An Impulse of Human Activities to Carbon Dioxide Gas Emissions in the Sub-Saharan Africa Region

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Abstract
It is complicated to determine with exactitude the share of responsibility of the various sources of pollution for Africa. This intricacy emphasizes that pollution is not always considered a major risk for the continent. The existing data are still too few and often too imprecise to assess the extent of pollution on the continent. Sub-Saharan Africa is challenged by increasing pollution reinforced by a lack of politics and goodwill to formulate and implement good practices to deal with climate change issues. This paper highlight trends in carbon emissions due to agricultural land, energy use, agriculture-forestry and fisheries (value adds), real gross domestic product, and industry and construction based on their importance to the productive capacity of SSA. The output from the proposed study of causality between variables using the impulse response functions and the forecast error decomposition revealed this: the rise in agriculture/forestry, and fisheries, and energy use has positive shocks on CO_2 emissions. The carbon emissions growth in the SSA does not necessarily reckon on agricultural land, industry construction or manufactual construction, and real gross domestic product.
Keywords: Pollution, atmospheric pollutants, CO_2 emissions, climate change, policy

1. Introduction
Climate change and its effects now seem to be proven and linked, at least in part, to the additional anthropogenic greenhouse effect, which is reflected in the inclusion of this major issue on global political agendas(Levine and Kline 2017). The natural greenhouse effect that makes the Earth home has been modified by human activities [Solomon et al.(2007)and Society(2021)]. These activities emit greenhouse gases (GHGs) and change the atmosphere's quality (Mikhaylov *et al.* 2020). GHGs and atmospheric pollutants are today the main emitters and have an identical source (transport, housing, industry, and agriculture)(Eurostat 2015). There is evidence that burning fossil fuel leads to the increase of carbon dioxide and other harmful gases in the atmosphere(*NAS* 2021)and (Manisalidis *et al.*2020). Observed across the planet, carbon dioxide (CO_2) is the main representative of GHGs emissions that come from human activities during combustions of fossil resources such as petroleum, natural gas, or coal for heating and transport(Abeydeera, Mesthrige, and Samarasinghalage 2019). The issue of atmosphere degradation relates to the redefinition of methods of access to resources, of risk sharing, of the ability to integrate the environmental issue for groups operating in multiple environments (natural, social, institutional, political, administrative, expertise), interacting and evolving (Hummels and Argyrou 2021). The main propeller of global change is the increase in human needs (Bush *et al.* 2018). As a result of this global change made possible by the growing human population's demand, we now suffer from ozone depletion, climate change, widespread species extinction, air and water pollution, desertification, and other large-scale shifts (Wickham *et al.* 2019).

Besides being affected by climatic change, sub-Saharan Africa remains one of the most susceptible regions to climate disasters due to its low adaptive capability (Serdeczny *et al.* 2017). The recent study of Nangombe et al. (2019)demonstrated that earth temperatures in Africa will rise faster and the continent will know extreme heat in the more arid regions. The lack of policy structuration, as well as the need to integrate new criteria, are major drawbacks in dealing with the climate problem in the region (Omisore 2018). The region now finds itself afflicted by the consequences of inappropriate policies, as well as by almost endemic political instability, an inability to manage its economies effectively, and an increasingly hostile external economic milieu(Shishaye 2017). As simple survival has become more problematic, it has become increasingly difficult to avoid overexploiting natural resources and degrading the environment.

More often than not, poverty contributes to environmental degradation (Masron and Subramaniam 2019), the poor deplete the natural resources on which economic development depends. Due to a lack of sufficient resources and improper knowledge, people overuse every free resource available(Miller *et al.* 2021). They cannot cover the additional short-term expenses necessary to adopt environmentally sustainable development practices. To access energy, Sub-Saharan Africa is the world's poorest in the electricity region(Blimpo and Cosgrove-Davies 2019). The primary source of energy in the region is solid biomass like fuelwood and charcoal which accounts for more than 75 percent of the total energy consumed in the region (Bär *et al.* 2021).

Among causes of environmental issues, it is furtherly clear that our energy consumption has a detrimental impact on the environment and our health(Xing *et al.* 2019). Sub Saharan Africa is certainly the most contrasted

continent with a very dichotomy of energy systems (Ganda and Ngwakwe 2014). Inefficient traditional forms of energy, mainly fuelwood and charcoal, continue to dominate in most countries of sub-Saharan Africa, especially for cooking uses(Manfred Hafner, Simone Tagliapietra, and Lucia De Strasser 2018). The impacts are diverse, concern human health, ecosystems, buildings, plant crops, landscapes, and climate change, and vary according to the different energy sources(Frantál, Pasqualetti and van Der Horst 2014).

