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Energy–Climate–Economy–Population Nexus: An Empirical Analysis in Kenya, Senegal, and Eswatini

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Abstract: Motivated by the Sustainable Development Goals (SDGs) and its impact by 2030, this study examines the relationship between energy consumption (SDG 7), climate (SDG 13), economic growth and population in Kenya, Senegal and Eswatini. We employ a Kernel Regularized Least Squares (KRLS) machine learning technique and econometric methods such as Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Squares (FMOLS) regression, the Mean-Group (MG) and Pooled Mean-Group (PMG) estimation models. The econometric techniques confirm the Environmental Kuznets Curve (EKC) hypothesis between income level and CO_2 emissions while the machine learning method confirms the scale effect hypothesis. We find that while CO_2 emissions, population and income level spur energy demand and utilization, economic development is driven by energy use and population dynamics. This demonstrates that income, population growth, energy and CO_2 emissions are inseparable, but require a collective participative decision in the achievement of the SDGs.

Keywords: kernel regularized least squares; environmental Kuznets curve; climate change; Kenya; Senegal; Eswatini; energy–growth–population nexus; panel data; heterogeneity; Kaya identity

1. Introduction

The United Nations (UN) sustainable development goals (SDGs) cover multiple pressing issues that are established to help address key global as well as local challenges by 2030. They seek to address challenges such as eradication of poverty, hunger, good health/wellbeing, quality education, gender equality, clean water and sanitation, clean energy, decent jobs, industrial innovation, climate, sustainable consumption and production, amongst others [1,2]. Motivated by the UN SDGs and their potential impact by 2030, this study examines the relationship between energy consumption (SDG 7), climate (SDG 13), economic growth (SDG 8) and population in selected sub-Saharan African (SSA) countries namely Kenya, Senegal and Eswatini located in three regions in East Africa, West Africa and Southern Africa, respectively.

There exist a bulk of well-documented literature on the nexus between pollutant emissions and economic growth. Since the groundbreaking study on the nexus between energy consumption and gross national product [3], there has been more discourse on the energy-growth nexus. The theme was popularized in a study that examined the inverse relationship between economic growth and pollutant emissions [4]. This phenomenon is also regarded as the Environmental Kuznets Curve (EKC) hypothesis—where emphasis is placed on economic growth compared to environmental quality. Several other studies have augmented the pollutant-growth relationship with other macro indicators such as foreign direct investment, urbanization, globalization, trade openness, democracy and employment [5–7]. For instance, a study incorporated democracy [6], institutional quality [8], financial development [9] in the EKC framework for several countries. The study [6] reveals that a democratic regime dampens environmental degradation over the sampled period. Thus, suggesting that political regime is pivotal to environmental quality.

The present study complements the extant literature which could be divided into four hypotheses namely first, the growth literature [10] where economic growth trajectory is a driver for energy consumption. Second, the conservative hypothesis focuses on energy consumption as the driver of economic growth [11] while the third hypothesis details the feedback relationship—where there is a mutual effect between energy and economic growth [12]. The neutrality hypothesis [13] posits independence between growth and energy. Thus, both economic growth and energy do not control each other. Several studies on economic development and energy utilization from country-specific time series to panel data settings have been presented extensively but lack consensus [7]. While several multivariate studies are based on econometric techniques and substitution of data series, none of such studies employs machine learning-based methods to understand the complexity of relationships between socio-economic and environmental indicators.

The current study augments the EKC framework by incorporating a demographic indicator measured by population into the mix. Sub-Saharan Africa (SSA) has little entry into the theme; therefore, it provides an opportunity for empirical assessment. This is timely, owing to the limited and sporadic studies on the theme across three strategic countries with a similar path to independence. Hence, we contribute to the limited literature for SSA using Kenya (East Africa), Senegal (West Africa) and Eswatini (Southern Africa) holistically. The objectives of the study include, first, to test the validity of the EKC hypothesis. Second, to examine the heterogeneous effects of socio-economic indicators on CO_2 emissions. Third, to assess the drivers of energy consumption and economic development. This implies that understanding the patterns and magnitude of drivers of anthropogenic emissions are requirements for predicting future climate change and its impacts. We contribute methodologically to the extant literature on panel data modelling by using the novel Kernel regularized least squares, a machine learning approach based on panel estimation approach that accounts for misspecification bias without assuming linearity, additivity and strong parametric specifications. Besides, the Kernel-based Regularized Least Squares panel estimation approach is robust, consistent and produces unbiased estimates in models with interactive effects, heterogeneous effects, and nonlinearities.

