International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 3 Mar 2022, pp: 868-886 www.ijaem.net ISSN: 2395-5252

A dynamic spatial model estimation of the effects of energy usage, spatial spillover of CO_2 emissions and exports on CO_2 emissions in Africa

Emmanuel Owusu[1], Li Fanglin[1], Nelly Ataawomba Afuubi[1], Emmanuel Sogbou Kenne[2], Michael Verner Menyah[3]
[1] School of Finance and Economics, Jiangsu University, Zhenjiang 212013, P.R China
[2]School of Transportation, East China Jiaotong University, 808 Shuanggang new development Zone, China
[3]School of Management, Jiangsu University, Zhenjiang 212013, P.R China

Submitted: 10-03-2022 Revised: 21-03-2022 Accepted: 25-03-2022

ABSTRACT
Many energy-climate policies throughout the world have made net-zero CO_2 emissions an explicit goal. To achieve this aim, high-income countries must dramatically reduce their emissions while also obviating large increase in emissions in lower and low economies. However, most studies concentrate on emissions reductions in high income countries, with little attention paid to lower and low economies. The present study analyses the spillover effect of CO_2, effects of exports, and energy usage on CO_2 emissions in Africa using the dynamic spatial Durbin model. The Hausman test was again performed to determine the choice between the random effects and the fixed effects. The results indicated the existence of spatial spillover effect of CO_2emissions among some countries in Africa. The findings suggest that increasing both exports of goods and energy consumption in a focal country, turns to increase the country's own CO_2 emissions and also increases the emissions of its adjacent countries. Comparing the direct effect from the dynamic SDM effects to the SDM effects revealed that exports of goods a variation of 0.085%. The results further confirmed an inverted U-shaped between emissions of CO_2 and GDP. Finally, expotrs and energy consumption have a positive and significant total effects on CO_2 emissions. Based on the findings obtained, a set policies implications was suggested.

Keywords: Energy consumption, Exports, Economic growth, CO_2 emissions, Dynamic Spatial econometric model, Africa.

I. INTRODUCTION

Carbon dioxide (CO_2) emissions are said to be the primary contributor of Greenhouse emissions (GHG) [1, 2]. The global emissions of GHG were said to attain an approximate 49.0 gigatons of CO_2 equivalent in 2016, and currently, CO_2 accounts for roughly 73% of the total GHG emissions, an increase of 8% since 1970 [2, 3]. Despite the fact that CO_2 is an important constituent of the ecosystem, its excessive assiduity in the atmosphere, together with other GHG emissions, causes pollution and global warming, leading to environmental degradation and climate change [4]. [5]inquired into possibilities for future global warming and CO_2 emissions and they revealed that global temperature would climb more than 4 degrees Celsius by the year 2100. Thus, the share of CO_2 emissions to global pollution keeps increasing hence, the need of discovering the contributing factors for this rise in CO_2 emissions is essential [6].

Understanding the contributions of Africa to global anthropogenic CO_2 emissions is a crucial measure in reducing atmospheric GHGs. Africa's economy is dominated by Developing Countries (DC's) and Least Developed Countries (LDC's) with a population of 1.3 billion people [7]. Africa accounted for about 4% of global CO_2 emissions in 2017, with the lowest CO_2 emissions intensity of 34.9 tCO_2/TJ and CO_2 emissions per capita of 0.9 TCO_2/capita when compared to all other area of the world [8]. Nevertheless, Africa's CO_2 emissions/GDP at 0.5 $kgCO_2$/\$ were higher than all other regions, with the exception of Asia which had 0.6 $kgCO_2$/\$ [9]. Oil discoveries in Africa waxed emissions by 0.9 percent per year on an average between 1990 and 2017, led by oil-rich countries such as Nigeria, Angola, Lybia, Egypt. Though, most African countries are presently considered as low emitters, they could turn large producers of CO_2 emissions as a result of the discovery of oil (Nanibia, Cote d'ivore, Ghana, and Gabon) [10, 11]. Consequently, CO_2 emissions in Africa in the next decade could be significantly climb exponentially. Figure 1 depicts the outline of the boundaries of the countries in the study.

The factors that contribute to the increment of CO_2 emissions have thoroughly been investigated, with majority of the studies focusing on the environmental Kuznets curves (EKC) hypothesis, that is the effect of economic growth (GDP) on CO_2 emissions [12, 13]. In accordance with this hypothesis, the early phases of economic development, which includes industrialization, results in heightening the level of CO_2, whereas at the later stages of economic development, which include knowledge-based products and restructuring toward service, which results in lessen CO_2 emissions.

Energy usage is considered as another factor that has an effect on CO_2 emissions [14]. In actuality, energy consumption increases economic opportunities and improves the industrial sector all of which contribute to urban change. Since energy is a necessary input in the cumulative production process, economic growth has been linked to energy usage. However, the association of CO_2 emissions with energy consumption cannot be written off. The Neoclassical Economics Theory positions that demand and supply in the energy market are the impulsive force derrierre energy pricing, consumption, and production [15]. As a result, increased energy prices will correspond to lower energy usage and, as such lower CO_2 emissions.Furthermore, a higher energy price implies a greater degree of energy scarcity, which advocates the replacement of expensive energy sources for less expensive ones, thus, regulating the energy supply [16]. Thus, it is critical to identify the effect of energy consumption in Africa in order to design sustainable growth policies for the continent, and also aid to the debate over the use of fossil fuels and reduce climate change.

Another significant determinant of CO_2 emissions is exports of goods [17]. Some recent researches have looked into the connection between energy usage, CO_2 emissions, and exports of goods [18, 19]. This is due to a significant increase in international trade of goods, service and capital over the last two decades. The percentage of international trade of Africa to the world has climbed by nearly 3%, this astonishing expansion in trade has made the Africa economy more reliant on it, with it share of global GDP increasing by 3.7% from 2017 [20]. It is common knowledge that trade cannot take place without transportation. As a result, transportation plays a critical role in international trade. Despite its importance in international trade, the transportation sector consumes a significant amount of energy and pollutes the environment [21]. As a result, there may be a link between trade, CO_2 emissions, and energy usage. Furthermore, studies on the relationship between energy usage and CO_2 emissions and trade are scarce [22, 23]. The outcomes of these studies are mixed. [24] stated that exports have a favorable long term-term and short-term influence on CO_2 emissions during their work in new industrialized countries. The study by [25] revealed that exports has a negative impacts of CO_2 emissions only in the short run, while Aghasafari, Aminizadeh (26), also posit that exports has no significant impact on CO_2 emissions in MENA countries.

From the above studies, it was evidenced that most of them focused on the causative relationship among exports, CO_2 emissions, and energy consumption. As a result, this study contributes to literature in three ways; Firstly, unlike previous studies in Africa, this study inquires the non-linearity amongst CO_2 emissions and economic growth and exports of goods, this non-linearity provides more illumination to this relationship as mixed results (negative and positive) was obtained by previous studies. Secondly, the study analyzed how the effects of CO_2 emissions in a local country affect neighboring countries. It is common knowledge that sovereign nations with land border restrictions still have unrestricted spatial interaction. Validating the spatial dependency of CO_2 emissions acquaints crucial policy resolutions in terms of international organizations centering on CO_2 emissions, hence this analysis is necessary. Thirdly, the study incorporates the spatial econometric models in evaluating the emissions of CO_2 and its determinants, thus, the study annuls the bias that comes with traditional panel estimations approaches like; fixed effect approach, AMG estimation, and FMOLS/DOLS estimation. Thus, this study may possibly provide deep insight into how energy pricing could be used in formulating policies to make the continent's CO_2 emissions neutral.

