

III. EXPLORATORY DATA ANALYSIS

1.3 Data and Descriptive Statistics

The study used a balanced data from 10 West African countries (Benin, Burkina Faso, Cote d'Ivoire, Ghana, Gambia, Mali, Niger, Nigeria, Senegal, and Togo) from 1998 to 2018 to reveal the influencing factors of CO_2 emissions and the spatial effect of CO_2 emissions in the region. All data were taken from the World Bank database, with the exception of the biomass data, which was obtained from the global material flow database. The variable used, their definitions, as well as their abbreviations, can be seen in Table 1. To explain the resulting coefficients as elasticities, the natural logarithm was applied to the variables. Inferring to Table 2, there is no substantial association between the independent variables with the coefficient of correlation being less than 0.7. In conclusion, each of the explanatory variable influence the dependent variable in a unique way.

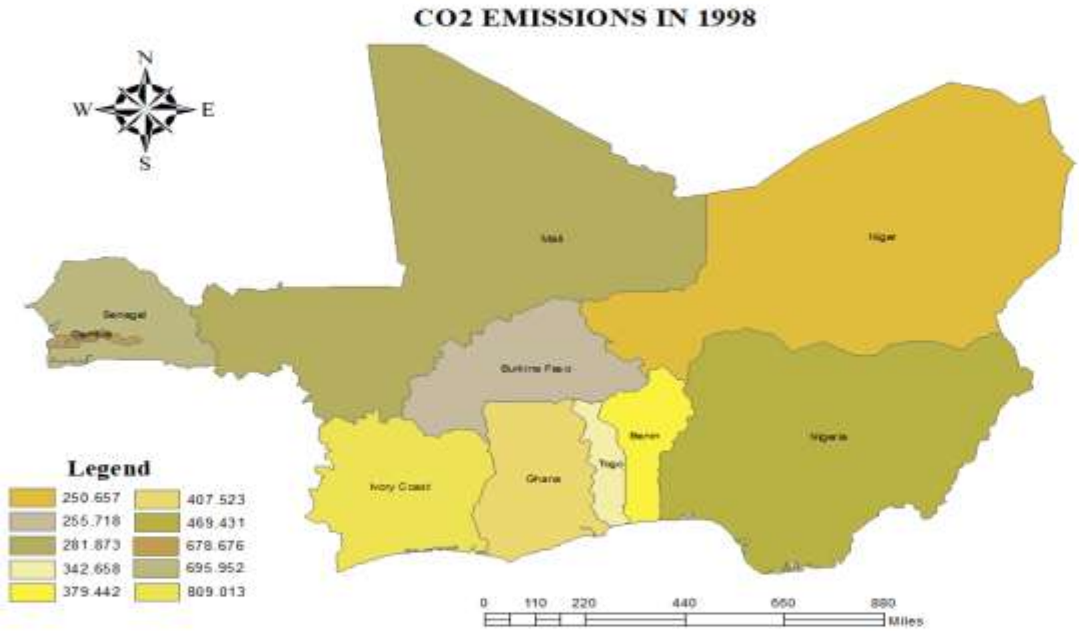
TABLE 1

TABLE 2

1.4 Cross-section dependence test, and distribution of variables

Before moving on to the empirical evaluation, the study used both the first- and second-generation unit root test to examine the stationarity of the employed variables. From Table 3, it could be observed that in the first generation both the level and the first difference were I (1), however, in the second generation, the variables were I (0) at level but followed to be I (1) after the first difference. The concentrations of CO_2 emissions, the range of biomass energy consumption, and FDI in West Africa are depicted in Figure 1, Figure 2, and Figure 3 respectively for the selected countries for the years 1998 and 2018.