Agricultural sub -Saharan African takes place in savanna and forest areas which support most of the continent's cropland and pasture(Larmie 2019). Future changes in land exploitation could have an impact on these symbolic landscapes. Palmer et al. (2019)demonstrated that Africa's tropical land releases CO_2 emissions. This is because the land surface is covered by tropical forests and peatlands, environments that typically absorb huge amounts of CO_2 from the atmosphere(Leng, Ahmed, and Jalloh 2019). African greenhouse gas emissions produced on the continent contribute to the modification of the regional climate(Niang *et al.*2015). Some African countries are already committed to a growth model that is resilient to climate change, but this path promises to be difficult due to a lack of resources. The challenge is therefore how to ensure economic and technical progress with the current pace while simultaneously taking into account two aspects: socio-economic and environmental. This question is crucial because of the lack of awareness leading to a bad understanding of the action programs and bad practices. The success of environmental policies throughout the world and particularly in developing regions such as sub-Saharan Africa requires awareness combined with the participation of those who are concerned(Howes *et al.* 2007). Five keys considered as drivers of pollution in SSA are reviewed in detail in this study: agricultural land, energy use, agriculture-forestry and fisheries (value adds), real gross domestic product, and industry-construction based on their importance to the productive capacity of SSA and their contribution to current and future GHG emissions.

Far through literature review, a series of empirical studies have been carried out to illustrate the relationship between human activities and CO_2 emissions. These studies do not use the same approaches. They are based on the EKC (Environmental Kuznets Curve) hypothesis, and the gravity model for some, and the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) approach for others. Scholars have also extended it beyond income levels & the environment and focus on CO_2 emissions impacts. For example, (Ameyaw and Yao 2018)examine the relationship between the real gross domestic product (RGDP) and CO_2 emissions in West African countries within the period of 2007–2014 based on a panel data model. The output from the analysis revealed a unidirectional causality running from GDP to CO_2 emissions. In the same context, studies have been recorded an impact of agriculture, manufacturing industry, and service sector's value-added in the GDP on the CO_2 emissions(IPCC, 2015).

Using an EKC in selected south Asian countries, Alam(2015) has found that a value adds of agriculture in the GDP has a negative significant impact on CO_2 emissions where industrial and services value-added in the GDP has a great significant impact on CO_2 emissions. Pant (2009) reviewed the literature on both aspects and test empirically what causes emissions of carbon dioxide to the atmosphere. Multiple linear regression analysis revealed that agricultural land, irrigation, forest area, biomass energy, and energy use lead to the increase of Carbon dioxide emission (Zhang *et al.* 2020). However, using an autoregressive distributed lag (ARDL) approach and Granger causality tests, Mehdi and Mounir (2017) investigate the dynamic causal links between carbon dioxide (CO_2) emissions, real Gross Domestic Product (RGDP), combustible renewables and waste consumption, maritime, and rail transport in Tunisia spanning the period 1980–2011. The empirical results suggest a bidirectional short-run causality between CO2 emissions and maritime transport, and a unidirectional causality running from real GDP, combustible renewables, waste consumption, and rail transport to CO_2 emissions. Sarkodie and Owusu (2017) estimated a relationship between carbon dioxide, crop, and livestock production index in Ghana. Estimating the long-run elasticities and variance decomposition by employing a time series data spanning from 1960-2013 using both fit regression and ARDL models. The study evidence has shown a bidirectional causality between crop production index and carbon dioxide emissions, and a unidirectional causality exists from livestock production index to carbon dioxide emissions. The variance decomposition has shown that future fluctuations in carbon dioxide emissions are due to shocks in the crop production index.

Scientists such as Zhao et al. (2018) and Sperry et al. (2019) believe that current developments will lead to increased extreme events (high magnitude storms and cyclones, catastrophic floods, or multi-year drought), as well as an increase in annual average temperatures over large areas of the globe. The primary cause of global warming would be the emission of increasing amounts of carbon dioxide in the atmosphere associated with the large-scale use of fossil fuels (coal, oil, natural gas). Carbon dioxide (CO_2) emissions linked to the use of energy have been stabilized in the world in 2019 IEA(2019). It is the result of the development of renewable energies in developed economies.

An extended Kaya identity and the Logarithm Mean Divisia Index (LMDI I) have been applied by Engo (2019) to identify, quantify, and explain the main driver of CO_2 emissions in Cameroon from 2007 to 2014. Regarding contributions to the increase of CO_2 emissions, findings have shown that population is the most positive whereas energy intensity, the substitution of fossil fuels, and penetration of renewable energies have contributed

to the CO_2 emission reduction. Yorgancı (2018) employed an IPAT model as a framework using the Vector Error Correction Model (VECM). The results indicated the long-run responsiveness of CO_2 emissions for the population is positive and significant. Max William Ssali (2018) conducted a unit root test, co-integration test, VECM, and FMOLS to assess the impact of economic growth, energy consumption, and population growth on carbon emissions. The output revealed that an increase in energy consumption and population growth would cause an increase in CO_2 concentration.

Though in general, there are a lot of studies for Africa related to energy consumption, not much of them have been focused on the sub-Sahara African CO_2 emissions. Again, causes of CO_2 have been investigated in their aggregated form focusing primarily on causality analysis without exploring its dynamic impacts.

