Volume 6, Issue 10, October – 2021 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165

Ecological Footprint and Climate Change: The role of Gas Consumption in Five African Macro Economies

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Abstract:- The African continent does not come behind in global emissions and non-renewable energy consumption. The continent still depend largely on non-renewable sources for energy production, even when other continents have achieve some success in their energy mix. Also, proper waste management through harmless discharge and disposal can help reduce the ecological footprint. This study examined the relationship between ecological footprint, carbon dioxide emission as a measure of climate change and gas consumption in five African macroeconomic countries. The study engaged a Levin-Lin-Chu and Covariate Augmented Dickey-Fuller tests for the presence of Unit root, then the Autoregressive Distributed Lag Bound tests methods for co-integration between the variables. The variables became stationary at the first order of differencing. Furthermore, the ARDL bound tests proved the absence of co-integration between the variables in the region for the period 1980 to 2017. Hence, no co-integrating pattern among the variables. However, dry gas consumption is significant to ecological footprint in the countries.

I. INTRODUCTION

Ecological Footprint compares how quickly we utilize resources and generate wastes to how quickly ecosystem can absorb and produce resources. Mankind has suffered ecological overrun as far back as the 1970s, with yearly resource requirements surpassing Earth's bio-capacity. To deliver the resources we utilize and absorb human waste, humankind consumes the equivalent of 1.7 Earths presently. This implies that the Earth currently needs a year and eight months to replenish what humans consume annually. By excessive fishing, excessive harvesting of forests, and venting more CO2 into the environment than forests can absorb, we utilize natural resources and services than the ecosystems can replenish (Global Footprint Network, 2021a).

In Africa, biodiversity has plummeted by 40percent in the last four decades. This decrease demonstrates the deterioration of natural systems that are essential to Africa's present and projected wealth (World Wide Fund, 2012). According to (Nick Conger, 2013), about 70percent of the global population will reside in cities by 2050, this percentage is nearly as many as the population in 2013. This migration is primarily taking place in less developed regions with a fast growing middle class, which puts extra pressure on resources due to its increased purchasing power. This description fits that of the African region. Furthermore, the fast population development and rising wealth are altering consumption trends, resulting in a steady increase in Africa's ecological footprint, and consequently the area required to generate the resources consumed by a specific group or activity. By 2040, Africa's entire ecological impact is expected to double (World Wide Fund, 2012), and by 2050, it will take the size of two planets to absorb the effect of the waste the earth generates (Simione Talanoa, 2008). Apparently, an ecological footprint overshoot is a very dangerous situation for global society. The further we linger in overshoot, the higher the possibility of negative effects for fisheries, woodlands, as well as other natural ecosystems that constitute mankind's life-support structures, and the more likely ecosystems will be unable to return to previous levels of productivity. (I Love A Clean San Diego, 2017; Kushal Naharki, 2019) describe means to reduce the ecological footprint. Some of these means include: (a.) Decreasing the use of the plastic materials; (b.) Switching to Renewable Energy; (c.) Decreasing Waste; (d.) Using Cleaner Transport; (e.) Planting trees. Sadly, Africa has much to catch up with in this regard, when compared to other continents.

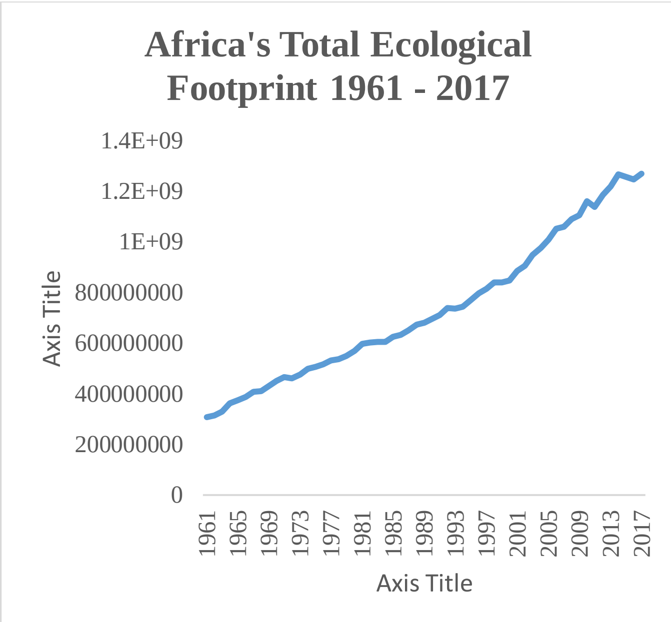

Figure 1: Africa's Total Ecological Footprint 1961 – 2017 (Global Footprint Network, 2021b)