TABLE 3



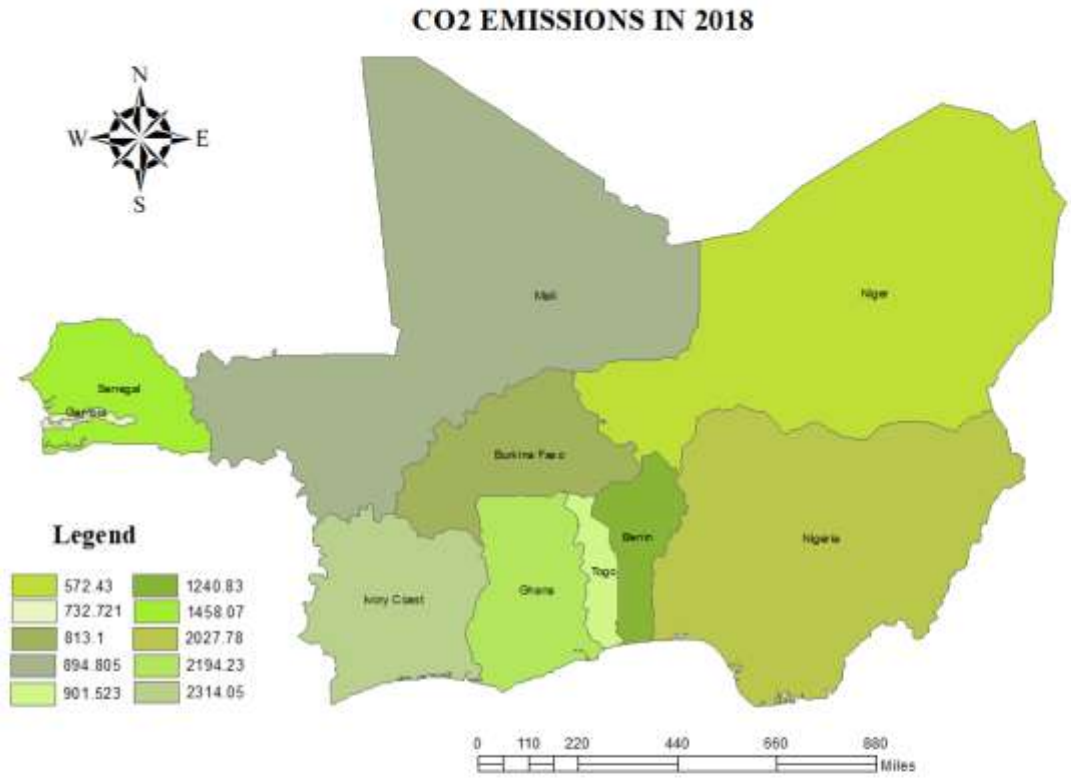


FIGURE 1: CO_2 emissions in West Africa for the years 1998 and 2018

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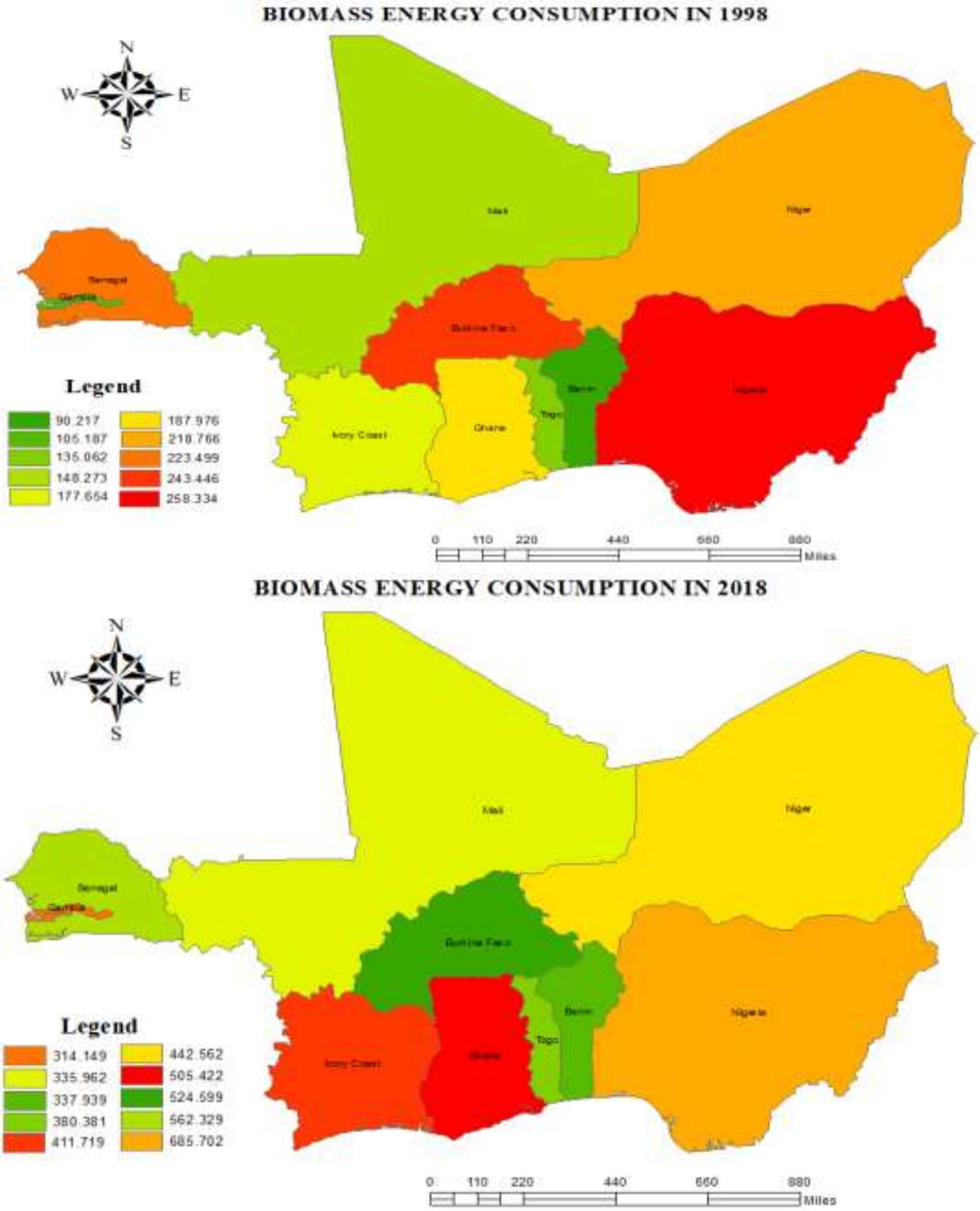