2. Material and methodology approach

2.1 Econometric method

This research is a type of descriptive analysis research with a quantitative approach. It is a time-series data type and consists of Sub -Saharan Africa region. We have chosen the best explanatory variables covering the period 1981-2014, which are directly correlated with the CO2 emissions under the constraint of the availability of data from various reviews available on the British Petroleum Council and World Bank.

$$CO_2 = \beta_0 + \beta_1 AL_{it} + \beta_2 EU_{it} + \beta_3 AGRIF_{it} + \beta_4 GDPC_{it} + \beta_5 INDCO_{it} + \varepsilon_t \qquad (1)$$

Where:

CO_2:   Carbon dioxide(kt)
AL: Agricultural land
EU: Energy use
$AGRIF$:   Agriculture-forestry and fisheries (value adds)
$GDPC$:   (Real)Gross domestic product
$INDCO$:   Industry/construction (value adds)
ε: Error term

2.2 Econometric approach

The non-stationarity of several macroeconomic and financial series represents a problem for the application of the usual econometric methods. For the study of the evolution of these long-term series, we use the theory of cointegration which allows studying them whose linear combination is stationary. The study makes it possible to specify long-term stable relationships while jointly analyzing the short-term dynamics of the variables considered. The interest of this theory is that it provides a method of analyzing the non-stationary time series while avoiding the problem of spurious regressions ((Wang and Hafner, 2018). Analysis of these time series is primarily concerned with examining their stationary character.

There are two types of stationarity:

- A Strict Sense Stationary (SSS) process:
  We say that the process $X_t, t \in \tau$ is stationary in the strict sense (SSS), if for all $\{t_1, t_2, \ldots, t_n\}$ the probability distribution of $\{X_{t1}, X_{t2}, \ldots, X_{tn}\}$ is the same as that for $\{X_{t_{1+k}}, X_{t_{2+k}}, \ldots, X_{t_{n+k}}\}$ K>=0. We denote by $(X_t, t \in \tau) \sim SSS$ where τ is the set of indices. It should be noted that the conditions of stationarity generally retained are those of second-order stationarity (or weak or in the broad sense or asymptotic or covariance stationarity).

- *Second-order stationarity (weak stationarity):*
  The process $(X_t, t \in \tau)$ is stationary of second-order (SL) if:
  - $E(X_t^2) < \infty \ \forall t \in \tau$: moments of order 2 are finite,
  - $E(X_t) = \mu \forall t \in \tau$: the mean of the process is constant which reflects the stability of its behavior over time,
  - $Cov(X_t, X_{t+h} = \gamma \forall t \in \tau, \forall h \in \tau$: the covariance between 2 periods t and $t + h$ is only a function of the time difference h.

  If at least one of its first two moments varies with time, the time series is then said to be non-stationary.

Economists focus their attention on a single equation representing for example a global consumption function, an equation teaches that these equations belong to a system or a subset of interdependent equations of which each equation makes it possible to give causal interpretations. This system is used to make simultaneous forecasts on a set of related variables. But, in a system of simultaneous equations containing one or more equations, it is not possible to obtain numerical values of each parameter in each equation because the equations are indistinguishable on the plane of the observation or they are gathered together too much we speak here of an identification problem. To do this, Sims (1980) proposed the VAR models [see Hanck et al.(2018)] as an alternative to traditional structural models with several equations. If there is real simultaneity between a series of variables, they should all be treated on an equal footing and there should be no distinction a priori between endogenous and exogenous variables.

Modern Econometrics uses methods to establish the relational model among economic variables in a nonstructural way: the vector autoregressive model (VAR) and vector error correction model (VEC). Assuming $Y_t = (y_{1t}, y_{2t}, \dots, y_{kt})'$ as k-dimensional stochastic time series, $t = 1,2, \dots T$ and $Y_t \sim I(1)$, each $y_{it} \sim$ $I(1), i = 1,2,\dots$ is affected by exogenous time series of d-dimension $X_t = (x_{1t}, x_{2t}, \dots, x_{dt})'$; .the VAR model can be formulated as below:

$$Y_t = A_1 y_{t-1} + A_2 y_{t-1} + \cdots + A_p y_{t-p} + B_t + u_t , \qquad (2)$$

$t = 1,2, \dots T$. If Y_t is not affected by exogenous time series of d dimension $X_t = (x_{1t}, x_{2t}, \dots, x_{dt})'$; VAR model of equation (2) becomes:

$$Y_t = A_1 y_{t-1} + A_2 y_{t-1} + \cdots + A_p y_{t-p} + u_t \qquad (3)$$

$t = 1,2, \dots T$.

From the specification above, it is interested to study the causality and analyze the effect of a shock of one of the variables considered on the others through the impulse response functions and the decomposition of the variance of the forecast error.

To study the existence of a cointegrating relationship, two approaches are often used: the method of Engle and Granger (1987) and the maximum likelihood method (Johansen (1988,1991)). Those approaches make it possible to determine the number of long-run equilibrium relationships between integrated variables of the same order regardless of the standardization used. Johansen represented a vector X_t containing N variables all $I(1)$ as a VAR(p) model.

$$X_t = \emptyset_1 X_{t-1} +, \dots \emptyset_p X_{t-p} + \varepsilon_t \qquad (4)$$

Where $\varepsilon_t \sim BB(0, \Omega)$ and $\emptyset_i = (i = 1, \dots, p)$ are matrixes of parameters of size $(N \times N)$. We start first by estimating the parameters constrained by the cointegration hypothesis. We rewrite Equation (9) in the form of an error correction model:

$$\Delta X_t = \pi_1 \Delta X_{t-1} +, \dots, \pi_{p-1} \Delta X_{t-p+1} + \pi_p X_{t-p} + \varepsilon_t \qquad (5)$$

With: $\pi_i = -I + \emptyset_1 + \emptyset_2 +, \dots, \emptyset_i$ for $i = 1, \dots, p$.