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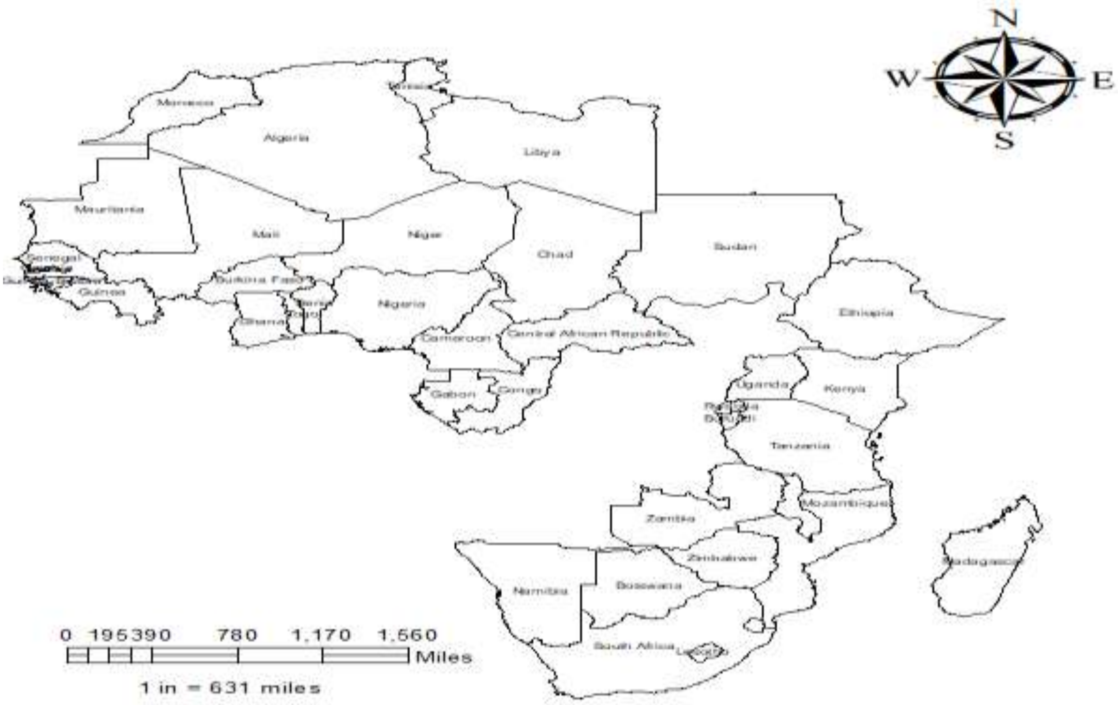

Figure 1: Outline of the boundaries of the African countries included in the model

II. METHODOLOGY

1.1 Model Specification

Following studies such as [27, 28], the multivariate framework for this study to unveil the effects of the explanatory variables on CO_2 emissions in Africa was given as;

$$LnCO_{2i,t} = f(\,ENG_{i,t}\,, EXP_{i,t}, GDP_{i,t}, URB_{i,t}) \tag{1}$$

Where $ENG_{i,t}, EXP_{i,t}, GDP_{i,t}, URB_{i,t}, CO_{2i,t}$ represent energy consumption, exports of goods, economic growth, urbanization and CO_2 emissionsof country $i$in year t, respectively. The study implements the dynamic spatial panel model to unwrap the spatial and dynamic effects, which may allow us to accredit the disequilibrium shocks the factors (ENG, EXP, GDP, URB) to CO_2 emissions through Spatio-temporal lags and temporal. Thus, the fixed effects from the dynamic spatial panel model for the study is as follows;

$$\begin{aligned} LnCO_{2i,t} = {} & \alpha_i + \tau LnCO_{2i,t-1} + \rho \sum_{j=1}^{N} W_{ij}\, LnCO_{2i,t} + \beta_1 LnENG_{i,t} + \beta_2 LnEXP_{i,t} + \beta_3 LnGDP_{i,t} + \beta_4 LnURB_{i,t} \\ & + \gamma_1 \sum_{j=1}^{N} W_{ij}\, LnENG_{i,t} + \gamma_2 \sum_{j=1}^{N} W_{ij}\, LnEXP_{i,t} + \gamma_3 \sum_{j=1}^{N} W_{ij}\, LnGDP_{i,t} + \gamma_4 \sum_{j=1}^{N} W_{ij}\, LnURB_{i,t} \\ & + \pi_{it} \end{aligned} \tag{2}$$

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

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

(a) endogenous spatial impacts;

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

(b) exogenous spatial impacts;

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$$\sum_{j=1}^{N} W_{ij}\, LnENG_{i,t}\, , \sum_{j=1}^{N} W_{ij}\, LnEXP_{i,t}\, , \sum_{j=1}^{N} W_{ij}\, LnGDP_{i,t}\, , \sum_{j=1}^{N} W_{ij}\, LnURB_{i,t}$$

and,

(c) residual spatial impacts;

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

Where the fixed parameter is given by α_i, the coefficients for the spatial effects are given by ρ, β and ϑ. e_{it} is the estimated residual term being normally distributed $N(0, \sigma_e^2)$ and identically independently distributed (iid). The spatial weight is given by W_{ij} for $1 < i, j < N$ of a pre-assigned row-standardized, non-negative distance function spatial weight matrix W[29]. Thus, these three spatial interactions cannot be embedded in one model at the same time due to parameter estimation requirements [30]. As a result of these spatial interactions, three simple spatial panel data models could be extracted from the model (2) [31, 32]; (a) the spatial Durbin model (SDM), incorporates spatial exogenous and endogenous interactions $(\sigma = 0)$, and it given by equation;

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij}\, y_{ij} + \beta x_{ij} + \mu_i + \vartheta \sum_{j=1}^{N} W_{ij}\, \pi_{it} + e_{it} \tag{3}$$

(b) Secondly, the spatial autoregression model (SAR), which takes into account endogenous spatial effects $(\gamma = 0 \;\; \sigma = 0)$. Thus, its specific equation is given by;

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij}\, y_{ij} + \beta x_{ij} + \mu_i + \epsilon_{it} \tag{4}$$

(c) lastly, the SEM, known as the spatial error model which delimitate a spatial interaction of the error term $(\gamma = \rho \; = 0)$, thus, also given by the equation;

$$\begin{cases} y_{it} = \beta x_{it} + u_i + \pi_{it} \\ \pi_{it} = \vartheta \sum_{j=1}^{N} W_{ij}\, \pi_{it} + e_{it} \end{cases} \tag{5}$$

Thus, the static spatial panel models include these three simple spatial models. These three models could, however, be altered to dynamic spatial panel models by the addition of temporal-spatial lag constituents to the response variable. The study employed the dynamic spatial Durbin error model (SDM). The SDM provides reliable and unbiased estimates and also increases the explicatory power of the explanatory variables on the response variable [30, 31]. The dynamic SDM is given as;

$$\begin{aligned} LnCO_{2i,t} = {} & \alpha_i + \tau LnCO_{2i,t-1} + \rho \sum_{j=1}^{N} W_{ij}\, LnCO_{2i,t} + \beta_1 LnENG_{i,t} + \beta_2 LnEXP_{i,t} + \beta_3 LnGDP_{i,t} + \beta_4 LnURB_{i,t} \\ & + \gamma_1 \sum_{j=1}^{N} W_{ij}\, LnENG_{i,t} + \gamma_2 \sum_{j=1}^{N} W_{ij}\, LnEXP_{i,t} + \gamma_2 \sum_{j=1}^{N} W_{ij}\, LnGDP_{i,t} + \gamma_3 \sum_{j=1}^{N} W_{ij}\, LnURB_{i,t} \\ & + e_{it} \end{aligned} \tag{6}$$

As a result of the subsistence of endogenous impacts, the traditional OLS estimation approach will produce skewed and discrepant results. Thus, to solve this challenge and accurately forecast the dynamic SDM, the study followed the work of [33] and use the quasi-maximum likelihood (QML) method instead of the traditional OLS method.