FIGURE 2: CO_2 emissions in West Africa for the years 1998 and 2018

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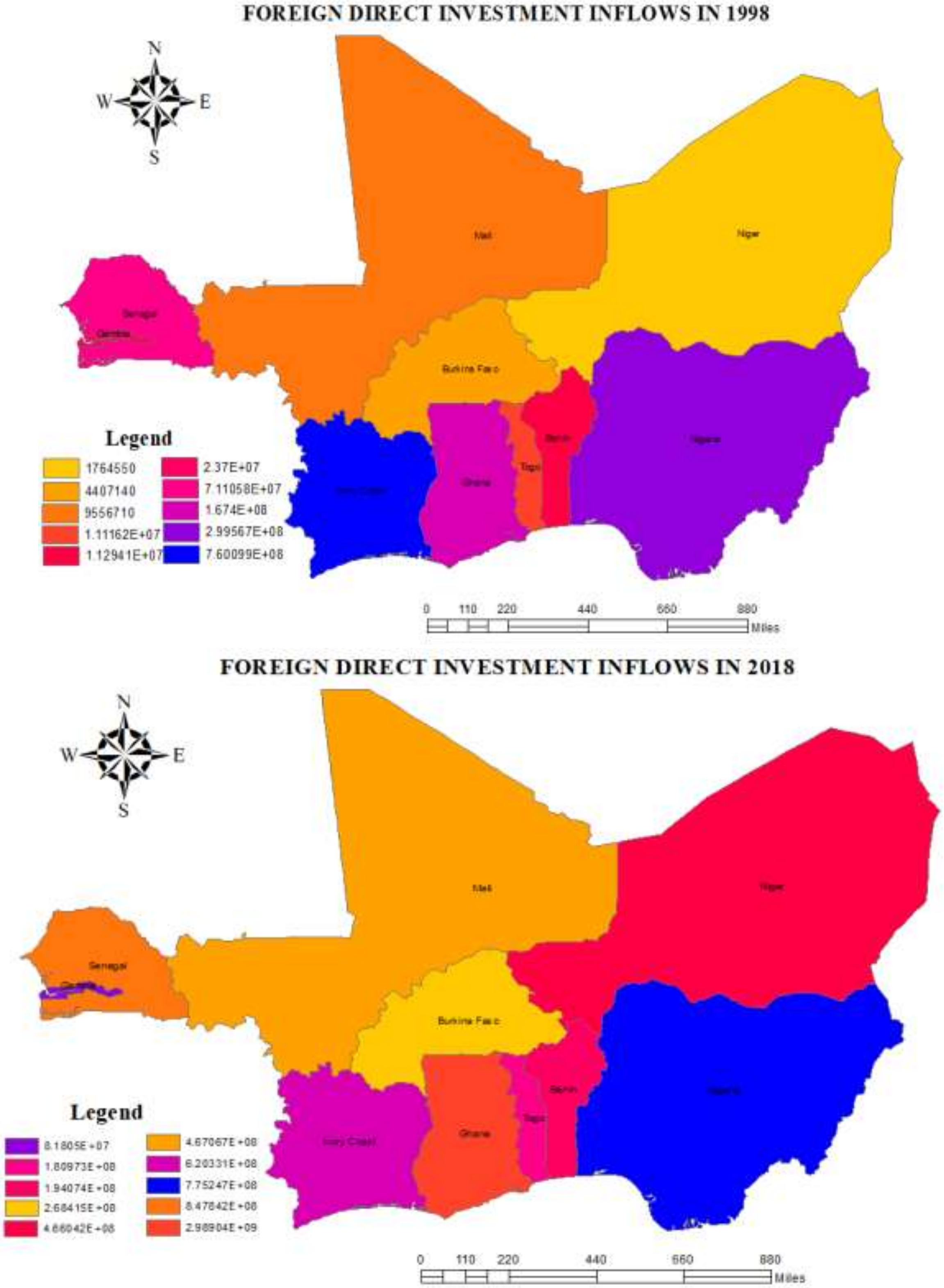

FIGURE 3: CO_2 emissions in West Africa for the years 1998 and 2018

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IV. RESULTS

1.5 Global Moran's I and LISA map

Figure 4 depicts the regional distribution of CO_2 emissions by country in West Africa. There are obvious spatial disparities between countries. Throughout the selected years (1998, 2005, 2012, and 2018), Nigeria was observed to have a High-High CO_2 emissions pattern (H-H), whereas Ghana, Cote d'Ivoire, and Senegal had a High-Low CO_2 pattern (H-L). However, Ghana and Cote d'ivoire becaome a high emiiter of CO_2 in 2018. Benin, Burkina Faso, and Mali were observed to be Low-High emitters of CO_2 emissions. In summary, CO_2 has been highly emitted by Nigeria, Ghana, and Cote d'Ivoire, with Nigeria as the highest emitter of CO_2, which also indicates that oil-rich countries (Nigeria, Ghana, and Cote d'Ivoire) have higher emissions of CO_2. To again detect the global spatial autocorrelation of CO_2 emissions, the Global Moran I was performed. The overall values of the Global Moran I of CO_2 emissions were observed to be positive between 0.281 and 0.625 and significant at a 1% confidence level. This revealed a positive significant spatial autocorrelation of CO_2 emissions, as well as significant clustering rather than random patterns of CO_2 emissions in West Africa. Table 4 provides the Moran I's value obtained with Figure 5 showing the Moran's plot in 1998, 2005, 2012, and 2018.