The remainder of this study is structured as: Section 2 presents a synopsis on the three countries investigated. Section 3 dwells on the data and methodological procedures while 4 focuses on empirical results discussion. Finally, Section 5 presents the concluding remark and policy implication(s).

2. Brief Background on Kenya, Senegal and Eswatini

2.1. Kenya

Kenya, with a total area of 580,370 km^2 is in East Africa on 0.0236° S, 37.9062° E of the southern hemisphere based on the decimal degree system (Figure 1). The country's population is currently estimated at 48.4 million (Table 1) [14]. The increased population is reported to be a result of the reduced mortality rate and a relatively high birth rate (Table 1). The country's energy sector is heavily dependent on traditional biomass accounting for 68% (especially for the urban poor, informal settlements, and rural communities), petroleum (22%) and others (10%) [15] (Table 1). As of 2017, primary energy supply included 17,281 ktoe biofuels and waste, 4866 ktoe of oil, 4143 ktoe of geothermal, wind, solar, and others, 463 ktoe of coal and 276 ktoe of hydro [16]. The government targets to have at least 65% of the country electrified by 2022 from the current rate %. Currently, 27.1 million, representing 56% of Kenyans, out of the total population of 48.4 million have access to electrification. With regards to policy, Kenya's National Energy Policy (NEP) document implemented in the year 2018 is intended to help provide a comprehensive policy framework for the energy sector. Additionally, the NEP seeks to provide strategic directions for the development of the energy and allied sectors. The NEP seemed harmonized with the current national vision document, that is Kenya Vision 2030 (commenced in the year 2008). Kenya Vision 2030 targets at helping to transform the country to a middle-income industrialized country and consequent improvement in livelihood, socioeconomics, and environmental sustainability.

2.2. Senegal

Senegal with a total area of 580,370 km^2 is in West Africa on 14.4974° N, 14.4524° W of the northern hemisphere based on decimal degree system. The country borders Gambia, Guinea, Guinea-Bissau, Mali, Mauritania, and the North Atlantic Ocean (Figure 1). Senegal's current population is estimated at 15 million (Table 1) [14]. In Senegal, 65% of the population has access to electricity. As of 2017, primary energy supply included 2286 ktoe of oil, 1575 ktoe biofuels and waste, 379 ktoe of coal, 29 ktoe of hydro, 20 ktoe of natural gas, and 12 ktoe of wind, solar, and other [16]. Senegal's 'Plan Senegal Emergent' underscores the importance of energy sector development in attaining emerging economy by 2025 [17]. Strong policies and incentives have supported liquefied petroleum gas (LPG) use and less than 25% of the urban population now relies on solid biomass for cooking [16]. Senegalese Law № 98-29 enacted in 1998, is the primary act regulating the electricity sector in the country as well as providing the enabling legal and regulatory framework. To complement Senegalese Law № 98-29, the country enacted renewable energy, that is law № 2010-21, to support the development, deployment and diffusion of renewable energy. Biofuel Law № 2010-22 focused on biofuel development is designed to complement the Renewable Energy Law № 2010-21 (mentioned earlier above). Biofuel Law № 2010-22 provides exemptions from value-added tax and customs duties to produce biofuels as well as incentives for the acquisition of equipment, seeds, seedlings for biofuels cultivation and biofuels production for domestic Senegalese market [18].

2.3. Eswatini

Eswatini, with a total area of 17,364 km^2, is located in Southern Africa at 26.5225° S, 31.4659° E of the southern hemisphere based on the decimal degree system. The landlocked country borders Mozambique and South Africa (Figure 1). Currently, 65.8% of Eswatini out of the total population of 1.09 million have access to electrification. Eswatini encounters frequent weather-related challenges including droughts, intermittent heavy precipitation, and flooding [14]. Eswatini's National Development Strategy (NDS) (1997–2022), was established to help improve the country's economy and living standards, amongst other development indicators and plans of national interest [19]. It is currently unclear to what extent the targets stipulated in Eswatini's NDS has been achieved to date. This would require *post*-NDS assessment after completion of the current phase of NDS, which is the year 2022. Results from such as assessment would be invaluable to help identify possible gaps in the current NDS and to inform on future strategy development for Eswatini.

Table 1. Socio-economic, demographic, energy indices and related emissions for Kenya, Senegal and Eswatini.