1.2 Spatial correlation test

The study used the Moran's I in evaluating the spatial correlation if country-level CO_2 in Africa is geographically dependent [27, 28]. The construction of the Moran's I as defined by Moran (34) is given below;

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$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}^{A}\,(Z_i - \bar{Z})\,(Z_j - \bar{Z})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}^{A})\sum_{i}^{n}(Z_i - \bar{Z})^2} \quad (7)$$

Where the adjacent space weight matrix is represented by W_{ij}^{A}, number of countries is n, Z_i represent the attribute value of the variables (CO_2, energy consumption and exports) in-country i, and Z_j represent the ascribe value of the variable (CO_2, energy consumption and exports) in-country j. W is defined as fist-order rook adjacency in this study (Matrix of queen contiguity). In Moran I's evaluation, the Z-score is commonly used to determine its importance, the Z-score is given by;

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

To ascertain the best model that fits the data, the non-spatial fixed models were fixed estimated by using the likelihood ratio test (LR). The spatial autocorrelation test of residual error and its robustness followed using the Lagrange multiplier (LM) test to ascertain which fixed effect must be included [35]. The LM tests are typically employed to ascertain coherent estimates for the test spatial autocorrelation residual error [29]. Secondly, the selection of the best model between SAR, SDM, or SEM models was based on the Wald and LR test results. The null hypothesis for the Wald test ($H_0 : \gamma = 0$) was used to assess whether or not the SDM is most suitable to SAR, against its null hypothesis of the LR test ($H_0 : \gamma + \rho\beta = 0$), which assesses the suitability of the SDM to the SEM model [36]. The chi-square distribution was used in both tests. If both hypotheses are declined, thus, the SDM model is the most suitable model. The acceptance of the first hypothesis implies the use of the SAR model, while the acceptance of the second hypothesis connotes the suitability of the SEM model.

III. EXPLORATORY DATA ANALYSIS

1.3 Data and Descriptive statistics

To divulge the impacts of energy consumption, exports, economic growth, and and spatial factors on CO_2 emissions in Africa, the study employed a balanced data from 35 countries from 1996 to 2018. All data were extracted from the world bank database, with the CO_2 emissions extracted from Air Quality Index. Table 1 presents the variables employed, their definition and abbreviation. The natural logarithm was applied to the employed variables, so to explicate the obtained coefficients as elasticities.The descriptive statistics of the employed variables are presented in Table 1. From Table 2, it was evidenced that a strong relationship among the independent variables does not exist since the coefficient correlation among all the variables was seen to be less than 0.7. As a result, each explanatory variable had a distinct effect on the dependent variable.

TABLE 1

TABLE 2

1.4 Cross-section dependence test, and distrbution of variables

The study further assessed the unit root of the variables using the second generations (CIPS and CADF) panel unit root tests before moving on to the empirical examination. From the stationary test in Table 3, it was observed that some variables were I (0) at level, however, they all turned to be I (1) after the first difference. Figure 2, Figure 3, and Figure 4 depicts the concentrations of CO_2 emissions, the range of exports, and energy usage in 1996 and 2018 for the selected African countries.

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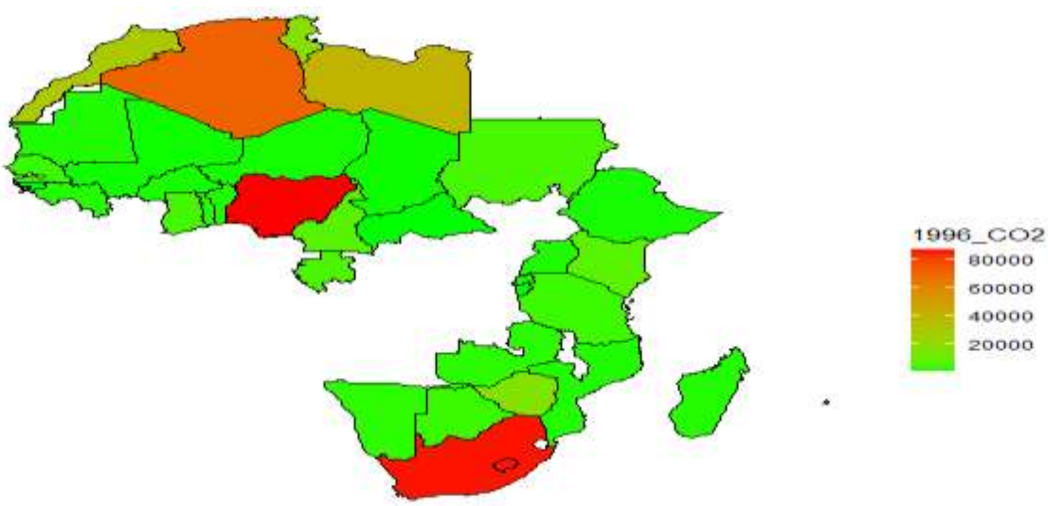
TABLE 3