ISSN No:-2456-2165

Carbon emissions are a form of greenhouse gas (GHG) that occurs when carbon dioxide is released into the atmosphere as a result of a human action or process. They are important in this discussion because they are the most substantial sort of emission in terms of volume. Carbon emissions accounted for 82% of the entire greenhouse gas (GHG) emissions in the United States in 2017 (Stephanie Osmanski, 2020). Greenhouse gases have preserved Global average temperature liveable for humankind and countless other creatures by capturing heat from the sun. However, those gases have become out of equilibrium, threatening to significantly alter which living creatures can live on earth and where they can survive (National Geographic, 2019). Burning organic resources such as coal, oil, gas, wood, and solid waste produces the majority of carbon dioxide emissions (National Geographic, 2019). South Africa is ranked the 12th largest greenhouse gases emitting country globally (Naledi Mashishi, 2021) and the largest in Africa followed by Egypt, Algeria and Nigeria, in that order (Ayompe et al., 2021).

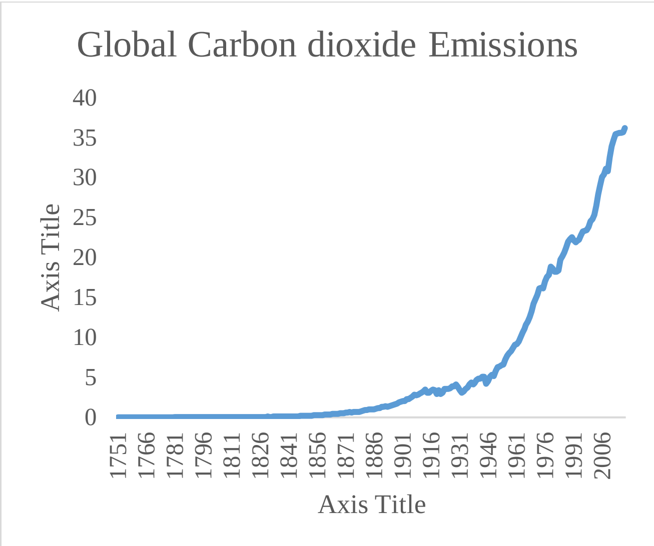

Figure 2: Carbon dioxide emission trend between 1751and 2012 (U.S. Energy Information Administration, 2020).

Although Africa's quota in the global warming is said to be insignificant, the (UN Climate Change Conference, 2006) stated that she is the continent most vulnerable to climate change's consequences, even her Gross Domestic Product (Foresight Africa, 2020) and that having a grasp of global patterns requires studying and monitoring Africa's weather, climate and environment. It also added that, measures, in terms of policies should be made and implemented, so that climate change will not result to decreased food production, flooding and deluge of coastal region and deltas, the development of water - related diseases and the danger of malaria, as well as cause disturbances in natural ecosystems and biodiversity loss in the close future, thereby propounding the food insecurity and other current challenges faced by the continent.

In Africa, urbanization is on the increase, and this trend is projected to continue. Infrastructure and land usage planning, particularly waste management, are not keeping up with the increase of metropolitan areas, which is a source of worry (about 3.5 percent yearly, highest in the planet). Despite this growth and the need to meet the demands of the population, many African countries still struggles to minimize or rather recycle her harmful pollutants, inorganic and organic wastes such as the GHGs from machines, vehicles, and others. Also, polythene and plastic bags for packaging, Agricultural and bio-wastes, where necessary. Other continents have made reasonable progress in taking measures that reduces and minimize the garbage. Electric cars and so many others are means they use in this process. Africa's gas use and generation will increase at one of the world's quickest rates through 2040 (African Energy Chamber, 2021). This use cuts across industries, transportation, power and so on. Invariably, gas powers to a large extent, the African economy. It is therefore essential to study the effect of gas use on Africa's emissions and footprint bearing the environmental needs of the future generation.