The matrices $\pi_i (i = 1, \dots, p)$ have $(N \times N)$ size. All terms of this model are $I(0)$ except X_{t-p} which is $I(1)$. There is therefore an imbalance between the order of integration of the left limb and the terms of the right limb.

For both members to be $I(0)$ a necessary condition is that $\pi_p X_{t-p}$ become $I(0)$. We set $\pi_p = -\beta \acute{\alpha}$ where $\acute{\alpha}$ a matrix (r, N) that contains the r cointegrating vectors and β a matrix (N, r) that contains the weights associated with each cointegrating vector.

Equation (4) is rewritten:

$$X_t = \pi_1 \Delta X_{t-1} +, \dots, +\pi_{p-1} \Delta X_{t-p+1} - \beta \acute{\alpha} X_{t-p} + \varepsilon_t \qquad (6)$$

To estimate the different matrices, Johansen (1988, 1989) proposes to use the maximum likelihood method. Under the assumption of normality of ε_t, the log-likelihood is written:

$$LogL(\beta, \alpha, \pi_1, \dots, \pi_{p-1}, \Omega) = -\frac{NT}{2} Log2\pi - \frac{T}{2} Log[(det\Omega)] - \frac{1}{2} \sum_{t=1}^{T} \acute{\varepsilon}_t \Omega^{-1} \varepsilon_t \qquad (7)$$

Where T is the number of observations, N is the number of variables contained in X and $det\Omega$ denotes the determinant of the variance-covariance matrix of ε_t.

We concentrate on the log-likelihood concerning the parameters $\pi_1, \pi_2, \dots, \pi_{p-1}$. This amount to performing the regression of e_{ot} on e_{pt}. These are the residuals estimated by the OLS of the relations:

$$\begin{cases} \Delta X_t = \theta_{01} \Delta X_{t-1} +, \dots, + \theta_{0p-1} \Delta_{t-p+1} + e_{ot} \\ X_{t-1} = \theta_{11} \Delta X_{t-1} +, \dots, + \theta_{1p-1} \Delta_{t-p+1} + e_{pt} \end{cases} \forall i = 1, \dots, p-1 \qquad (8)$$

With: $\theta_{0i} = (\pi_i - \beta \alpha \pi_i)$ and $\theta_{1i} = \pi_i$

Using equation (4) again, it comes:

$$X_t + \beta \acute{\alpha} X_{t-p} = \pi_1 \Delta X_{t-1} +, \dots, + \pi_{p-1} \Delta X_{t-p+1} + \varepsilon_t \qquad (9)$$

$$X_t + \beta \acute{\alpha} X_{t-p} = \pi_1 \Delta X_{t-1} +, \dots, + \pi_{p-1} \Delta X_{t-p+1} + \beta \acute{\alpha} [\pi_1 \Delta X_{t-1} +, \dots, + \pi_{p-1} \Delta X_{t-p+1}] - \beta \acute{\alpha} [\pi_1 \Delta X_{t-1} +, \dots, + \pi_{p-1} \Delta X_{t-p+1}] + \varepsilon_t \qquad (10)$$

The maximum likelihood estimators of the parameters $(\pi_1, \dots, \pi_{p-1})$ and β are provided from the OLS applied to equation (10) having previously replaced α by its estimator $\hat{\alpha}$.

The estimators of β and Ω are:

$$\begin{cases} \hat{\beta} = -S_{po} \hat{\alpha} (\hat{\alpha}' S_{PP} \hat{\alpha})^{-1} = -S_{po} \hat{\alpha} \\ \hat{\Omega} = S_{oo} - S_{op} \hat{\alpha} \hat{\alpha}' S_{po} = S_{oo} - \hat{\beta} \hat{\beta}' \end{cases} \qquad (11)$$

The r cointegrating vectors are provided by the r most significant eigenvectors, i.e., the r eigenvectors which correspond to the r largest eigenvalues solutions of the equation: $|\lambda S_{pp} - S_{po} S_{oo}^{-1} S_{po}| = 0$

To find the value of r (i.e., the number of cointegrating vectors) Johansen proposed to use two statistics:

$$\lambda_{trace} = TR = -T \sum_{i=q+1}^{N} Log(1 - \hat{\lambda}_i)$$

$$VP_{max} = -T Log(1 - \hat{\lambda}_{q+1})$$

λ_{trace} tests null hypothesis: that is, there are at most r cointegrating vectors. This test amounts to testing the rank of the matrix π_p i.e., we test $H_0: Rg(\pi_p) = r$

Johansen (1988) showed that under H_0 the statistic trace has for asymptotic law of:

$$\int_0^1 W(r)dW'(r) \left(\int_0^1 W(r)W'(r)dr\right)^{-1} \int_0^1 d\,W(r)dW'(r)$$

Where W is a Brownian motion of the variance-covariance matrix the identity matrix. The critical values of the λ_{trace} Statistics have been tabulated by Johansen and Juseluis (1990) then by Osterwald-Lenum (1992). We reject the null hypothesis of r cointegrating relations when the statistic λ_{trace} trace is greater than its critical value.

Theories of cointegration allow specifying stable long-term relationships while jointly analyzing the short-term dynamics of the variables considered. This requires the use of a particular class of models directly related to cointegration: VECM. Consequently, VEC modeling and cointegration give a new dimension to dynamic modeling by providing it with solid theoretical bases and by making it possible to consistently identify the long-term properties of time series.