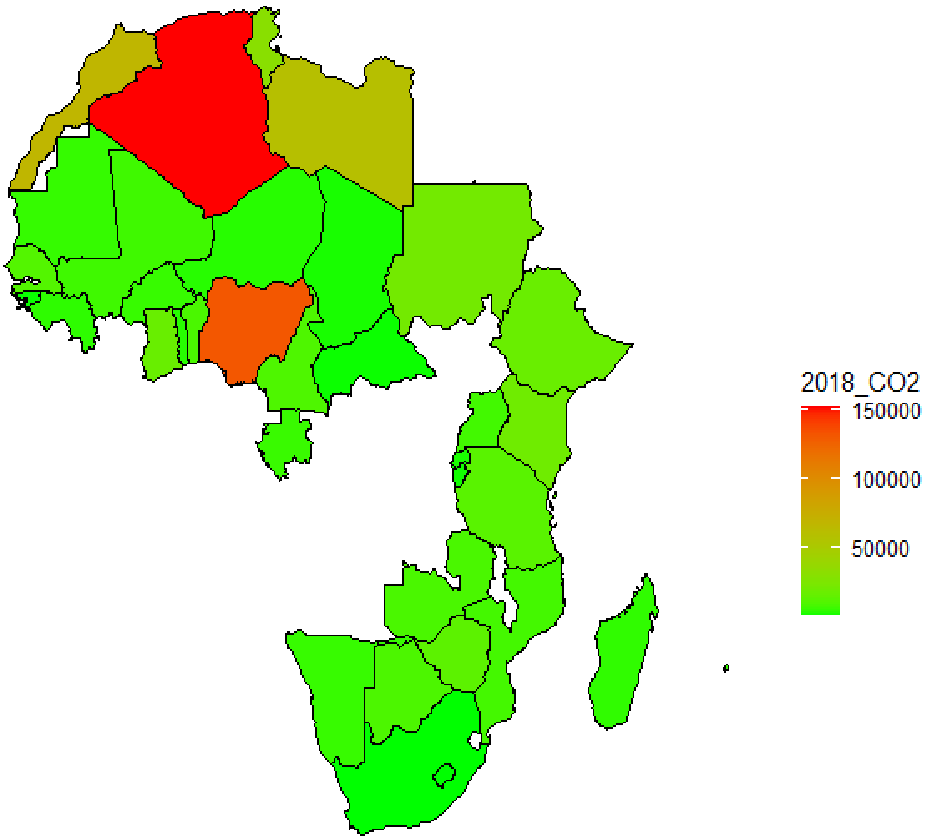


FIGURE 2: CO_2 emissions in Africa for the years 1996 and 201

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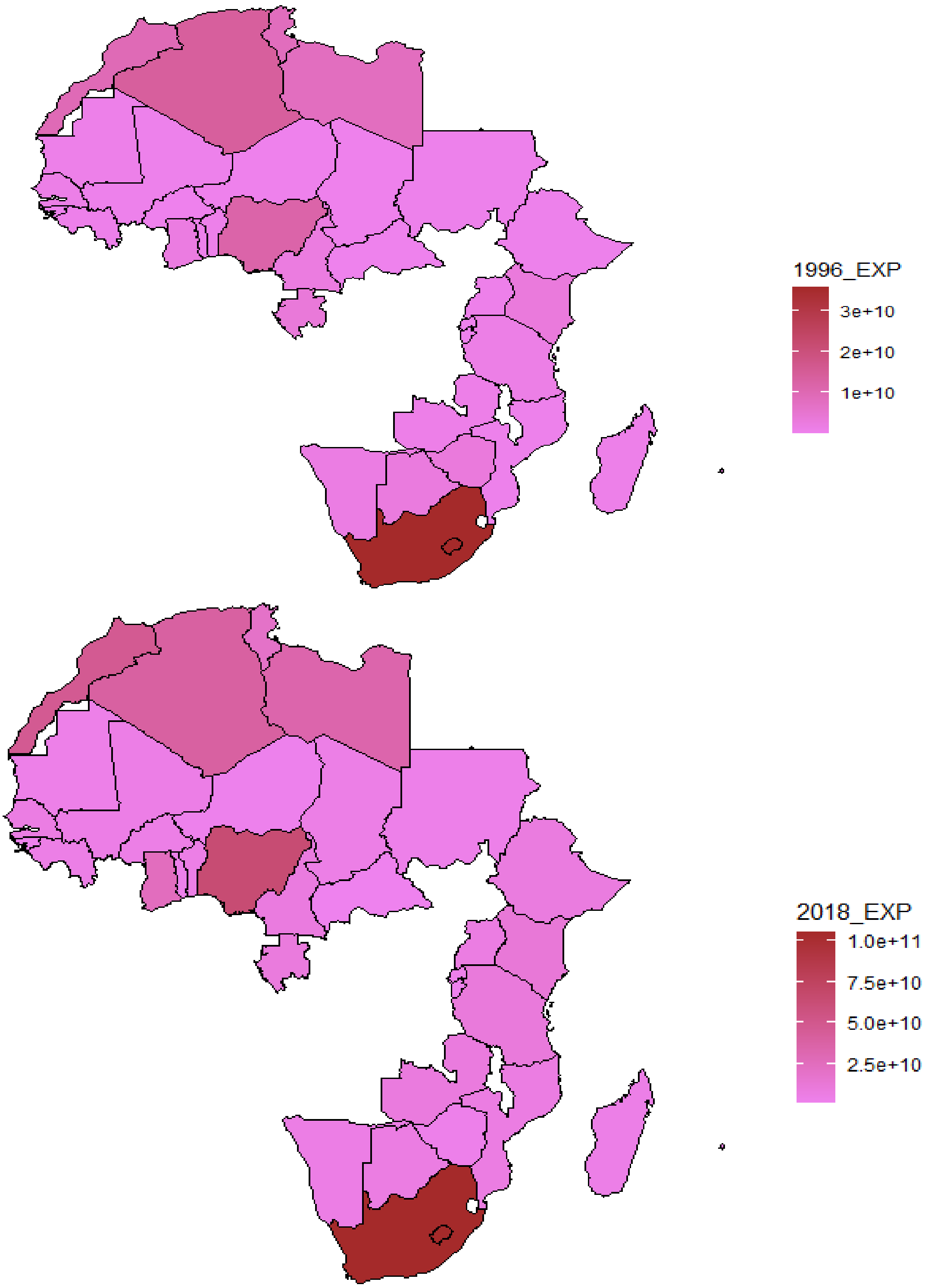

FIGURE 3: Exports of goods and services in Africa for the years 1996 and 2018

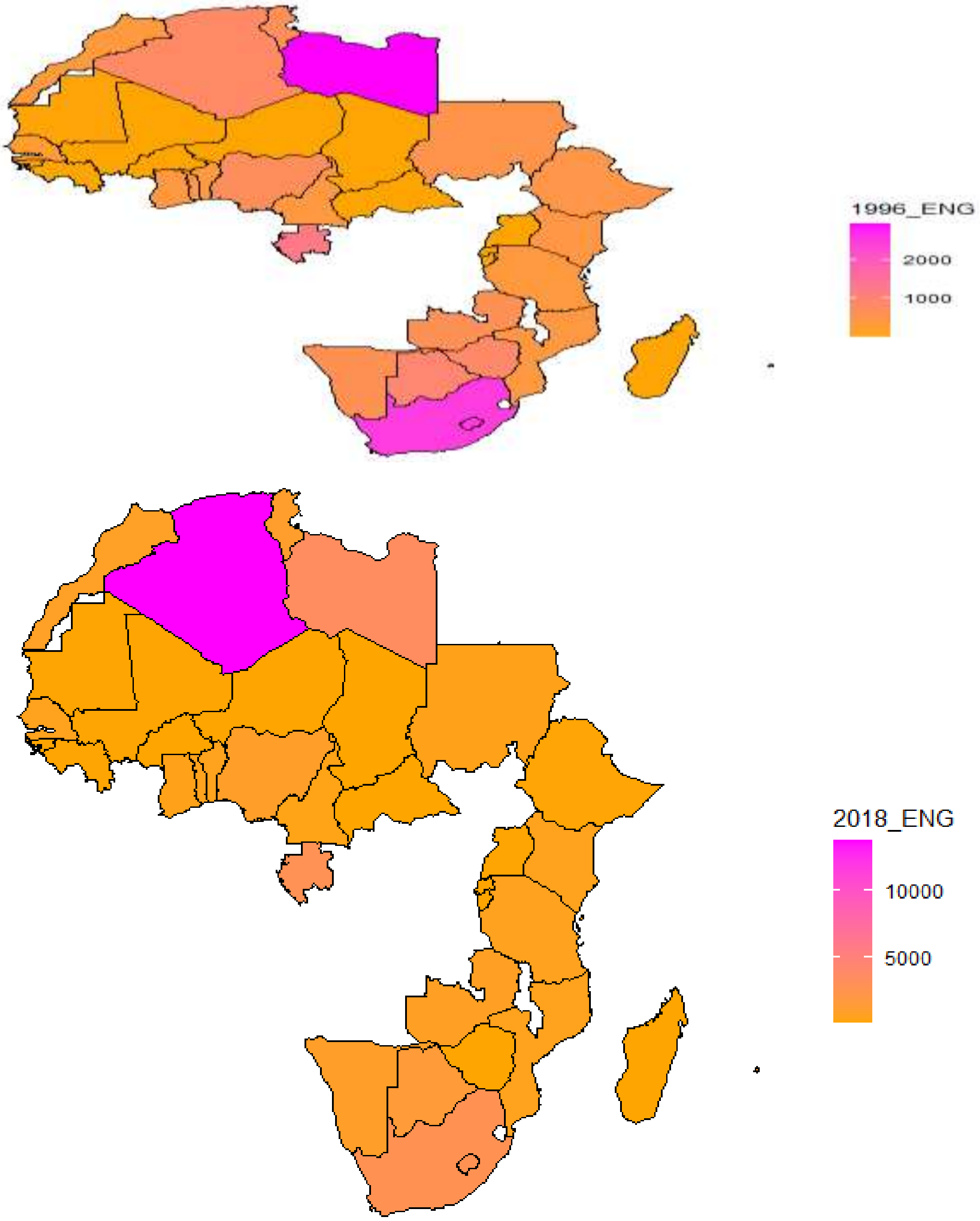

FIGURE 4: Energy consumption in Africa for the years 1996 and 2018

IV. EMPIRICAL RESULTS AND DISCUSSION

1.5 The Spatial autocorrelation assertion

Prior to the estimation of the spillover effect of energy consumption and exports on CO_2emissions, the spatial autocorrelation of Ln$CO_2$was screened to assess whether a country's CO_2emissions influences the neighboring countries. This was done by using the Moran's I assessment and the Local Indicators of Spatial Association (LISA) analytical tool. The Moran'I assessment for the countries selected is presented in Table 4, the index revealed a value greater than 1.5. As a result, CO_2emissions have a geographical autocorrelation. Furthermore, the Moran's plots for the years 1996, 2003, 2010, and 2018 were assessed as shown in