II. LITERATURE REVIEW

Investigating the pattern of household energy usage could indicate quite an amount of information. It could help evaluate the effectiveness of energy efficient household appliances, since the option is best adopted for household use rather than the industrial use, and it has been adopted widely, especially in developed countries, inclusive of small scale renewable energy use. Also, it could indicate the role of house energy use in the overall carbon dioxide emissions and ultimately, global warming. (Azevedo et al., 2013) investigated the cost (economic and efforts) and time frame required to drastically reduce residential energy consumption and consequently the carbon dioxide emissions in the United States. It was discovered that overnight substitution of the entire stock of main household appliances results in a carbon dioxide reduction of little over 710 x 10 (6) tonnes per year, or a 56 percent reduction in baseline residential emissions. A policy aimed at reducing usage of energy rather than carbon dioxide emission, on the other hand, would result in a 48 percent reduction in carbon dioxide emission from the nine most energy-intensive home end-uses. Although, 20 percent of the overall greenhouse gas emissions in the United States is caused by household energy consumption, (Goldstein et al., 2020) found that decarbonizing the residential energy usage can be helpful in achieving 28 percent decrement in the emissions. Furthermore, income and economic wellbeing has an influence on household energy-emission nexus, as wealthier citizens in the United States have 25 percent per capital carbon footprint more than citizens with low-income. The difference in emission nexus could be as high as fifteen times from a neighbouring community.

Between 1965 and 2015, (Khan et al., 2020) discovered that energy use and economic development raises the carbon dioxide emissions in Pakistan both in short period and long period, from an Autoregressive Distributed Lag model. (Abbas et al., 2021) also considered Pakistan in investigating the effect energy consumption from all sources traditional energy (coal, fossil fuels, nuclear and natural gas inclusive) and renewable energy sources, has on carbon dioxide emissions. However, ecological footprint, urbanization and transportation were introduced in the study. In an Autoregressive Distributed Lag model study on the variables within 1970 and 2018, ecological footprint, traditional and renewable sources of energy contributes to carbon dioxide emissions in the short-term, although the relationship is insignificant. Furthermore, traditional energy sources have a positive relationship with emissions, while renewable sources have a negative relationship in the long term.

Examining the Environmental Kuznets' Curve (EKC) in six Central American countries, (N Apergis, 2009) studied the carbon dioxide emissions, energy usage and output in the region. Covering the period 1971 to 2004, the study employed the panel vector error correlation technique and discovered that Energy usage has a statistically significant positive effect on emissions in long-term equilibrium, whereas real output follows the inverted U-shape trend linked with the Environmental Kuznets Curve (EKC) concept. The short-term dynamics show one-way directional and two-way directional causality betwixt energy usage and real output, respectively to carbon dioxide emissions, as well as a two way directional causality between energy usage and real output. There seems to be two-way directional causality between energy usage and carbon dioxide emissions in the long term.

In consideration of a macro-scale, (Tong et al., 2020) examined economic development, energy usage and emissions in E-7 (Brazil, India, Indonesia, Mexico, People's Republic of China, Russia, and Turkey). The bootstrap Autoregressive Distributed Lag (ARDL) study reveals that co-integration does not exist between economic development, energy usage, and carbon dioxide emissions in China, Mexico, Turkey and Indonesia. However, when carbon dioxide emissions was the predicted variable, an evidence of co-integration was found for Brazil and in India and Russia when energy usage was the predicted variable. Only Indonesia defies the existence of short-term granger causality, in the other E-7 countries, existence of granger causality was confirmed. The outcomes of the study consistently proved that energy consumption is a lead cause of emissions.

In Ghana, (Asumadu-Sarkodie & Owusu, 2016) studied the interaction between carbon dioxide emissions, Gross Domestic Product, energy usage, and population growth between 1971 and 2013. The Autoregressive Distributed Lag methods and the Vector Error Correlation Model given co-integration were used in the study before the Granger Causality test was conducted. Two-way directional causality was found between energy usage and Gross Domestic Product, as well as one-way directional causality between carbon dioxide emissions and energy usage, carbon dioxide emissions and Gross Domestic Product, carbon dioxide emissions and population, and population to energy use. According to long-run elasticities, a 1 percent rise in Ghana's population will result in 1.72 billion tons of carbon dioxide escaping into the atmosphere. There was found an evidence of a short-period equilibrium interaction between energy usage and CO2 emissions, as well as between Gross Domestic Product and CO2 emissions. Very similar to this study is the examination of (Zoundi, 2017) on 25 African countries for the period 1980 through 2012. The study engaged a panel co-integration method to check if there is a relationship between carbon dioxide emissions, renewable energy and the Environmental Kuznets' Curve. The findings show that EKC forecasts are not completely validated. CO2 emissions, on the other hand, appear to rise in tandem with per capita income. Overall, the estimates show that renewable energy, with a negative impact on Carbon dioxide emission and a growing long-term effect, remains a viable alternative to traditional fossil-fuelled energy. In the short and long period, however, the influence of renewable energy is dwarfed by primary energy use, implying more worldwide synergy for meeting environmental concerns.