TABLE 4

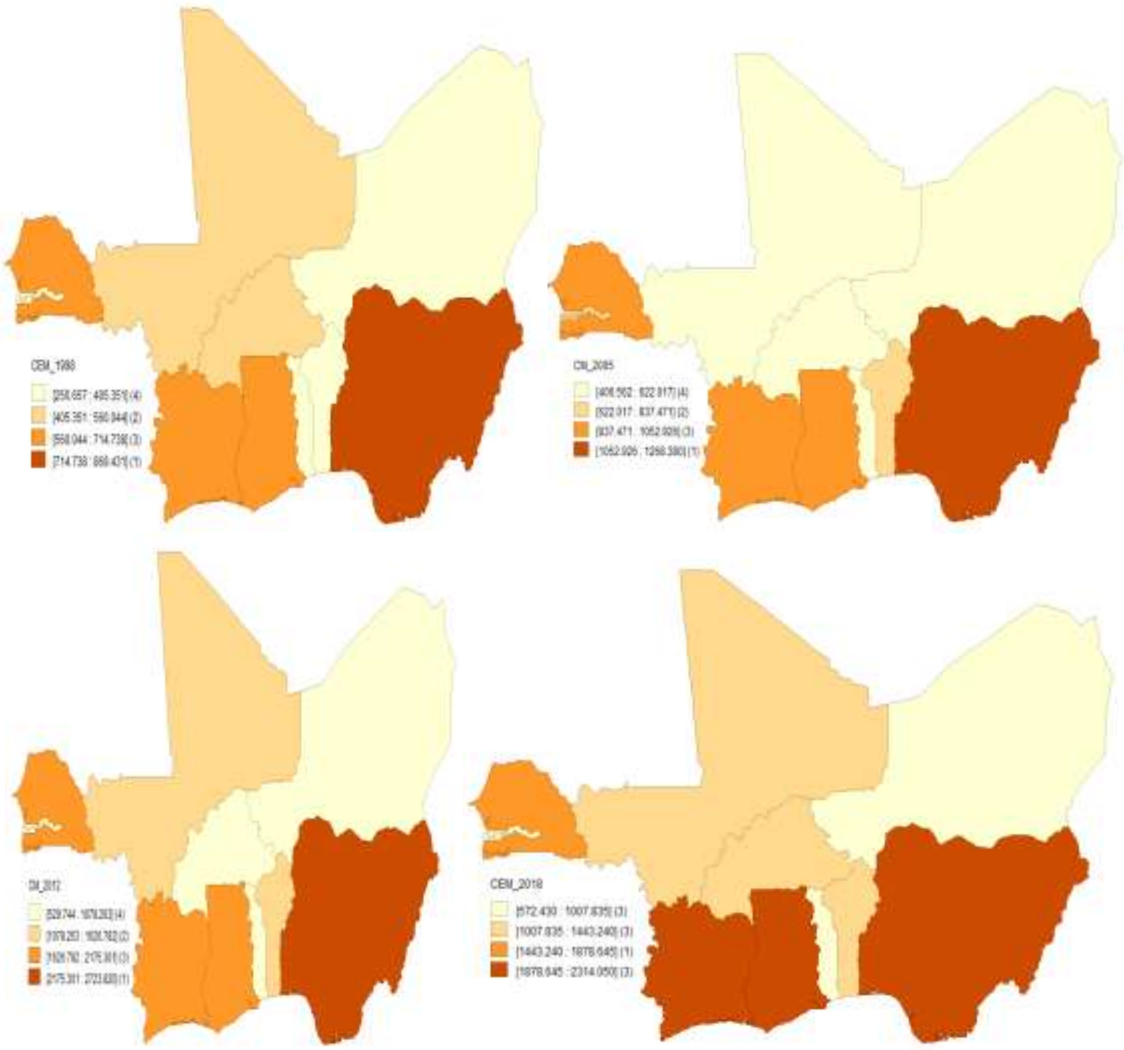

FIGURE 4: CO_2 emissions in West Africa for the years 1998, 2005, 2012, and 2018

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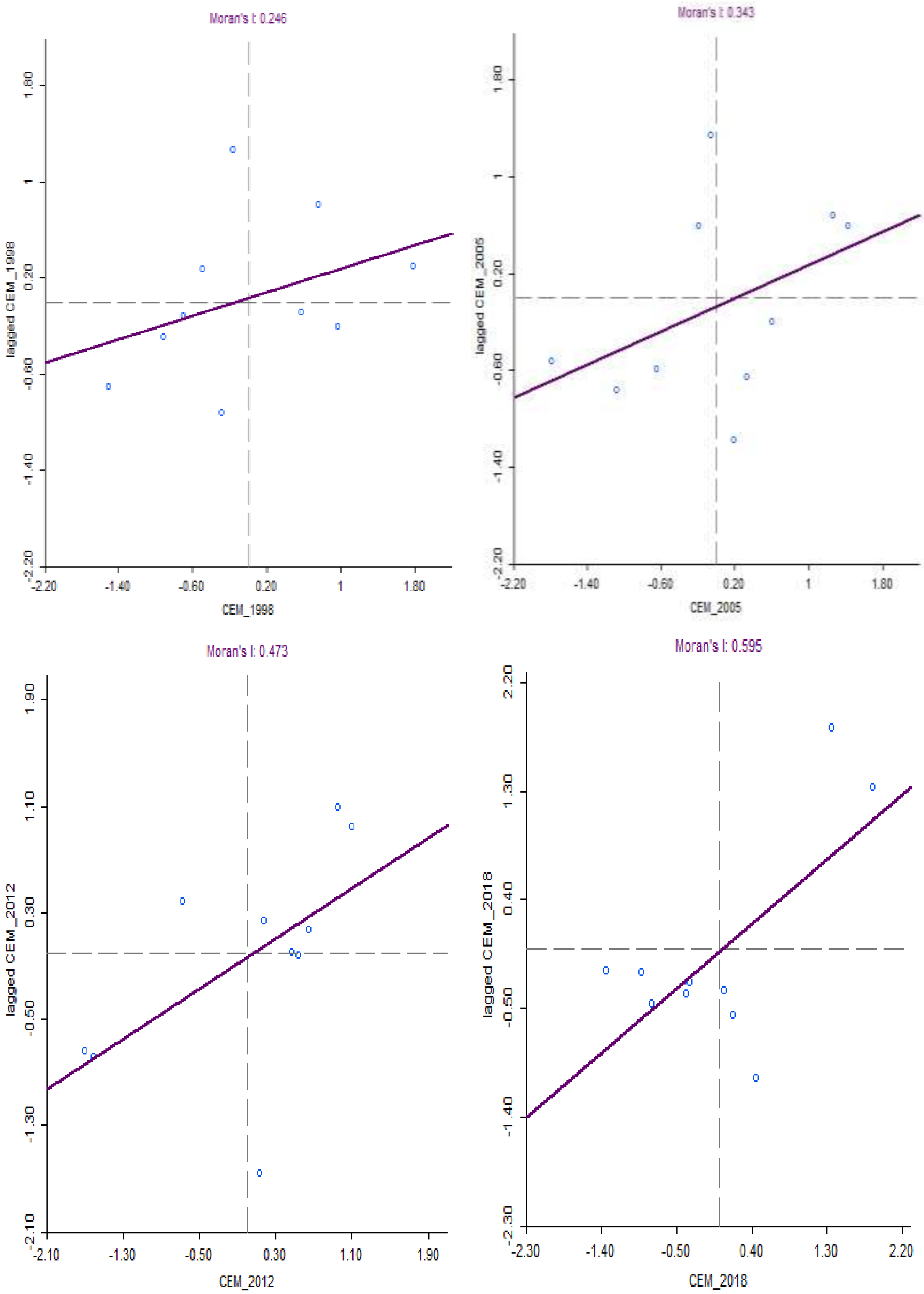

FIGURE 5: Moran's I plot in West Africa for 1998, 2005, 2012 and 2018

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1.6 Coefficients estimates and Spatial spillover

Table 5 presents the results for the Wald test and the LM tests for the selection of the best spatial model. The LM lag and error test statistics were non-significant; thus, the robustness of the LM test was performed for both the SLM and SEM. The results obtained indicate that the robust LM lag statistic was more efficient and significant than the robust LM error test, implying that the SLM is the best model to be used in the study compared to the SEM. As a result, the SLM was used to investigate the spillover effects of the employed variables. Lastly, the Hausman test revealed that the fixed effect is best in explaining the coefficients obtained for the study.