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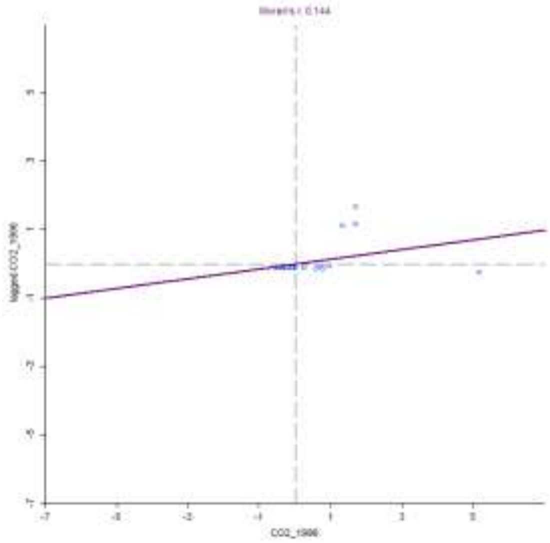
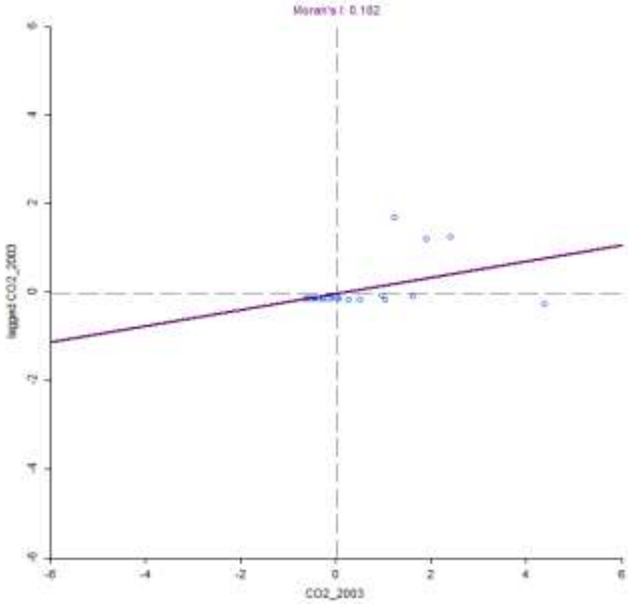
Figure 5 to further explore the spatial autocorrelation. Consequently, The LISA map (Figure 5) indicates that CO_2emissions obtained a significant local spatial agglomeration impact, in countries such Algeria, South Africa and Nigeria obtaining a High-High pattern (H-H), whereas countries like Lybia and Morocco had a Low-High pattern (L-H) for the years 1996 and 2003. For the years 2010 and 2018, Algeria and Nigeria obtaining a High-High pattern (H-H), Lybia and South Africa observed a high-Low (H-L) spatial agglomeration impact, whereeas Morocco had a Low-High pattern (L-H).

TABLE 4





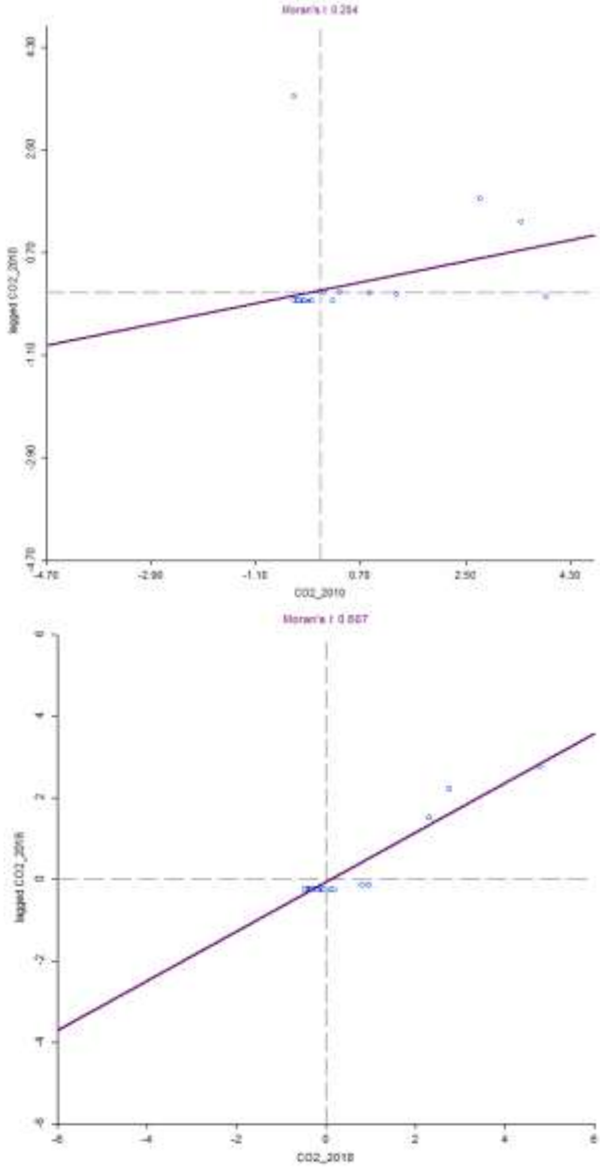


Figure 5: Scatter plot for the Moran I's index in Africa for the years 1996, 2003, 2010, and 2018