There are many studies in literature, a bulk of which considered the effect of energy consumption on emissions, some also considered ecological footprint. However, the African continent has not been well understudied. Many of the researches emphasize the pertinence of reducing emissions by renewable energy consumption over the conventional means. Of concern is still the dependence of Africa on these conventional sources of energy. Hence, this study aims to investigate the impact of gas usage, which is from a traditional energy source on both carbon dioxide emissions and ecological footprint in five Africa macroeconomic countries, namely: Algeria, Egypt, Morocco, Nigeria and South Africa.

III. METHODS AND MATERIALS

The Global Footprint Network was explored and a time series data on ecological footprint measured in global hectare (gha). The carbon dioxide emissions dataset was collected from the World Bank database, measured in metric tons per capita, while the dataset on gas consumption was gotten from the United States Energy Information Administration, measured in billion cubic feet (bcf). The time series spans the period 1980 to 2017.

3.1. Unit Root Test

According to the requirements of the classical time series model, the series $\{y_t\}$ must be stationary, and errors must have a zero mean and finite variance. Without confirming stationarity, traditional time series modelling will result in spurious/false regression (Granger & Newbold, 1974).

3.1.1.Augmented Dickey Fuller Unit Root Test

The t-statistic of the λ_i coefficient of the given regression below is known as the Augmented Dickey-Fuller test (Dickey & Fuller, 1979):

$$\Delta y_{it} = \lambda_i y_{it-1} + \sum_{j=1}^{P} \eta_j \Delta y_{it-j} + \mathcal{E}_{it}\,, \qquad 1$$

Where $\lambda_i = \rho_i - 1$
The null hypothesis (non-stationarity) is given as:

$$H_0: \lambda_i = 0 \; (or \; \rho_i = 1)$$

For the panel unit root test based on the ADF regression, the alternative hypothesis is uncommon

$$H_1: \lambda_i = \lambda < 0 \; (or \; \rho_i = \rho < 1) \; for \; all \; panels$$
$$H_1: \lambda_i < 0 \; (or \; \rho_i < 1) \; for \; some \; panels$$

Where, Δ *is the first differencing operator, having P numbers of lags*, ε_{it} is a stationary stochastic error balancing the autocorrelation error.

The model for the Covariate Augmented Dickey-Fuller Unit Root test is given as:

$$a(L)\Delta y_t = \mu + \theta t + \delta y_{t-1} + b(L)'\Delta x_t + e_t \qquad 2$$

L is the lag operator. Hypothesis is as thus:

$$H_0: \delta = 0$$
$$H_1: \delta < 0$$

3.2. Autoregressive Distributed Lags

Autoregressive Distributed Lags specification employs both endogeneity and exogeneity. It differs from the Vector Autoregression (VAR) technique, which only utilizes endogeneity. Autoregressive Distributed Lags is advantageous than other techniques based on some points. Firstly, the Johansen technique is less advantageous than the Autoregressive Distributed Lags model for small and finite sample sizes, which is prevalent in climate modelling, as contrasted to other co-integration tests. Another point is that, while the Autoregressive Distributed Lags model needs that no variables be integrated of order 2, the technique could still be used with variables that are integrated of order 1, integrated of order 0, or a mixture of both. Also, the Autoregressive Distributed Lags model only requires the setup of a single equation, making it easier to estimate and comprehend than alternative methods that demands the construction of many equations. Lastly, the Error Correlation Model and the long run coefficients are used in the Autoregressive Distributed Lags model to construct short-run correlations (Zoundi, 2017). The Autoregressive Distributed Lags model is specified as:

$$Y_t = \gamma_{0i} + \sum_{i=1}^{p} \delta_i Y_{t-1} + \sum_{i=0}^{q} \beta_i' X_{t-i} + \varepsilon_{it} \qquad 3$$

Where,
Y_t' is a vector of the dependent variable.
The variables in $(X_t')'$ are allowed to be only $I(0)$ or $I(1)$ or co-integrated,
β and δ are coefficients and γ is a constant,
$i = 1, \dots, k; p, q$ are optimal lag orders,
ε_{it} is a stochastic error vector.