Country		Kenya			Senegal			Eswatini		
Parameter	**Unit**	**Value**	**Reference Year (s)**	**Source**	**Value**	**Reference Year (s)**	**Source**	**Value**	**Reference Year (s)**	**Source**
Population	Million	48.4	2018 (est.)	CIA [14]	15	2018 (est.)	CIA [14]	1.09	2018 (est.)	CIA [14]
Population growth rate	%	1.6	2018 (est.)	CIA [14]	2.4	2018 (est.)	CIA [14]	0.8	2018 (est.)	CIA [14]
Urbanization	% of total population	27.5	2019	CIA [14]	47.7	2019	CIA [14]	24	2019	CIA [14]
GDP	Billion USD	79.2	2017 (est.)	CIA [14]	21.1	2017 (est.)	CIA [14]	4.4	2017 (est.)	CIA [14]
GDP real growth rate	%	4.9	2017 (est.)	CIA [14]	7.2	2017 (est.)	CIA [14]	1.6	2017 (est.)	CIA [14]
GDP Per capita (PPP)	USD	3500	2017 (est.)	CIA [14]	3500	2017 (est.)	CIA [14]	10,100	2017 (est.)	CIA [14]
GDP-composition, by sector of origin										
agriculture	%	34.5	2017 (est.)	CIA [14]	16.9	2017 (est.)	CIA [14]	6.5	2017 (est.)	CIA [14]
industry	%	17.8	2017 (est.)	CIA [14]	24.3	2017 (est.)	CIA [14]	45	2017 (est.)	CIA [14]
services	%	47.5	2017 (est.)	CIA [14]	58.8	2017 (est.)	CIA [14]	48.6	2017 (est.)	CIA [14]
Human development index	-	0.579 (ranked 147 of 189 countries)	2018	UNDP [20]	0.514 (ranked 166 of 189 countries)	2018	UNDP [20]	0.608 (ranked 138 of 189 countries)	2018	UNDP [20]
Electricity access										
population without electricity	million	13	2017	CIA [14]	6	2017	CIA [14]	-	-	-
electrification-total population	%	56	2016	CIA [14]	65	2017	CIA [14]	65.8	2016	CIA [14]
electrification-urban areas	%	77.6	2016	CIA [14]	90	2017	CIA [14]	82.8	2016	CIA [14]
electrification-rural areas	%	39.3	2016	CIA [14]	43	2017	CIA [14]	61.2	2016	CIA [14]
Energy Production	Quadrillion Btu	0.075	2017	IEA [21]	0.0069	2017	IEA [21]	0.0065	2017	IEA [21]
Electricity-Consumption	billion kWh	7.8	2016	CIA [14]	3.5	2016	CIA [14]	1.4	2016 (est.)	CIA [14]
Electricity-installed generating capacity	million kW	2.4	2016 (est.)	CIA [14]	1.0	2016 (est.)	CIA [14]	0.3	2016 (est.)	CIA [14]
Electricity-from fossil fuels	% of total installed capacity	33	2016 (est.)	CIA [14]	82	2016 (est.)	CIA [14]	39	2016 (est.)	CIA [14]
Electricity-from hydroelectric plants	% of total installed capacity	34	2017 (est.)	CIA [14]	7	2017 (est.)	CIA [14]	20	2016 (est.)	CIA [14]
Electricity-from other renewables	% of total installed capacity	33	2017 (est.)	CIA [14]	11	2017 (est.)	CIA [14]	41	2016 (est.)	CIA [14]
CO_2 emissions from consumption of energy	million tonnes	18	2017 (est.)	CIA [14]	8.6	2017 (est.)	CIA [14]	1.1	2017 (est.)	CIA [14]

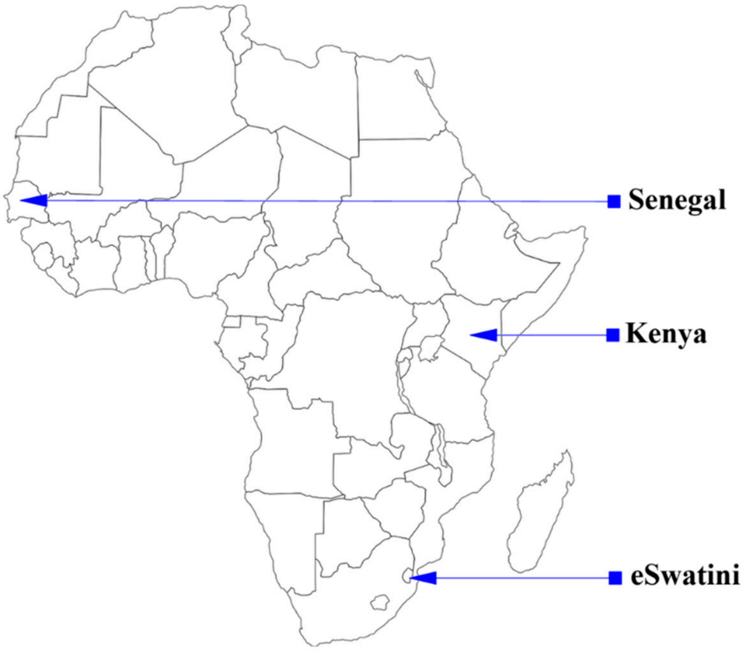

Figure 1. Sketch of Africa showing the location of Senegal (West Africa), Kenya (East Africa), and Eswatini (Southern Africa).