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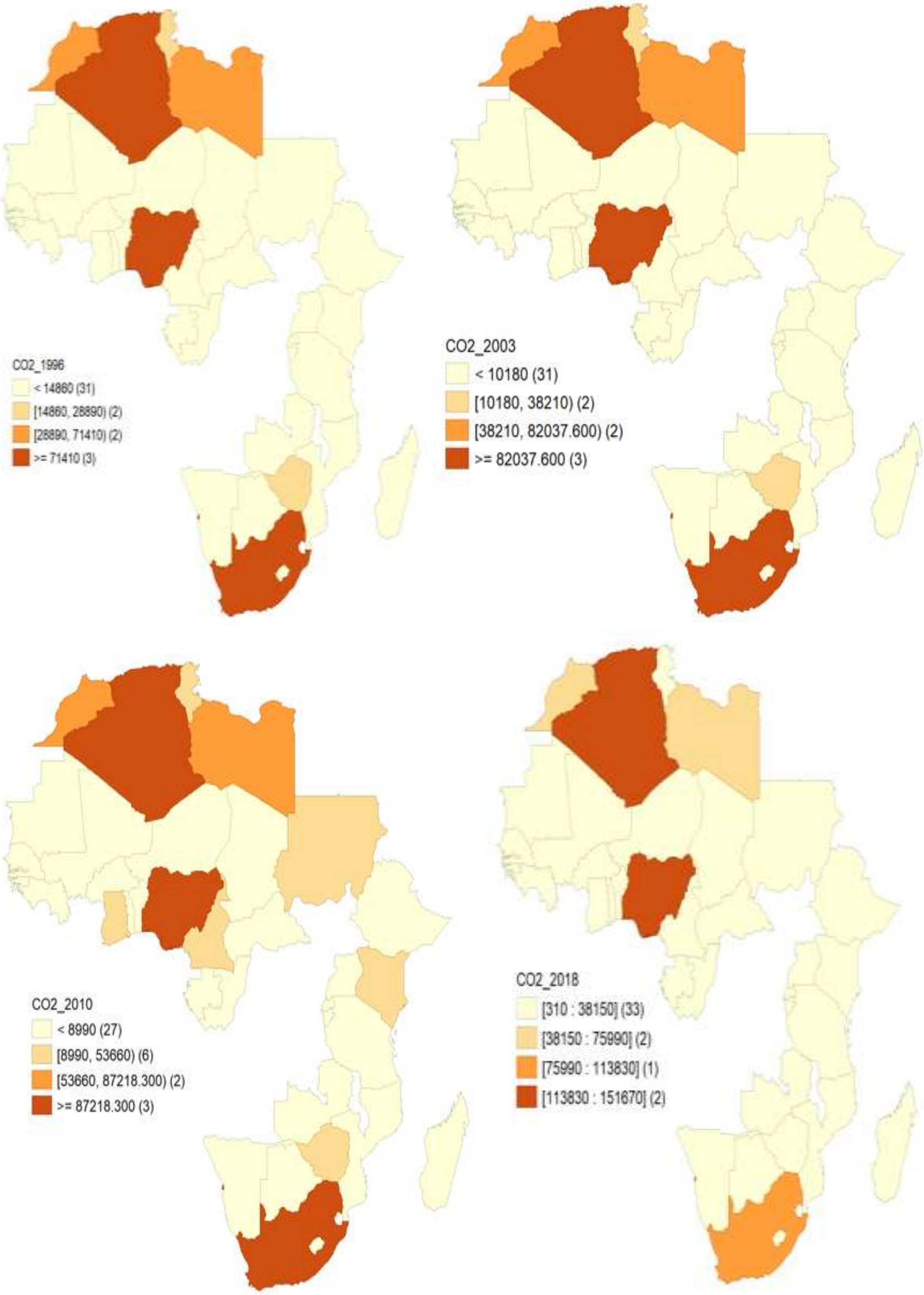

Figure 6: LISA plots for CO_2 emissions in Africa for the years 1996, 2003, 2010, and 2018

1.6 Non-Spatial panel model

As a result of considerable spatial autocorrelation, the study used non-spatial panel model in probing the existence of spatial dependency across spatial units using traditional Lagrange multiplier test before creating the spatial model for the influence of exports and energy usage on CO_2emissions. The rejection of the non-spatial models indicates that the spatial model must be used to captivate the spatiality via the processes outlined in section 2.2. The non-spatial results are revealed in Table 5. The geographic dependence variable was examined through the LM and its robust tests. The results revealed that all the four types of fixed effects affirm at a 1% significance level the spatial lag model. The pooled effects spatial and time-fixed effects, and the error and its robust spatial lag LM tests with time effects were significant.

As a result, the findings refute the hypothesis that spatial dependency does not exist, thus, confirming the existence of spatial correlation. The null hypothesis that time effects and spatial fixed effects was rejected by the LM test at a 1% significance level, revealing the importance of introducing spatial dependency elements, as well as justifying the model's extension to include time period fixed effects and space-fixed effects.

TABLE 5

1.7 Spatial Durbin model

Relying on the LR test and Wald test, the selection between the SAR, the SDM, or the SEM was done. At a 1% significance level, the Wald test $(47.01, DF = 25, P = 0.000)$ points that the SDM model is more suitable to the SAR. Likewise, the LR test $(33.83, DF = 25, P = 0.000)$, rejected the suitability of the SEM model, thus it was concluded that the SDM model is more convenient. The Hausman test was also performed to ascertain the best model between the random effects and the fixed effects. Table 6, indicates that at a 1% significance level, with the Hausman test $(112.69, DF = 31)$, the fixed-effect model is more appropriate in explaining the estimates. From Table 6, it could be seen that with a 0.8327 goodness-of-fit and a log-likelihood value (123.806), the spatial fixed effect model (column 2) surmount the other models. As a result, the interpretations will be restricted to its coefficients.

The coefficient of the spatial lagged component of the response variable was significant and positive, indicating that CO_2emissions from the surrounding countries have a positive impact on the focal CO_2emissions. This outcome is in line with the Moran I's plots and the spatial autocorrelation LR test in Table 4. This result shows that a 1% rise in an average CO_2emissions of the surrounding countries tend to increase the level $CO_2$of the focal county by 0.201%. This value suggests that countries with standardized air pollution tend to cluster together. As a result of the geographical autocorrelation, the estimates for the explanatory variables from the SDM model can't be stated as marginal effects and can't effectively capture the spatial spillover effect of CO_2emissions. Thus, to measure the impact of the explanatory variable and their spatial spillover on CO_2emissions, the study relies on the indirect, direct, and total effects.

TABLE 6

1.8 The estimates of direct, indirect, and total effects of SDM model

Table 7, reveals the decomposition of the indirect and direct effects from both the SDM and dynamic SDM models. The estimates' direct effects from the dynamic SDM models are very closed to the matching to the spatial fixed effects, indicating that the estimates are consistent and effecacious. However, the existing deviation in values is due to the existence of feedback effects which egest from adjacent countries and backward to the countries themselves. This is contained the estimates from the spatially lagged explanatory variables $(\sum W_{it} X_{it\gamma})$.

The weight of exports exerted on CO_2 emissions was identify to be positive and statistically significant in both the dynamic SDM and SDM models. To be more specific, based on the dynamic DSM estimates, a 1% increment in trade has the possibility of increasing CO_2 emissions by 0.111% in a the focal country. The possible inference that could be made on the positive impact of exports on CO_2 emissions is that free trade among the African countries has positive environmental outcomes due to the technique, effects of scale, and composition. This free trade has helped expand the trading partners of the economies either geographically close trading partners or far. Generally, trade has a positive impact on the environment through 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 than 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. Whereas for the indirect effect, a 1% percent increase in exports in the neighboring countries turns to positive CO_2 emissions by 0.045% in the target country. Thus, in its total effect, a rise in exports will correspond to a positive in the levels CO_2 by 0.156 in the local country. Due to spatial aggregation, the direct effect of exports (0.111) compared to the fixed effect model in the SDM was 0.127, revealing a feedback effects which amounts to 0.144 or 14.144% of the direct effect. These findings indicate that heightening a country's own exports increases emissions of CO_2 in its adjacent countries and its own territory. The provided results propose that exports has a positive and substantial impact on the *emissions of* CO_2, thus, exports had a increasing effect on CO_2 emissions. The positive impact of exports obtained on the emissions of CO_2 is in line with work done by Dauda, Long (37) in the Africa, where they revealed that exports has a positive impact on the emissions of CO_2. Likewise, the study done by Shahnazi and Shabani (38), confirmed a positive impact of exports on the emissions of CO_2.