IV. RESULTS AND DISCUSSION

3.3. Data Visualization

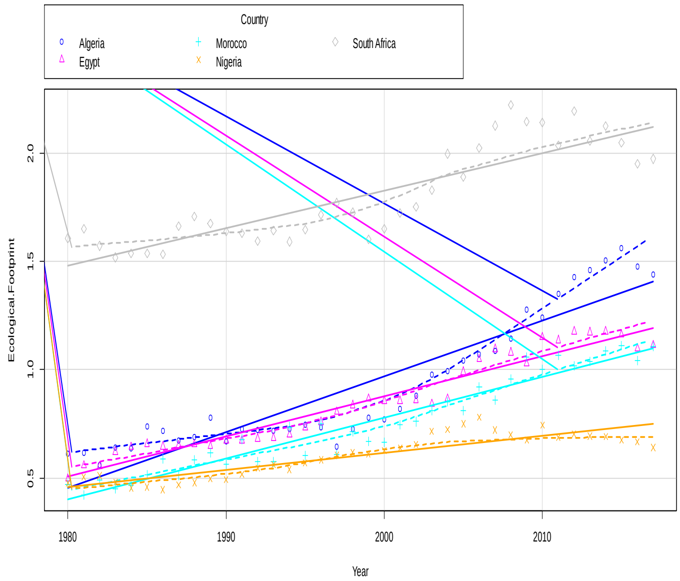

Figure 3: Scatter Plot for Ecological Footprint in the top five African macro economies between 1980 and 2017

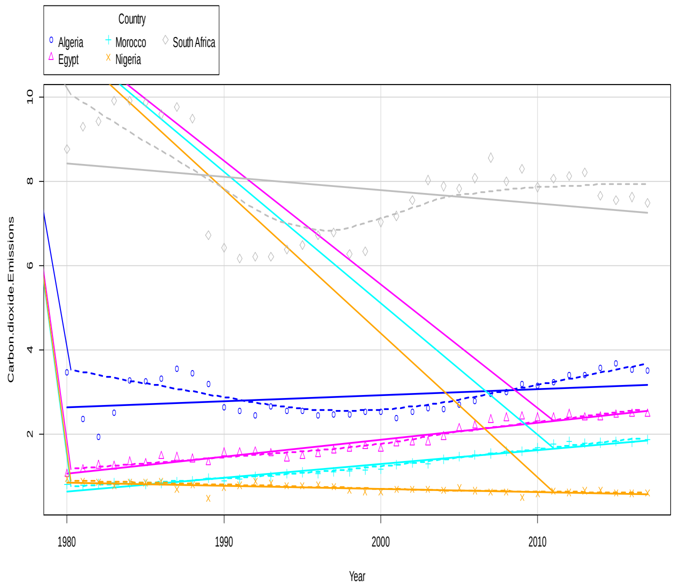

Figure 4: Scatter Plot for Carbon Dioxide Emissions in the top five African macro economies between 1980 and 2017

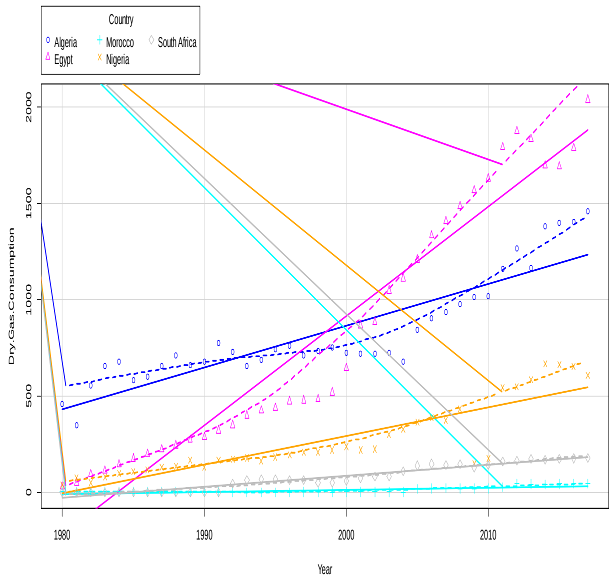

Figure 5: Scatter Plot for Dry Gas Consumption in the top five African macro economies between 1980 and 2017