With cointegration transformation of formula (3), we can get that:

$\Delta Y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + u_t$ (12)

Where $\Pi = \sum_{i=1}^{p} A_i - I$,   (13)

       $\Gamma_i = -\sum_{j=i+1}^{p} A_j$

If Y_t has a cointegration relationship, then $\Pi y_{t-1} \sim I(0)$ and formula (28) can be written as follows:

$\Delta Y_t = \alpha \acute{\beta} y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t$ (14)

Where, $\acute{\beta} y_{t-1} = ecm_{t-1}$ is the error correction term, which reflects the long-term equilibrium relationships between variables. Equation (14) comes:

$\Delta Y_t = \alpha ecm_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t$ (15)

Formula (15) is the vector error correction model (VECM), in which each equation is an error correction model.

3. Results and Discussion

3.1 Unit root tests application (ADF, PP, KPSS).

The analysis of chronological/times series is primarily concerned with examining their stationary nature by presenting the various tests used in this context. When studying time series, we need to test for the presence of a unit root to demonstrate whether or not a chronicle is stationary and to determine the correct way of stationary. The Dickey and Fuller tests (DF and ADF) are the most widely used due to their great simplicity, but they also suffer from several criticisms which have led to the development of other unit root tests including those by Phillips and Perron (PP) (1988), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1988) which we present in table 1.

Table1: Unit root tests on variables

Variables	At level			At first Difference			Conclusion	
	ADF	PP	KPSS	ADF	PP	KPSS		
Ln(CO2)	-1.5055	-1.5161	0.1632	-6.0138***	-6.0185**	0.0795*	**I (1)**	
Ln(AL)	-2.2444	-2.3341	0.0924	-5.7704**	-6.5570**	0.1444**	**I (1)**	
Ln(EU)	-1.4898	-1.3111	0.1762	-7.5507***	-7.5851***	0.0973***	**I (1)**	
Ln(AGRIF)	-1.4917	-1.4917	0.1975	-3.8916**	-3.8173**	0.0679***	**I (1)**	
Ln(GDPC)	-2.3362	-2.2111	0.1979	-3.4963*	-3.4440*	0.0928***	**I (1)**	
Ln(INDCO)	-2.6044	-2.5583	0.1957	-4.5181***	-4.4609***	0.1038***	**I (1)**	

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant
*MacKinnon (1996) one-sided p-values
KPSS: The test says the p-value is significant (with p-value < 0.05) and hence, you can reject the null hypothesis (series is stationary) and derive that the series is NOT stationary.
Source: Author's calculations.

All series are non-stationary in their level at the various critical thresholds since all the calculated values are greater than those tabulated, which implies the rejection of the null hypothesis of stationarity. On the other hand, it is not stationary in the tendency to critical thresholds 1%, 5% and 10% since the test statistics are lower than the critical values so we accept the null hypothesis of stationarity. Based on all performed unit root tests statistics, it was concluded that most of the variables are non-stationary at their level but stationary after taking the first difference i.e., I (1) variables.

3.2. Estimation of VAR Model.

The presence of one or more cointegration relations, therefore, allows us to go further and estimate a certain error correction model allowing us to specify the short-term dynamics of the variables present to reach the stable equilibrium long term.

The first step of this analysis consists of determining the number of lags of the VAR model (p). To do this, we estimate a certain number of autoregressive processes and we retain the one that jointly minimizes the criteria of Akaike and Schwartz. Table 2 shows all the results retained.

Table 2: Determination of Lag Length Criteria

Lag	Log L	LR	FPE	AIC	SC	HQ
0	263.0797	NA	4.24e-15	-16.06748	-15.79266	-15.97639
1	422.8284	249.607*	1.94e-18	-23.80177	-21.8779*	-23.1640*
2	464.4242	49.39501	1.76e-18*	-24.1515*	-20.57878	-22.96725

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level
 FPE: Final prediction error
AIC: Akaike information criterion
 SC: Schwarz information criterion
 HQ: Hannan-Quinn information criterion
Source: Author's calculations.

3.3 Johansen cointegration test (trace test)
The trace test assumes the absence of the trend in the cointegrating relationship and the absence of the constant in the error correction model. This choice can be justified economically by assuming that the long-term equilibrium relationships do not contain a trend. We, therefore, test the cointegration link between CO2 emissions and the factors that influence it, according to our study, namely AL, EU, AGRIF, GDPC, and INDCO. We apply the test of Johansen (1988) of the trace (χ_{trace}) and of the eigenvalue (χ_{max}).

Table3: Johansen cointegration test results

Ho: Rang r	Eigenvalue	χ_{trace}	0.05 Critical Value	Ho: Rang r	χ_{tmax}	0.05 Critical Value
r=0 *	0.768545	119.5026	95.75366	r=0 *	48.82787	40.07757
r≤1 *	0.651531	72.67474	69.81889	r≤1	33.73456	33.87687
r≤2	0.471245	38.94019	47.85613	r≤2	20.39138	27.58434
r≤3	0.274117	18.54880	29.79707	r≤3	10.25172	21.13162
r≤4	0.227945	8.297088	15.49471	r≤4	8.278368	14.26460
r≤5	0.000585	0.018720	3.841466	r≤5	0.018720	3.8841466

Trace test indicates 2 cointegrating equation(s) at the 0.05 level
 * denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values
Source: Author's calculations.