The coefficients of ENG from the SDM and dynamic SDM models were statistically significant at 1% level. Notably, on the basis of dynamic SDM estimates, a 1% increment in ENG has the likelihood of increasing CO_2 emissions by 0.203%. The possible explanation of the positive effect of ENG on CO_2 emissions is that about 90% of the energy requirements in Africa countries are met by fossil fuel consumption (Wu et al., 2021). Inferring to this observation, a 1% increase in energy usage will result in a 0.203% step up CO_2emissions in the local region. An indirect effect of -0.097 was also revealed in Table 6. Meaning that a 1% step up on energy usage in the neighboring countries results in a 0.097% diminution of CO_2 in the local country. Considering the total effect, a rise of energy usage by a percentage turns to increase CO_2 in the local country by 0.300%. Thus, heightening a country's own energy usage increases CO_2 emissions in its adjacent countries and so does it step up its own territory's CO_2 emissions. The significant positive impact ENG on CO_2 emissions is affirmed by the work done by Mosikari and Eita (39), where they ascertained a positive impact of ENG on CO_2 emissions during their study on the impact of oil rents on greenhouse emission for the Gulf Cooperation Council countries. The positive effect of energy usage on CO_2 emissions observed is also in line with the work done by Hongxing, Abban (40) who stated that energy consumption has a positive impact on CO_2 emissions in Africa.

The coefficients of GDP on both the dynamic SDM and SDM are statistically significant and positively affect CO_2 emissions at a 10% level of significance. Specifically, in regards to the dynamic SDM model, a percentage gain in GDP turns to increase CO_2 emissions to rise at 0.113%. One reason for the positive effects may be that African countries' growth is still based on conventional fossil fuels. While there have been the campaign renewable energy usage, the rate of oil and coal usage to primary energy usage is still very high [41]. As a result, the usage of oil and coal combustion yields a significant rise in CO_2 emissions. Thus, increased economic growth could result in increased CO_2 emissions. Inferring to the positive effects of GDP on CO_2 emissions, it was concluded that the African economies must change their energy system toward a sustainable and clean structure if they want to achieve the decoupling of CO_2 emissions from economic growth. Similarly, the results revealed that CO_2 emissions are induced by GDP, with both indirect and direct effects been statistically significant and positive, however, the square of GDP had a negative impact on the emissions of CO_2. As a result, an inverted U-shaped was observed between GDP and the emissions of CO_2 in the selected African countries and thus the EKC hypothesis is confirmed. The inverted U-shape obtained in this study is in line with the work done by Balado-Naves, Baños-Pino (42), where they affirmed the presence of inverted U-shape in Europe.

Considering the marginal effects of other parameters in the model, it was revealed that IND, and URB all observed an indirect effects on CO_2 emissions. Meaning that IND, and URB in the local country and its adjacent countries will both heighten the emissions of CO_2 in the local country. Thus, it was argued that spatial effect exists. With regards to the difference between the direct effect and the SDM fixed effect with the variable urbanization resulted in a feedback effect (0.128). With urbanization having a direct effect been statistically significant and positive, it indicates that urbanization is a vital factor indicator of air pollution in the local country. Likewise, with its indirect effects also been positive and significant, reveals that CO_2 emissions in the adjacent countries have the possibility of affecting the local country by 0.069%. These outcomes are possibly because of the rapid expansion of the capital cities in countries which have resulted in more air pollution. The coefficient predicted for the direct effect of IND is statistically significant and negative, unveiling that a 1% increase of IND in the local country reduces the emissions of CO_2 by 0.096%. As result, a country with a higher IND is inclined to have fewer CO_2 emissions. However, the adjacent countries' emissions reduction by IND to the local country is 0.048%.

TABLE 7

V. CONCLUSION AND POLICIES IMPLICATION

The effects of exports and energy consumption on the emissions of CO_2 were explored using the spatial econometric approaches a dataset of 39 countries in African from 1996 to 2018. Thus, some important outcomes and conclusions based on the aforementioned results and discussions were as follows; The Moran's index revealed a downward trend across the period of the study, thus indicating that the spatial autocorrelation is reinforced. As a result, the possibility of reducing the difference between countries' emissions is the most effective strategy to reduce CO_2 emissions. The findings suggest that increasing energy price in a focal country turns to reduce the country's own CO_2 emissions and also reduces the emissions of its adjacent countries. Consequently, based on the observation obtained during the study, some policy implications derived are as follows;

(a) Countries in Africa must open up its trading policies and shift its competitive advantage in favor of cleaner production, as well as boost inter-country technology collaboration, including both emissions and production, in order to maintain the emissions of CO_2 at a low level. Again, to prevent countries from becoming more polluting in the future, the African Union could impose stringent regulations, such as imposing more technological procedures, which will allow emissions to be suppressed and, ultimately, environmental quality to improve. (b) The African Union could develop appropriate policies to optimize energy consumption and endeavor to break free from the chains of traditional energy consumption as quickly as feasible by all its countries. When it comes to the impact of energy consumption on the emissions of CO_2, traditional energy consumption (coal and oil) is heavily in most countries. Thus, the African Union should continue to enhance the share of the new energy sources in the energy consumption structure, such as natural gas, solar, and wind energy. As a result, the African Union should pay close attention to the growth of the renewable energy industry, implement appropriate preference policies, encourage the development of renewable energy industry, and enhance the proportion of renewable energy consumption. (c) Environmental legislation should have a moderating influence on energy structure and efficiency, and the African Union should take steps to support this. When it comes to environmental control and energy structure, the African Union should establish policies to emphasize both punishments and rewards equally. The African Union's incentive policy should favor the creation and usage of new energy firms, thereby encouraging energy-saving and new energy consumption. Punitive measures could be utilized to restrain businesses' obsolete and backward energy consumption behavior, while interest regulation (such as income redistribution) could be utilized to constantly optimize the energy usage structure. The African Union could create a market structure that encourages the trade of energy-saving technology and products, as well as clarify the property right of technological innovation, in order to encourage businesses to innovate.

Ethics approval and consent to participate
Not applicable
Consent for publication
Not applicable
Competing interests
The authors declare that they have no competing interests.
Acknowledgments
No
Funding
National Natural Science Foundation of China and with grant number 71503105
Credit Author Statement
Li Fanglin: Supervision and Validation**:** **Emmanuel Owusu:** Conceptualization, Methodology; **Emmanuel Owusu and Nelly Ataawomba Afuubi:** Data curation, Estimations, Writing of Original draft; **Emmanuel Owusu, Emmanuel Sogbou Kenne and Michael Verner Menyah:** Reviewing and Editing; **Olivier Joseph Abban**: Visualization and Software.

Table 1: Descriptive statistics

Variable	**Definition**	**Mean**	**Std.Dev**	**Min**	**Max**
LnCO$_2$	CO2 emissions (kt)	8.569	1.782	3.055	12.130
LnGDP	GDP per capita (current US$)	12.217	3.104	5.077	23.234
LnENG	Energy use (kg of oil equivalent per capita)	6.137	1.022	-0.608	8.277
LnEXP	Exports of goods and	21.018	1.769	17.905	24.282

	services (current US$)				
LnIND	Industry value added	1.634	1.634	4.567	-1.819
LnURB	Urbanization (Total)	11.327	2.019	5.957	14.908

Table 2: Correlation test results

Variable	$LnCO_2$	LnGDP	LnENG	LnEXP	LnIND	LnURB	Collinearity Statistics	
							VIF	Tolerance
$LnCO_2$	**1**							
LnGDP	0.416	**1**					1.892	0.240
LnENG	0.272	0.184	**1**				1.273	0.371
LnEXP	0.511	0.202	0.311	**1**			2.024	0.493
LnIND	0.187	-0.317	0.231	0.325	**1**		1.255	0.598
LnURB	0.167	0.289	0.105	0.271	0.233	**1**	2.894	0.677