Figures 3-5 displays the scatterplot of the variables: Ecological Footprint, Carbon dioxide emissions and Dry gas consumption in the five countries. Carbon dioxide emissions and ecological footprint distinct range in South Africa than in the other four economies. Gas consumption only slightly increased over the period in Morocco, lesser than that of South Africa, while Egypt and Algeria had the sharpest increase. Carbon dioxide emissions seems to decrease over time in Nigeria and South Africa. Ecological footprint has increased generally in the five countries, with Nigeria having the lowest increment. From the fluctuations in figures 3 and 4, it can be deduced that ecological footprint and carbon dioxide emissions are unstable in South Africa than in the other countries.

3.4. Unit Root Tests

Table 1: Unit Root Tests for Dry Gas Consumption

Tests (Gas Consumption)	Value	p-value
CADF Unit Root Test (no differencing)	-3.2618	0.07594
Levin-Lin-Chu Unit-Root Test (first order differencing)	-9.0635	< 2.2e-16

Table 1 presents the unit root tests for dry gas consumption. Although the p-value of the CADF is slightly greater than the significance level with no differencing, Levin-Lin-Chu unit-root test is less than the significance level (0.05) at the first order differencing, implying stationarity.

Table 2: Unit Root Tests for Carbon Dioxide Emissions

Tests (Carbon dioxide Emissions)	Value	p-value
CADF Unit Root Test (first order differencing)	-11.251	< 2.2e-16
Levin-Lin-Chu Unit-Root Test (first order differencing)	-11.843	< 2.2e-16

Table 2 shows the unit root tests for carbon dioxide emissions, both the CADF and the Levin-Lin-Chu unit root tests have p values less than the significant level (0.05), implying that the series is stationary at the first order of differencing.

Table 3: Unit Root Tests for Ecological Footprint

Tests (Ecological Footprint)	Value	p-value
CADF Unit Root Test (first order differencing)	-11.9	< 2.2e-16
Levin-Lin-Chu Unit-Root Test (first order differencing)	-15.847	< 2.2e-16

Table 3 shows the unit root tests for ecological footprint, both the CADF and the Levin-Lin-Chu unit root tests have p values less than the significant level (0.05), implying that the ecological footprint series is stationary at the first order of differencing.

3.5. Autoregressive Distributed Lags

The Autoregressive Distributed Lag is suitable for series that are stationary after at most the second level of integration. The order of integration of the series under study does not also have to be the same.

Table 4: ARDL Model summary for Ecological Footprint against Gas Consumption

Coefficients					
	Estimates	Std. Error	t-statistics	p-value	significance
(Intercept)	3.29E-02	2.19E-02	1.504	0.134	
L(Ecological Footprint, 1)	9.07E-01	7.40E-02	12.262	< 2e-16	***
L(Ecological Footprint, 2)	7.23E-02	7.46E-02	0.969	0.334	
Dry Gas Consumption	2.86E-04	4.57E-05	6.267	2.60E-09	***
L(Dry Gas Consumption, 1)	-2.72E-04	6.44E-05	-4.219	3.87E-05	***
L(Dry Gas Consumption, 2)	-2.57E-05	5.06E-05	-0.508	0.612	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1208
Multiple R-squared: 0.9379
Adjusted R-squared: 0.9362

From table 4, which presents the ARDL coefficients and their significance. Ecological footprint at lag 1, dry gas consumption at lags 0 and 1 are significant in the model at 5 percent levels, even at 1 percent. The first lag of the dry gas consumption however has a negative relationship with ecological footprint. The R squared and Adjusted R squared values indicates that the independent variables were able to explain over 93% of the variations in ecological footprint. This means the model has a good performance.

Table 5: ARDL Model Evaluation (Ecological Footprint against Gas Consumption)

F-statistic	Degree of Freedom	p-value
549.4	182	< 2.2e-16

From table 5, the p-value of the F-statistic being <2.2e-16, is less than 0.05, meaning that the model is very significant statistically. Hence, a good model.