3. Method

To achieve the objectives of the study, we employ four-time series data spanning 1980-2013. The data comprise of carbon dioxide emissions (CO_2 (kt)), economic growth (GDP (current USD)), Population (POP) derived from the World Bank Development Indicators [22] while Total primary energy consumption (PEC(quadrillion Btu)] is derived from the international energy statistics of the US Energy Information Administration (EIA) [23]. The selection of the data series is both supported by economic theories and Sustainable Development indicators for achieving environmental quality, energy efficiency and sustained economic growth [1]. According to the IPCC 5th Assessment report, economic growth, population and energy consumption are the immediate driver of anthropogenic emissions and main backbone of the SDGs [24].

In this study, we examine the multifactorial relationship between CO_2 emissions, population, economic growth and energy consumption following the path of the EKC, energy intensity and growth hypotheses. These selected indicators of anthropogenic emissions are in line with the Kaya identity that controls for economic, demographic and technological drivers of emission trends [25]. The EKC hypothesis is necessary to derive policy implications for Kenya, Senegal and Eswatini. The models follow equations expressed in a linear relationship as:

$$\text{Panel A}: \ CO_2 = f\left(GDP,\ GDP^2,\ PEC,\ POP\right) \quad (1)$$

$$\text{Panel B}: \ CO_2 = f(GDP,\ PEC,\ POP) \quad (2)$$

$$\text{Panel C}: \ PEC = f(GDP,\ CO_2,\ POP) \quad (3)$$

$$\text{Panel D}: \ GDP = f(PEC,\ CO_2,\ POP) \quad (4)$$

The Sustainable Development Goal 13 underscores the mitigation of climate change through a reduction in anthropogenic emissions. Given this, the EKC hypothesis is examined in Panel A by controlling for the role of energy utilization and population. We introduce a second-order polynomial of economic growth alongside growth, as a top-bottom approach to increase the complexity of the model. This means that our a priori expectation of achieving Sustainable Development Goal 13 requires GDP to be positive whereas squared GDP is negative to validate the EKC hypothesis. If the expectation is not met, the nexus between environmental quality and wealth can further be examined inclusively while accounting for energy utilization and population increase. In contrast, the same data series are replicated in Panel B excluding the second-order polynomial of GDP, to ascertain whether the relationship between emissions, growth and population remains intact in a smaller and simple model. The driving factors of energy utilization are examined in Panel C by accounting for the impact of economic growth, emissions and population increase. This model is essential to examine the Sustainable Development Goal 12 of ensuring sustainable consumption patterns. Thus, this procedure provides a simplified version of probing the level of energy efficiency across countries. In Panel D, the Sustainable Development Goal 8 of ensuring sustained economic growth in tested by accounting from energy consumption and population increase in the era of emissions in a growth function. Our a priori expectation requires all regressors excluding emissions to be positive to achieve sustainable economic development.

Using the model specification in Equation (1), we test the long-run equilibrium relationship using the residual-based Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) estimators [26,27]. However, as a precondition, the variables under observation must meet the cointegration condition. To fulfil this requirement, the study employs the residual panel cointegration tests to examine the cointegration between the dependent variable and the regressors. Kao [28] proposed five statistical tests in a heterogeneous panel with medium-large cross-sectional units N and large sample observations T under the null hypothesis of no cointegration in the panel with one or more non-stationary regressors. Kao [28] reports five test statistics namely modified Dickey–Fuller t, Dickey–Fuller t, augmented Dickey–Fuller t, unadjusted modified Dickey–Fuller t, and Unadjusted Dickey–Fuller t. The simplified panel estimation technique can be expressed as:

$$y_{i,\,t} = \alpha_i + \beta x_{i,\,t} + \varepsilon_{i,\,t} \tag{5}$$

where y and x are the dependent and independent variables, parameter α_i denotes the individual effect required to be heterogeneous, β_i denotes the slope coefficients across the cross-sectional units $i = 1, \ldots, N$ at period $t = 1, \ldots, T$, required to be homogeneous.