Table 3: Unit root test of the employed variables

	CIPS						**CADF**					
	Levels			**First difference**			**Levels**			**First difference**		
Variable	Constant	Constant &Trend	Inf.	Constant	Constant &Trend	Inf.	Constant	Constant &Trend	Inf.	Constant	Constant &Trend	Inf.
$LnCO_2$	-1.201	-1.302	**I (0)**	-3.463[a]	-3.430[a]	**I (1)**	-1.034	-1.162	**I (0)**	-4.837[a]	-4.923[a]	**I (1)**
LnGDP	-1.370	-1.502	**I (0)**	-4.537[a]	-4.765[a]	**I (1)**	-1.224	-1.273	**I (0)**	-4.547[a]	-4.754[a]	**I (1)**
LnENG	-1.411	-1.342	**I (0)**	-4.966[a]	-4.647[a]	**I (1)**	-1.315	-1.144	**I (0)**	-4.779[a]	-4.870[a]	**I (1)**
LnEXP	-1.133	-1.154	**I (0)**	-5.081[a]	-4.985[a]	**I (1)**	-1.077	-1.207	**I (0)**	-5.105[a]	-4.549[a]	**I (1)**
LnIND	-1.400	-1.407	**I (0)**	-5.106[a]	-5.005[a]	**I (1)**	-1.241	-1.311	**I (0)**	-3.875[a]	-5.140[a]	**I (1)**
LnURB	-1.154	-1.093	**I (0)**	-4.778[a]	-4.980[a]	**I (1)**	-1.207	-1.312	**I (0)**	-4.113[a]	-4.767[a]	**I (1)**

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

Table 4: Moran' I statistics for CO_2 emissions

Year	Moran	Z-value	p-value	Year	Moran	Z-value	p-value
1996	0.151[a]	2.401	0.000	2008	0.197[a]	3.037	0.000
1997	0.153[a]	2.657	0.000	2009	0.231[a]	2.966	0.000
1998	0.155[a]	3.413	0.000	2010	0.325[a]	3.041	0.000
1999	0.158[a]	2.053	0.000	2011	0.371[a]	3.723	0.000
2000	0.163[a]	3.430	0.000	2012	0.403[a]	2.862	0.000
2001	0.168[a]	2.522	0.000	2013	0.471[a]	3.800	0.000

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 3 Mar 2022, pp: 868-886 www.ijaem.net ISSN: 2395-5252

2002	0.174^{a}	2.772	0.000	2014	0.467^{b}	2.977	0.000
2003	0.178^{a}	3.331	0.000	2015	0.473^{a}	2.895	0.000
2004	0.182^{b}	3.604	0.000	2016	0.492^{b}	3.233	0.000
2005	0.187^{a}	2.771	0.000	2017	0.544^{c}	2.996	0.000
2006	0.191^{c}	2.870	0.000	2018	0.573^{a}	2.657	0.000
2007	0.194^{a}	3.555	0.000				

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

Table 5: Non-Spatial panel model

Deteminants	Pooled OLS	Spatial-fixed effects	Time-fixed effects	Spatial and time-fixed effects
Constant	0.211^{a}	−	−	−
LnGDP	-0.143^{b}	-0.167^{c}	-0.263^{b}	-0.218^{b}
LnGDP2	-0.132^{a}	−0.288	−0.300	−0.317
LnENG	0.501^{c}	−0.321	−0.201	-0.308^{c}
LnEXP	0.146^{c}	0.103^{c}	0.022^{b}	0.019
LnIND	0.320^{b}	0.256	0.423^{c}	-0.219^{a}
LnURB	-0.411^{c}	-0.337^{a}	−0.300	−0.317
σ^2	0.033	0.021	0.0502	0.0321
R^2	7.811	7.114	7.002	6.871
Adjusted R^2	7.682	6.817	6.775	6.332
Log-likelihood	17.942	14.560	17.806	21.233
LM spatial lag	51.024 (0.000)	31.041(0.000)	27.117(0.000)	31.282(0.000)
Robust LM spatial lag	27.603 (0.000)	15.992(0.000)	20.541(0.000)	19.210(0.000)
LM spatial error	9.276 (0.000)	11.922(0.000)	8.986(0.000)	12.467(0.000)
Robust LM spatial error	7.450(0.000)	9.254(0.000)	9.938 (0.000)	7.965(0.000)
The joint test of significance LM	Fixed effects	Statistics	df	P-value
	Spatial fixed	121.367	34	0.000
	Time fixed	157.032	31	0.000

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

Table 6: Spatial Durbin model

Deteminants	Spatial-fixed effects (SDM)	Spatial-fixed effects (DSDM)	Time-period fixed effects	Spatial and time-fixed effects	Time-period random effects	Spatial and time-random effects
W* $LnCO_2$	0.353^{a}	0.201^{a}	0.243^{a}	0.189^{b}		0.177^{a}
LnGDP	-0.212^{b}	-0.132^{b}	-0.168^{a}	-0.177^{c}	-0.101^{a}	-0.126^{b}
LnGDP2	-0.163^{b}	−0.108	-0.110^{a}	-0.098^{c}	-0.123^{a}	−0.111
LnENG	0.417^{b}	0.312^{b}	0.122	0.131	0.125	0.133^{b}
LnEXP	0.188^{c}	0.127^{c}	0.244	0.287^{b}	0.312^{a}	0.270^{a}
LnIND	-0.176^{c}	-0.111^{c}	-0.103^{c}	-0.143^{c}	-0.122^{c}	−0.137
LnURB	0.347^{c}	0.302^{c}	0.416^{a}	0.168	0.441	0.322^{a}
W*LnGDP	-0.173^{c}	-0.097^{c}	-0.241^{b}	0.322^{a}	0.181^{c}	-0.233^{c}
W*LnENG	-0.277^{a}	-0.231^{a}	0.205^{c}	0.279	0.314^{a}	0.189^{a}
W*LnEXP	0.301^{b}	0.212^{b}	0.199	0.321^{a}	0.272^{a}	-0.281^{a}
W* LnIND	0.221^{b}	0.188^{b}	0.438^{c}	0.147	0.122^{c}	0.117^{c}
W*LnURB	-0.207^{a}	-0.132^{a}	−0.122	-0.181^{c}	-0.331^{a}	-0.260^{a}
σ^2	0.0091^{a}	0.0052^{a}	0.0039^{a}	0.0062^{a}	0.0022^{a}	0.0048^{a}
R^2	0.7038	0.8327	0.4331	0.2633	0.2153	0.5951
Log-likelihood	211.029	123.806	95.617	47.533	73.227	67.147

Diagnotic tests	Statitiscs	Df	P-value
Hausman test	112.69	31	0.000
Wald test spatial lag	47.07	25	0.000
LR test spatial error	33.83	25	0.000

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

Table 7: Decomposition estimates of direct, indirect, and total effects of SDM model

Variables	Dynamic SDM			SDM		
	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
LnGDP	-0.113^{a}	-0.048^{b}	-0.161^{a}	-0.216^{a}	-0.084^{a}	-0.300^{a}
LnGDP2	-0.074^{b}	-0.052^{a}	-0.126^{b}	-0.113^{a}	-0.022^{b}	-0.135^{a}
LnENG	0.203^{a}	0.097^{c}	0.300^{c}	0.236^{a}	0.103^{c}	0.339^{a}
LnEXP	0.111^{c}	0.045^{a}	0.156^{b}	0.196^{c}	0.072^{b}	0.268^{a}
LnIND	-0.096^{a}	-0.048^{c}	-0.144^{c}	-0.112^{b}	-0.057^{a}	-0.169^{a}
LnURB	0.174^{b}	0.069^{a}	0.243^{c}	0.193^{c}	0.072^{b}	0.265^{a}

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

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