The results of the Johansen test(table 3) show that the null hypothesis for the test of the trace $r = 0$ and r≤1 for the test of the eigenvalue is rejected at the threshold of 5% since the values calculated from these two statistics (119.5026 and 72.67474). On the other hand, the null hypothesis for the test of the trace $r = 0$ for the test of the maximum eigenvalue is rejected at the threshold of 5% through the values calculated from that statistic (48.82787) is greater than the corresponding critical value. The null hypothesis r≤1 cannot be rejected at the 5% threshold since the two test statistics are lower than the critical values associated with them.
The following long-term equilibrium equation is retained:

$$LnCO2 = 2.558Ln(AL)_t - 15.441Ln(EU)_t + 1.504Ln(AGRIF)_t + 6.178Ln(GDPC)_t - 5.671Ln(INDCO)_t - 5.671Ln(INDCO)_t + 139.8476 \qquad (16)$$

This cointegration relation shows that environmental and economic variables AGRIF, AL have a positive long-term relationship with CO2 emissions respectively. If natural resource exploitation increases by 1%, the environmental degradation which induces CO2 emissions follows the same trend with a percentage of 1.5% and 2.5% respectively. This cointegration goes hand in hand with the increase in income per habitat (GDPC) to ensure this relationship of cointegration. In favor of sustained energy consumption with a level of life more comfort, countries of sub-Saharan Africa highlight the decreasing carbon dioxide emissions. On the other hand, when energy consumption increases by 1%, CO2 emissions in the region undergo a decrease of 15.44%. Similarly, the increase in industries and constructions results in a decrease of 5.67% CO2 emissions.

It is possible to estimate a vector error correction model(VECM). As its name indicates, it consists of correcting the estimation bias induced by cointegration. Since we have six variables, the VECM will have six equations presented in Table 4.

Table 4. VECM estimation results and test

Error Correction:	D(LNCO2)	D(LNAL)	D(LNEU)	D(LNAGRIF)	D(LNGDP)	D(LNINDCO)
CointEq1	-0.114910	-0.031438	-0.032473	0.230806	0.053379	-0.033148
	[-2.28079]	[-1.41076]	[-2.12625]	[2.33440]	[0.56496]	[-0.25123]
D(LNCO2(-1))	0.030630	-0.017362	0.102600	-0.246978	-0.221675	-0.196759
	[0.13285]	[-0.17025]	[1.46800]	[-0.54585]	[-0.51268]	[-0.32585]
D(LNAL(-1))	-0.322750	-0.142696	0.018604	0.302737	0.186491	0.021580
	[-0.77306]	[-0.77274]	[0.14700]	[0.36950]	[0.23819]	[0.01974]
D(LNEU(-1))	0.481608	0.189113	-0.375866	-1.291758	-1.248027	-0.638851
	[0.66725]	[0.59236]	[-1.71787]	[-0.91195]	[-0.92201]	[-0.33796]
D(LNAGRIF(-1))	0.071891	-0.056267	0.040488	0.174520	0.017394	-0.246380
	[0.51901]	[-0.91839]	[0.96427]	[0.64202]	[0.06696]	[-0.67918]
D(LNGDPC(-1))	-0.335876	-0.220699	0.006934	1.299179	1.802981	2.386397
	[-0.84996]	[-1.26267]	[0.05788]	[1.67527]	[2.43292]	[2.30587]
D(LNINDCO(-1))	0.337634	0.247612	0.033978	-0.931347	-0.994235	-1.229316
	[1.19089]	[1.97455]	[0.39536]	[-1.67392]	[-1.86996]	[-1.65563]
C	0.014732	0.007457	-0.007775	0.054350	0.028213	0.061287
	[1.15319]	[1.31976]	[-2.00766]	[2.16783]	[1.17760]	[1.83178]
R-squared	0.223808	0.256853	0.385147	0.372406	0.452128	0.371843
Akaike AIC	-3.242267	-4.873754	-5.629429	-1.893868	-1.984684	-1.316731
Schwarz SC	-2.875833	-4.507320	-5.262995	-1.527434	-1.618250	-0.950297

Source: Author's calculations.

The equation which represents the short-run adjustments is the following equation relating to the variable LnCO2.

$$\Delta ln(CO2)_t = 0.0147 - 0.3227ln(AL)_{t-1} + 0.4816ln(EU)_{t-1} + 0.0718\ln(AGRIF)_{t-1} - 0.335\ln(GDPC)_{t-1} + 0.337ln(INDCO)_{t-1} - 0.1149\varepsilon_{t-1} \quad (17)$$

This correction is presented by the return force of 0.1149 which remains negative and significant especially since it is justified by a Student statistic of (2.28079) in absolute value at the 5% threshold. Also, the parameter of the error correction term is negative and significant, thus confirming the existence of a long-term relationship between CO2 emissions and the indicators considered. The value of this parameter further indicates that in the short-term imbalance, the CO2 emission seems to return fairly quickly to its equilibrium path (the speed of convergence is estimated at nearly 11%). In the same way, the cointegration equation which is the error correction term has been formulated and interpreted in the (16) equation. The VECM model is valid for these cointegrated variables.