TABLE 5

Comparing the results of the ordinary OLS to the SLM as it can be observed in Table 6, the R squared for the SLM was greater than that OLS, showing that the SLM captures more variations than the non-spatial linear modeling. Considering the spatial parameter value (ρ), its value is relatively large and significant statistically with a p-value less than 0.05. As a result, the SLM model has a lot of spatial autocorrelations. Furthermore, taking into consideration the parameters (R squared, SC, and AIC), their values divulged that the SLM estimates are a much better model than the OLS model. The SLM results highlighted an important conclusion considering the mechanism of CO_2 emissions. The regression estimate of ρ was statistically significant at 1%, showing a geographical spillover impact of CO_2 emissions in West Africa. In order words, a 1% rise in CO_2 emissions in a country in West Africa will turn to increase CO_2 emissions in the adjacent country by 0.302. In regards to the SLM results presented in Table 6, three variables (GDP, TOP, and FDI) all unveiled a positive significant effect on CO_2 emissions. Such that a percentage increase in these three variables increases CEM by 0.143%, 0.093%, and0.159%respectively. In the case of the negative impact, a 1% rise in BIO turns to decrease CO_2 emissions by 0.036%. The Breusch-Pagan test (4.183) and its p-value (0.648) revealed that there is no significant heteroskedasticity in the spatial lag model.

TABLE 6

V. DISCUSSION

5.1.1 Spatial spillover effect of CO_2 emissions

Because of the possible spatial spillover effect of CO_2 emissions across the West African region, these countries must work together on CO_2 emissions abridging strategies. In two ways, the positive significant spillover of CO_2 could be observed; (a) considering the spatial parameter (ρ), CO_2 emissions have endogenous geographical impacts indicating that a rise of CO_2 emissions in a neighboring country result in an increase a local country. As a result, the spatial parameter is consistent with the Moran's I result obtained in Table 4. (b) Considering the fact that West Africa is a collection of countries with considerable spatial inequalities, not only in geography, resource endowment, and climate but also in economic growth, household consumption, and industrial structure could explain these endogenous spatial impacts. As a result, these counties in the west of Africa must guarantee that their environmental laws are uniform and must work together on carbon-reduction technologies and policies. These results are consistent with the study done by Ameyaw et al. (2020), where they stated that CO_2 emissions have a spatial effect in west Africa during their work on forecasting the pathways to abridge CO_2 emissions.

5.1.2 The Effect decomposition of the Spatial lag model

As a result of the geographical autocorrelation, the regression weights of the SLM could not be relied on to explain the marginal effects, hence the study went further to assess the direct, indirect, and total effects of the exogenous variables.

Considering the negative relationship between CO_2 emissions and biomass energy consumption observed, it implies that biomass energy consumption improves the quality of air in the atmosphere in West African countries (Direct, Indirect and Total effect). This indicates that the effectuation of advanced biomass conversion technologies has the potential to lessen the environmental effect of pollutants. Thus, BIO contributes to economic growth by furnishing additional sources of income creation, which will keep the country afloat while also meeting the energy demands in the pursuit of long-term development. By shifting demand away from traditional energy sources and their associated goods, biomass energy consumption transforms decarbonized economies through pollution reduction. Biomass energy fosters a shift in the energy source to a more dependent internal energy supply that promotes long-term energy sustainability. Biomass energy consumption improves environmental quality by lowering fossil fuel usage, as well as it associated emissions that come with it. Since the production of biomass energy is a cost-effective one, it motivates the investment into biomass energy because increased

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economic growth creates opportunities. Biomass energy can be used for heating, transportation, and electrical production, which will replace fossil fuels to boost a country's growth. As a result, biomass energy can help societies tackle climate change and global warming, while simultaneously ensuring a country in West Africa's energy security. Biomass energy asseverates a low-carbon development paradigm that is linked to effective pollution control measures. These findings teach us that biomass energy help regulate pollution in the region. This observation collaborates with the study done by Gnansounou et al. (2020) in West Africa, where they revealed that agricultural residues as a biofuel has a negative effect on CO_2 emissions. Likewise, the work done by Maji et al. (2019) is in line with the results obtained in this study.

The coefficients of FDI from the direct and the indirect effects were statistically significant at 1% and 5% level of significance. Specifically, based on Table 7, a 1% increment in FDI has the possibility of increasing a country's own CO_2 emissions by 0.076% and also has the possibility of affecting a neighboring country by 0.042%. The possible explanation for the positive effect of FDI on CO_2 emissions could be attributed to the massive mining and other production operations by foreign corporations. These operations had raised the level of environmental degradation in the West Africa region. Generally, FDI has the potential to drive economic development in their host country by transferring sophisticated technologies which raise productivity and increase economic growth. FDI introduces new production methods to local enterprises and provides labor skills, management practices, and new products resulting in more job chances for indigenous people. Furthermore, FDI in West Africa has aided in the creation of a competitive corporate environment, which has fueled the strong economic expansion in West Africa resulting in outpacing the other African countries. The study done by Abdo et al. (2020) in some selected Arab countries collaborates with the result obtained in this study, where they stated that FDI has a positive impact on CO_2 emissions, however, the work done by Radmehr et al. (2021) contradicts this observation, they stated that FDI had a negative impact on CO_2 emissions in Europe.

The weight of trade openness exerted on CO_2 emissions was identified to be positive and statistically significant in both the direct and indirect effects at a 1% level of significance. More specifically, a 1% increment in TOP has the possibility of increasing CO_2 emissions by 0.053% in a local country while increasing it neighboring countries' emissions by 0.027%. The possible conclusion drawn from the positive impact of TOP on CO_2 emissions is that free trade among the West African countries has positive environmental consequences due to the technique, composition, and effects of scale. This free trade had facilitated economic growth among these trading partners in the region, in respect of their geographical proximity. Trade, in general, has a negative impact on the environment since it promotes economic growth. Due to the scale effect of enhancing energy consumption, economic growth usually has a positive effect on the environment at the betimes stages of development.Since more focus is directed on economic growth instead of pollution control in the early stages of development, the scale effect shows that pollutants emissions are raising as a result of increasing energy usage and economic activity. The result obtained in the study is in line with the work done by Khan et al. (2021) in emerging countries, where they posit that trade openness has a positive effect on CO_2 emissions. However, the work done by Ertugrul et al. (2016) contradicts this result, they stated that trade openness has a negative effect on CO_2 emissions in 10 larger CO_2 emissions countries.