Table 6: Optimal Lag for ARDL Model (Ecological Footprint against Gas Consumption)

S/N	Ecological Footprint	Dry Gas Consumption	BIC
1	1	1	-242.592
2	1	2	-235.006
3	2	2	-230.736

From table 6, the optimal lag combination is the lag 1 of both ecological footprint and dry gas consumption, having the lowest Bayesian Information Criterion.

Table 7: Bounds t-test for no Co-integration between Eco logical Footprint and Gas Consumption

Lower-boun d I(0)	t-statistics	Upper-boun d I(1)	p-value
-2.86	-1.0862	-3.22	0.7936

Since the t-statistic is not above the upper bound value of the bounds t-test, there is no possible co-integration between ecological footprint and dry gas consumption.

Table 8: Bounds F-test (Wald) for no Co-integration bet ween Ecological Footprint and Gas Consumption

Lower-bound I(0))	F (Wald) Test	Upper-bound I(1)	p-value
4.94	0.77848	5.73	0.8679

Since the F-statistic falls below of the lower of the bounds F-test, we conclude that there is no co-integration between ecological footprint and dry gas consumption in the countries.

Table 9: ARDL Model summary for Carbon Dioxide Emissions against Dry Gas Consumption

Coefficients				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.127912	0.091153	1.403	0.162
L(Carbon dioxide Emissions, 1)	1.06303	0.073288	14.505	<2e-16 ***
L(Carbon dioxide Emissions, 2)	-0.09383	0.07389	-1.27	0.206
Dry Gas Consumption	0.00027	0.000262	1.028	0.306
L(Dry Gas Consumption, 1)	-0.00042	0.000353	-1.197	0.233
L(Dry Gas Consumption, 2)	0.000118	0.000263	0.449	0.654

Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Residual standard error: 0.6943
Multiple R-squared: 0.9344
Adjusted R-squared: 0.9326

From table 9, which presents the ARDL coefficients and their significance. Only carbon dioxide emissions at lag 1, is significant in the model at 5 percent levels, even at 1 percent. It appears that dry gas consumption, up to the second lag order, is not statistically significant in carbon emissions. Also, the R squared and Adjusted R squared values indicates that the independent variables were able to explain over 93% of the variations in carbon dioxide emissions. This means the model has a good performance.

Table 10: ARDL Model Evaluation (Carbon Dioxide Em issions against Gas Consumption)

F-statistic	Degree of Freedom	p-value
518.2	182	< 2.2e-16

From table 10, the p-value of the F-statistic being <2.2e-16, is less than 0.05, meaning that the model is very significant statistically. Hence, a good model.

Table 11: Optimal Lag for ARDL Model (Carbon Dioxide Emissions against Gas Consumption)

S/N	Carbon dioxide Emissions	Dry Gas Consumption	BIC
1	1	0	418.1809
2	1	1	421.8207
3	2	2	426.8761

From table 6, the optimal lag combination is the lag 1 of carbon dioxide emissions and no lag for dry gas consumption, having the lowest Bayesian Information Criterion.

Table 12: Bounds t-test for no co-integration between Carbon Dioxide Emissions and Gas Consumption

Lower-bound I(0)	t- test	Upper-bound I(1)	p-value
-2.86	-1.5733	-3.22	0.6125

Since the t-statistic is not above the upper bound value of the bounds t-test, there is no possible co-integration between carbon dioxide emissions and dry gas consumption.

Table 13: Bounds F-test (Wald) for no Co-integration between Carbon Dioxide Emissions and Gas Consumption

Lower-bound I(0)	F (Wald) Test	Upper-bound I(1)	p-value
4.94	1.2442	5.73	0.7557

Since the F-statistic falls below of the lower of the bounds F-test, we conclude that there is no co-integration between carbon dioxide emissions and dry gas consumption in the countries.

V. CONCLUSION

This study investigated the relationship between ecological footprint, carbon dioxide emissions and dry gas consumption. The unit root test on the series was stationary at the first order differencing. The Levin-Lin-Chu and the Covariate Augmented Dickey-Fuller (CADF) Unit root tests were used in the study. The Autoregressive Distributed Lag bound tests were employed to test for co-integration relationship between the variables. No evidence was found for co-integration between carbon dioxide emissions and dry gas consumption, also between ecological footprint and dry gas consumption in the economies examined. Hence, there may not be need for further investigation on the nature of relationship or causality. However, dry gas consumption was found to be significant to ecological footprint, and can be used for prediction.

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