This VECM analysis sheds light on the meaning of the relationship between variables in the long and short-term but does not provide insight into the sense of reaction between these variables. To interpret the interrelationships between variables, we propose in the next section, to study the causality between them by using the impulse response functions and the forecast error decomposition.

3.4 Impulse response function and variance decomposition
We mainly focus on shock response functions and variance decompositions of forecast errors. These two instruments make it possible to synthesize the essence of the information contained in the dynamics of the estimated VAR system.
3.4.1 Impulse response function.
The impulse response function is used to perform shocks on the innovations of CO2 emissions at 10 years and to measure the influence of this shock on the whole system. First of all, the shock only affects the value of CO2 emissions on the orthogonality innovations. Then, throughout the dynamics of the system, this shock is transmitted to the following or future values of all variables.

Figure 1[ABCDE] retrace the impulse response functions. We consider that the amplitude of the shock is equal to twice the standard deviation and we are interested in the effects of the shock over 10 periods (i.e. 10 years). This horizon represents the time required for the variables to return to their long-term levels.
[A]After analysis of effects of CO2emissions, the CO2 emissions decrease rapidly after a sensitive shock, reach the lowest point in the third period, then increase slowly, reach a peak average in the 5th period, and then decline again until the lowest point in the $6^{1/2}$periode but return to a slow increase. This suggests that the positive shock of CO2 has a significant influence on its increasing, and the significant influence has relatively long sustained effectiveness.
[B]The results of different responses show that the response of CO2 emissions is characterized by a permanent

negative shock. It's far diagnosed that agricultural land could have positive externalities which include the provision of environmental offerings and amenities, for instance via water storage and purification, carbon sequestration, and the preservation of rural landscapes(Fanelli 2020).

[C]The energy (EU) chock has, also, positive shocks(consequences) on CO2 emissions. The shock increase during the 4-5 period. Afterward, the energy shock to the CO2 emission continues to increase in the long run.

[D]The impulse response of CO2 emissions caused by agriculture, forestry, and fisheries (AGRIF) is characterized by a positive and transitory shock. As seen in the figure, the first positive shock in the first period causes a quick increase, and CO2emissions reach a peak in the second-period, decrease until the 3rd period, and then remain at a stable level. If the changing demand and use of land, watershed, and forestry are not managed through rigorous planning and zoning regulatory framework, impacts in real terms are escalated uncontrolled development, increased energy demand and emissions, inefficient transport systems, overburdened water, and sanitation systems leading to reduced livelihoods.

[F]The impulse response function of carbon emission changes caused by industrial-construction is permanent negative. After a positive shock in the first period, carbon emissions decline to the lowest point in the third period and begin to rise slowly. Then carbon emissions reach a peak in the fourth period, stay at a stable level, and slowly decrease in the 5th period. The CO2 emissions become stable from the eighth period. This shows that a positive shock on industrial-construction can cause changes in carbon emissions, and its effect becomes gentle since the eighth period.

[E]The impulse response function of carbon emission changes caused by the real gross domestic product shows negative permanent effects. The general decrease in greenhouse gas intensities with the increase in income follows a certain logic. When this standard of living increases, we observe that certain consumptions, in particular, those of first necessity increase at a rate lower than that of the income (Engel low).
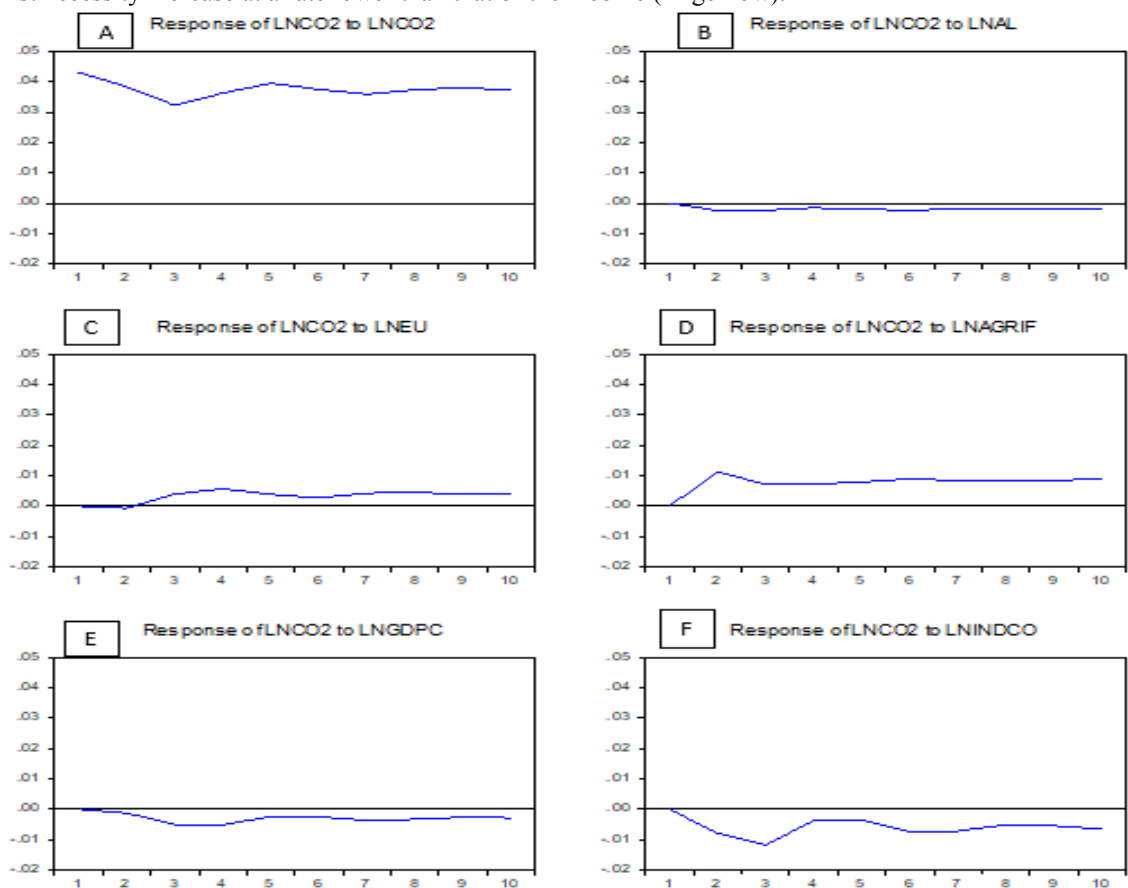