The coefficients of GDP on both the direct and indirect effects were also statistically significant and positively affect CO_2 emissions at a 5% and 10% level of significance respectively. More specifically, from Table 7, a percent gain in GDP turns to increase CO_2 emissions in a focal country by 0.107% and increase emissions in the neighboring country by 0.024%. One possible reason for the positive effects of GDP on emissions is that West African countries are still relying on conventional fossil fuels for economic growth. Thus, CO_2 emissions resulting from the combustion of oil and coal have increased significantly in the region. As a result, more economic expansion results in higher CO_2 emissions. Based on this positive of GDP on CEM, it could be concluded that if the West African countries aim to achieve the decouple CO_2 from economic growth, they must modify their energy system to a sustainable and clean structure. This observation collaborates with the results obtained by Halliru et al. (2021) on West Africa, where they stated that GDP has a harmful effect on the environment. Likewise, the study done by Balado-Naves et al. (2018) in 173 countries is in line with observation in this study, where they stated that GDP has a positive impact on CO_2 emissions.

The estimate of URB from both direct and indirect effect were statistically insignificant. Thus, from Table 7, a 1% increment in URB has no possible effect on CO_2 emissions. Since URB has

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no significant effect on CO_2 emissions at any significant level, excluding the variable URB from this study would have no significant impact on CO_2 emissions. However, energy and environmental policies that do not take into account the effect of URB on CO_2 emissions are unlikely to achieve their goals. In accordance with these findings, the absence of URB has little impact on CO_2 emissions reductions plans or sustainable development policies. In regards to the urbanization transition and ecological modernization theories, URB could have both deteriorating or beneficial effects on the environment, with the net effect being difficult to predict a priori. Higher levels of URB are linked to increased economic activities, with wealthier citizens frequently in demand of more energy-intensive products (air conditions, automobile, etc.) which in turn heighten the level of CO_2 emissions. In turn, these residents who are wealthier are most likely to be concerned about the degradation of the environment. Increased URB also aids in the development of economies of scale for public infrastructure, which results in less environmental deterioration. Thus, according to the findings of the study, URB could have two opposite effects on CO_2 emissions and tend to cancel each other out, with the net impact of URB on CO_2 emissions being statistically insignificant. The insignificant effect of URB is in line with the work done by Lv and Xu (2019) in 55 middle-income countries, while the work done by Zhang et al. (2018) revealed that URB has a positive impact on CO_2 emissions during their study in China.

TABLE 7

VI. CONCLUSION AND POLICY IMPLICATIONS

This study explored the spatial effect of CO_2 emissions and the influencing factors in 10 West African states using the spatial econometric approach from 1998 to 2018. As a result of the aforementioned discussions, some major conclusions that were arrived at were as follows; the Moran's I value, plots, and the LISA maps revealed the presence of local spatial agglomeration in West African's air pollution. The findings suggest that increasing biomass energy consumption in a local country turns to reduces the country's own CO_2 emissions and also reduces the emissions of its adjacent countries. Whereas increasing FDI increases emissions of CO_2 in the region. Consequently, based on the observation obtained during the study, some policy implications derived are as follows;

a) The West African governments should increase the investment in biomass energy projects, which could include research and development. This could help fight the environmental problems based on the findings obtained. These types of projects could attract foreign investors through FDI in funding to help improve the production of biomass energy production. CO_2 emissions could be reduced by using biomass instead of fossil fuel to attain the region's environmental sustainability goals. Biotechnology could also help increase the production of biomass while also expanding the range of its by-products.
b) To keep CO_2 emissions at a low level and possibly achieve a carbon-neutral environment, the West African states must open up their trading policies and alter their competitive advantage in favor of cleaner energy production, as well as increase inter-country collaboration, which includes both emissions and production. Thus, keeping these countries from becoming more polluted in years to come, strict regulations should be imposed on countries which would reduce emissions and, in turn, enhance environmental quality.
c) By means of cleaning up the West African environment, these countries should support ecologically friendly FDI inflow. Because biomass energy consumption improves the quality of the environment in these states, shifting energy consumption from energy mix to renewable energy is the best option. The establishment of the energy efficiency policy, the West African power pool and centre for energy efficiency and renewable energy created had appeared to have a positive outcome. Thus, the attraction of more environmentally friendly FDI and investing in the development of human capital is a necessity for the region because it would boost the total productivity factor and energy efficiency as well.

Ethics approval and consent to participate
Not applicable

Consent for publication
Not applicable

Competing interests
The authors declare that they have no competing interests.

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Table 1: Descriptive statistics

Variable	**Definition**	**Mean**	**Std.Dev**	**Min**	**Max**
$LnCO_2$	CO_2 emissions (kt)	6.709	1.021	3.055	8.530
LnGDP	GDP per capita (current US$)	8.417	2.145	4.877	10.311
LnBIO	Biomass consumption per capita (in kilogram)	7.543	1.232	5.871	8.361
LnTOP	Export of goods and services + import of goods and services (% of GDP)	5.763	1.769	5.325	9.180
LnURB	Urbanization (Total)	4.043	1.634	4.367	6.703
LnFDI	Foreign direct investment (net inflows)	11.013	1.211	4.775	9.165

Table 2: Correlation test results

Variable	**$LnCO_2$**	**LnGDP**	**LnBIO**	**LnTOP**	**LnURB**	**LnFDI**	**Collinearity Statistics**	
$LnCO_2$	**1**	0.377	0.217	0.521	0.101	0.106	**VIF**	**Tolerance**
LnGDP		**1**	0.027	0.355	0.327	0.451	2.128	0.663
LnBIO			**1**	0.231	0.266	0.227	1.873	0.376
LnTOP				**1**	0.411	-0.175	2.134	0.431
LnURB					**1**	0.293	1.701	0.288
LnFDI						**1**	2.331	0.473

Table 3: Unit root test of the employed variables

Variable	**Method**	**Fisher-ADF**	**Fisher-PP**	**CIPS**	**CADF**
Levels					
$LnCO_2$	Statistic	-6.149^a	-5.476^a	-1.102	-1.261
LnGDP	Statistic	-4.703^b	-11.345^b	-1.113	-1.371
LnBIO	Statistic	-5.055^b	-25.146^a	-1.054	-1.417
LnTOP	Statistic	-4.825^c	-10.054	-1.321	-1.026
LnURB	Statistic	-11.423^a	-13.056^a	-1.551	-1.430
LnFDI	Statistic	-8.544^a	-13.255^a	1.701	-1.322
First Difference					
$LnCO_2$	Statistic	-38.413^a	-17.017^a	-5.911^a	-5.753^a
LnGDP	Statistic	-19.334^c	-15.344^a	-4.732^a	-5.122^a
LnBIO	Statistic	-37.824^b	-22.002^a	-4.843^a	-5.137^a
LnTOP	Statistic	-41.0415^a	-43.019^a	-5.302^a	-5.028^a
LnURB	Statistic	-30.551^a	-64.722^a	-4.712^a	-4.933^a
LnFDI	Statistic	-22.403^a	-32.184^a	-4.703^a	-5.602^a

Note: $^{a, b, c}$indicates 1%, 5% and 10% statistical significance levels, respectively.

Table 4: Global Moran I test results

Year	**Moran**	**Z-value**	**p-value**	**Year**	**Moran**	**Z-value**	**p-value**
1998	0.281^a	2.112	0.000	2009	0.493^a	1.964	0.000

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1999	0.288[a]	1.987	0.000	2010	0.501[a]	2.266	0.000
2000	0.311[a]	2.013	0.000	2011	0.535[a]	2.081	0.000
2001	0.337[a]	2.077	0.000	2012	0.551[a]	2.433	0.000
2002	0.360[a]	1.990	0.000	2013	0.558[a]	2.302	0.000
2003	0.369[a]	2.502	0.000	2014	0.574[a]	2.540	0.000
2004	0.403[a]	2.242	0.000	2015	0.588[a]	2.271	0.000
2005	0.412[a]	2.331	0.000	2016	0.603[a]	2.012	0.000
2006	0.427[a]	2.104	0.000	2017	0.611[a]	1.983	0.000
2007	0.454[a]	1.975	0.000	2018	0.625[a]	2.456	0.000
2008	0.476[a]	2.170	0.000				

Note: [a, b, c]indicates 1%, 5%, and 10% statistical significance levels, respectively.

Table 5: Diagnostics for spatial dependence

Test Statistic	Statistic Value	p-value
Wald spatial lag	4.423	0.044
Wald spatial error	3.871	0.277
LM lag	1.934	0.147
Robust LM lag	5.398[b]	0.023
LM error	0.137	0.714
Robust LM error	3.688[b]	0.031
Hausman	153.287	0.000

Note: [a, b, c]indicates 1%, 5%, and 10% statistical significance levels, respectively.

Table 6: Estimation results from the SLM and OLS

Determinants	**Spatial Lag Model**				**Pooled Ordinary least square (POLS)**			
	Coefficient	Std. Error	z-value	p value	Coefficient	Std. Error	z-value	p value
LnGDP	0.143[a]	0.067	5.461	0.000	0.218[b]	0.018	3.287	0.027
LnBIO	−0.088[b]	0.108	4.104	0.011	−0.107[a]	0.127	0.317	0.000
LnTOP	0.093[a]	0.221	3.271	0.000	0.308[c]	0.201	0.308	0.060
LnURB	0.082	0.078	3.072	0.257	0.319[c]	0.155	0.019	0.071
LnFDI	0.159[b]	0.206	2.723	0.040	0.219[a]	0.293	0.219	0.000
AIC	74.213				72.567			
SC	82.509				81.044			
BP	4.183				0.648			
Log-likelihood		−24.432				−29.077		
$\mathbf{R^2}$		0.741				0.518		
Spatial parameter (ρ)		$\mathbf{0.302}$ ($\mathbf{p} < 0.01$)				−		

Note: [a, b, c]indicates 1%, 5%, and 10% statistical significance levels, respectively. **AIC:** Akaike information criterion. **SC:** Schwartz criterion. **BP:** Breusch-Pagan test.

Table 7: Effect decomposition of Spatial Lag model

Variables	Direct effects	Indirect effects	Total effects
LnGDP	0.107[b]	0.027[c]	0.131[b]
LnBIO	−0.048[a]	−0.012[b]	−0.060[a]
LnTOP	0.055[a]	0.027[c]	0.082[a]
LnURB	0.069[c]	0.034[b]	0.103[a]
LnFDI	0.076[b]	0.042[a]	0.118[a]

Note: [a, b, c]indicates 1%, 5% and 10% statistical significance levels, respectively.

REFERENCES

[1]. Abban OJ, Hongxing Y (2021) Investigation on the main contributors of economic growth in a dynamic heterogeneous panel data (DHPD) in Africa: evidence from their income classification Environmental Science and Pollution Research 28:27778-27798

[2]. Abdo A-B, Li B, Zhang X, Lu J, Rasheed A (2020) Influence of FDI on environmental pollution in selected Arab countries: a spatial econometric analysis perspective Environmental Science & Pollution Research 27

[3]. Ali MU, Gong Z, Ali MU, Wu X, Yao C (2021) Fossil energy consumption, economic development, inward FDI impact on CO2 emissions in Pakistan: Testing EKC hypothesis through ARDL model International Journal of Finance & Economics 26:3210-3221

[4]. Ameyaw B, Li Y, Annan A, Agyeman JK (2020) West Africa's CO 2 emissions: investigating the economic indicators, forecasting, and proposing pathways to reduce carbon emission levels Environmental Science and Pollution Research 27:13276-13300

[5]. Balado-Naves R, Baños-Pino JF, Mayor M (2018) Do countries influence neighbouring pollution? A spatial analysis of the EKC for CO2 emissions Energy Policy 123:266-279