Figure 1. Response to Cholesky One S.D. Innovations

3.4.2 Variance Decomposition

This study, based on impulse response functions, can be supplemented by an analysis of the variance decomposition of the forecast error. The objective is to calculate the contribution of each of the innovations to the variance of the error. We write the variance of the forecast error at a horizon h, in our case ranging from 1 to 10, depending on the variance of the error attributed to each of the six variables.

Table5: Variance decomposition of LNCO2

Period	S.E.	LNCO2	LNAL	LNEU	LNAGRIF	LNGDPC	LNINDCO
1	0.043014	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.059296	94.31938	0.172261	0.013527	3.676613	0.045819	1.772404
3	0.069206	90.88376	0.249033	0.340410	3.756450	0.577961	4.192382
4	0.078935	90.95158	0.230025	0.787427	3.718781	0.865278	3.446909
5	0.088808	91.56881	0.238105	0.810875	3.744965	0.759410	2.877832
6	0.097181	91.30279	0.251750	0.757541	3.986103	0.702072	2.999741
7	0.104352	91.00204	0.258264	0.827080	4.108069	0.732813	3.071736
8	0.111406	91.06544	0.257091	0.892215	4.146289	0.731805	2.907164
9	0.118248	91.13347	0.259037	0.897652	4.213505	0.699646	2.796695
10	0.124549	91.06317	0.262315	0.900827	4.294904	0.681767	2.797015

Source: Author's calculation**.**

The variance decomposition results [table 5] made it possible to deduce that the variance of the CO2 forecast error is due for 91.06%, over the 10 years horizon, to its innovations. It is largely due to 4.29%,2.79%, 0.90%, and 0.68% of agriculture, forestry, and fisheries, industrial construction, and energy use respectively.

4. Conclusion

The study empirically analyzes the impact of human activities on CO2 emissions in the Sub -Sahara African region by taking into account the stationary or non-stationary character of the data series. It was possible to estimate a vector error correction model (VECM) but the light on the meaning of the relationship between variables in the long and short-term did not provide insight into the sense of reaction between variables. We proposed then to study the causality between variables using the impulse response functions and the forecast error decomposition.

In the context of this work, it is important to summarize the main results:

The application of unit root tests revealed that all series are non-stationary in level but are integrated of the same order at their difference I (1). This has led to suspecting a possible long-term relationship (cointegration) between CO2 emissions and its explanatory variables.

Application of the Johansen cointegration test on variables found the existence of a long-term relationship between them. The output cointegration relation shows that environmental and economic variables agriculture, forestry, and fishing(value-added), Agricultural Land, and real Income have a positive long-term relationship with CO2 emissions. On the other hand, when energy consumption increases, CO2 emissions in the region undergo a decrease. Similarly, the increase in industry-construction results in a decrease in CO2emissions.

Through the impulse response function analysis, results of different responses showed that the impulse response of CO2emissions changes caused by agricultural land, industry-construction, and the real gross domestic product is characterized by a permanent negative shock. Good agricultural land management gives a healthy environment that provides resources for habitats and further leads to the decline of carbon emissions. The rise in agriculture, forestry, and fisheries (AGRIF), and energy (EU) has, besides, positive shocks(consequences) on CO2 emissions. This shows that the growth of carbon emissions in the SSA does not necessarily promote AL, INDCO, and RGDP growth, and the growth of those sectors in the country does not intensify the excessive pollutants to cause plenty of carbon emissions.

In the long- term, the agriculture, forestry, and fisheries sector, industry-construction, and energy use have a great influence on CO2emissions but the influence is leveling off in the short run. To prevent any kind of loss linked to atmospheric pollution, a massive investment in clean energies (wind, geothermal, solar…) and biofuels should make it possible to prevent CO2 emissions in the long term. As for forests and agriculture, stopping deforestation of tropical forests, launching of reforestation projects, reform of agricultural practices to protect soils. This sector has a strong potential for reducing emissions because forests and soils constitute sinks of natural carbon.

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No conflict of interest

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Author's Contribution
Jean Baptiste helped with topic conceptualization and writing the initial draft. All authors contributed to the research implementation, discussion of results and we both approve for manuscript publication.

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