[6]. Chishti MZ, Ahmed Z, Murshed M, Namkambe HH, Ulucak R (2021) The asymmetric associations between foreign direct investment inflows, terrorism, CO2 emissions, and economic growth: a tale of two shocks Environmental Science and Pollution Research:1-19

[7]. Dyson M, Engel A, Farbes J (2021) Economics of Clean Energy Portfolios: How Renewable and Distributed Energy Resources Are Outcompeting and Can Strand Investment in Natural Gas-Fired Generation. In: World Scientific Encyclopedia of Climate Change: Case Studies of Climate Risk, Action, and Opportunity Volume 2. World Scientific, pp 11-18

[8]. Elhorst JP (2014a) Matlab software for spatial panels International Regional Science Review 37:389-405

[9]. Elhorst JP (2014b) Spatial panel data models. In: Spatial econometrics. Springer, pp 37-93

[10]. Ertugrul HM, Cetin M, Seker F, Dogan E (2016) The impact of trade openness on global carbon dioxide emissions: Evidence from the top ten emitters among developing countries Ecological Indicators 67:543-555

[11]. Essandoh OK, Islam M, Kakinaka M (2020) Linking international trade and foreign direct investment to CO2 emissions: any differences between developed and developing countries? Science of the Total Environment 712:136437

[12]. Gnansounou E, Pachón ER, Sinsin B, Teka O, Togbé E, Mahamane A (2020) Using agricultural residues for sustainable transportation biofuels in 2050: Case of West Africa Bioresource technology 305:123080

[13]. Halliru AM, Loganathan N, Golam Hassan AA (2021) Does FDI and economic growth harm environment? Evidence from selected West African countries Transnational Corporations Review 13:237-251

[14]. Huang Y, Chen X, Zhu H, Huang C, Tian Z (2019) The heterogeneous effects of FDI and foreign trade on CO2 emissions: evidence from China Mathematical Problems in Engineering 2019

[15]. Khan AG, Hossain MA, Chen S (2021) Do financial development, trade openness, economic development, and energy consumption affect carbon emissions for an emerging country? Environmental Science and Pollution Research:1-11

[16]. Lv Z, Xu T (2019) Trade openness, urbanization and CO2 emissions: dynamic panel data analysis of middle-income countries The Journal of International Trade & Economic Development 28:317-330

[17]. Maji IK, Sulaiman C, Abdul-Rahim A (2019) Renewable energy consumption and economic growth nexus: A fresh evidence from West Africa Energy Reports 5:384-392

[18]. Matthew O et al. (2020) Carbon emissions, agricultural output and life expectancy in West Africa International Journal of Energy Economics and Policy 10:489-496

[19]. Moran PA (1950) Notes on continuous stochastic phenomena Biometrika 37:17-23

[20]. Muhammad B (2019) Energy consumption, CO2 emissions and economic growth in developed, emerging and Middle East and North Africa countries Energy 179:232-245

[21]. Popp J, Kovács S, Oláh J, Divéki Z, Balázs E (2021) Bioeconomy: Biomass and biomass-based energy supply and demand New Biotechnology 60:76-84

[22]. Qazi A, Hussain F, Rahim NA, Hardaker G, Alghazzawi D, Shaban K, Haruna K (2019)

Towards sustainable energy: a systematic review of renewable energy sources, technologies, and public opinions IEEE Access 7:63837-63851

[23]. Radmehr R, Henneberry SR, Shayanmehr S (2021) Renewable energy consumption, CO2 emissions, and economic growth nexus: a simultaneity spatial modeling analysis of EU countries Structural Change and Economic Dynamics 57:13-27

[24]. Ripa M, Di Felice L, Giampietro M (2021) The energy metabolism of post-industrial economies. A framework to account for externalization across scales Energy 214:118943

[25]. Sayed ET, Wilberforce T, Elsaid K, Rabaia MKH, Abdelkareem MA, Chae K-J, Olabi A (2021) A critical review on environmental impacts of renewable energy systems and mitigation strategies: Wind, hydro, biomass and geothermal Science of The Total Environment 766:144505

[26]. Sherwood J (2020) The significance of biomass in a circular economy Bioresource technology 300:122755

[27]. Tiba S (2019) Modeling the nexus between resources abundance and economic growth: An overview from the PSTR model Resources policy 64:101503

[28]. Tursi A (2019) A review on biomass: importance, chemistry, classification, and conversion Biofuel Research Journal 6:962-979

[29]. Wang S, Yuan Y, Wang H (2019) Corruption, hidden economy and environmental pollution: a spatial econometric analysis based on China's provincial panel data International journal of environmental research and public health 16:2871

[30]. Wang Z, Shen D, Wu C, Gu S (2018) State-of-the-art on the production and application of carbon nanomaterials from biomass Green Chemistry 20:5031-5057

[31]. Wu J, Abban OJ, Hongxing Y, Boadi AD, Ankomah-Asare ET (2021) The nexus amid foreign direct investment, urbanization, and CO2 emissions: Evidence from energy grouping along the ECOWAS community Environment, Development and Sustainability:1-25

[32]. Yusuf HA, Shittu WO, Akanbi SB, Umar HM, Abdulrahman IA (2020) The role of foreign direct investment, financial development, democracy and political (in) stability on economic growth in West Africa International Trade, Politics and Development

[33]. Zeng C, Stringer LC, Lv T (2021) The spatial spillover effect of fossil fuel energy trade on CO2 emissions Energy 223:120038

[34]. Zhang C, Zhou X (2016) Does foreign direct investment lead to lower CO2 emissions? Evidence from a regional analysis in China Renewable and Sustainable Energy Reviews 58:943-951

[35]. Zhang G, Zhang N, Liao W (2018) How do population and land urbanization affect CO2 emissions under gravity center change? A spatial econometric analysis Journal of Cleaner Production 202:510-523

[36]. Zhu Y, Wang Z, Yang J, Zhu L (2020) Does renewable energy technological innovation control China's air pollution? A spatial analysis Journal of Cleaner Production 250:119515

[37]. Zmami M, Ben-Salha O (2020) An empirical analysis of the determinants of CO2 emissions in GCC countries International Journal of Sustainable Development & World Ecology 27:469-480