The empirical specification of Equation (5) can be expanded as:

$$lnCO2_{i,\,t} = \alpha_i + \delta_{i,t} + \beta_{1i} lnGDP_{i,\,t} + \beta_{2i} lnGDP^2{}_{i,\,t} + \beta_{3i} lnPEC_{i,\,t} + \varepsilon_{i,\,t} \tag{6}$$

where parameters α_i and δ_i denote the individual and trend effects, $\beta_1, \ldots, \beta_3$ denotes the slope coefficients of the cross-sectional units $i = 1, \ldots, N$ at period $t = 1, \ldots, T$. $lnCO2_{i,\,t}$, $lnGDP_{i,\,t}$, $lnGDP^2{}_{i,\,t}$, and $lnPEC_{i,\,t}$ are integrated at order (I (.)) and cointegrated with slopes β_{1i}, β_{2i}, and β_{3i}, which can either be homogeneous or not across i.

It is important to note that, all variables are normalized (0, 100) to fulfil the assumption of normal distribution and make the data series comparable between the sampled countries. The normalization technique follows:

$$V' = \frac{100\,(V - V_{min})}{V_{max} - V_{min}} \tag{7}$$

where, V' is the normalized data and V is the original data.

Using the mean group and pooled mean group estimators, we test the long-run and short-run equilibrium relationship between CO_2 emission, economic growth, energy consumption and population using the model specification in Equation (2) expressed as:

$$\Delta y_{i,\,t} = \varphi * (y_{i,t-1} + \beta x_{i,t}) + \Delta y_{i,\,t-1} * \alpha_1 + \ldots + \Delta y_{i,\,t-p} * \alpha_p + \Delta x_{i,\,t} * \partial_1 + \ldots + \Delta x_{i,\,t-q} * \partial_q + \varepsilon_{i,\,t} \tag{8}$$

where y and x are the dependent and independent variables, φ represents the error-correction speed of adjustment, β denotes the slope coefficients with a $(k \times 1)$ vector of parameters, $\alpha_{1,\ldots}\alpha_p$ are p parameters to be estimated, $x_{i,\ t}$ is a $(1 \times k)$ vector of covariates, $\partial_{1,\ldots}\partial_q$ are q parameters to be estimated and $\varepsilon_{i,\ t}$ denotes the error term across the cross-sectional units $i = 1, \ldots, N$ at period $t = 1, \ldots, T_i$. In this model, logarithmic transformation was applied to all the data series.

Finally, we employ Kernel regularized least squares, a novel machine learning-based panel estimation approach that controls for misspecification bias without assuming additivity or linearity and strong parametric specification. Importantly, the Kernel regularized least squares approach is consistent and produces unbiased estimation in models with non-linearities, heterogeneity and interactive effects [29]. For brevity, the partial derivatives based on Kernel regularized least squares for the model specification of Equations (1)–(4) can be expressed as:

$$\frac{\delta \hat{y}}{\delta x_j^{(d)}} = \frac{-2}{\sigma^2} \sum_i c_i e^{\frac{-\|x_i - x_j\|^2}{\sigma^2}} \left(x_i^{(d)} - x_j^{(d)} \right). \tag{9}$$

where $\frac{\delta \hat{y}}{\delta x^{(d)}}$ represents the pointwise derivative of dependent variable y and predictors x, c_i denotes the scaled weight of the predictors, e means exponential, i is the unit of observations, j represents a single observation, and σ^2 is the kernel bandwidth.

4. Results and Discussion

The descriptive statistical analysis is always essential prior to the model estimation since it reveals the characteristics of the variables under investigation. Table 2 shows that the mean for CO_2 emissions for Kenya, Senegal and Eswatini is 4308 kt, while the mean economic growth, total primary energy consumption and the population is USD 8.55 billion, 0.074 quadrillion Btu, and 13,144,562 persons, respectively. Table 2 reveals that CO_2 and POP exhibit a platykurtic distribution while GDP and PEC exhibits a leptokurtic distribution. However, all the variables under investigation are positively skewed.

Table 2. Descriptive Statistical Analysis.

Statistic	CO_2	GDP	PEC	POP
Mean	4307.898	8.55E+09	0.0743	13,144,562
Median	3698.17	5.10E+09	0.0550	9,085,303
Maximum	13,457.89	5.51E+10	0.2470	44,826,849
Minimum	132.012	3.61E+08	0.0077	603,372
Std. Dev.	3491.428	1.04E+10	0.0633	12,935,509
Skewness	0.789782	2.596235	0.9352	0.889964
Kurtosis	2.815526	9.967597	3.0433	2.605364

The initial panel estimation began by testing for cross-section dependence, a challenge that renders the choice of selecting panel unit root tests difficult. The results of the cross-section dependence (CD) test using the estimation procedure proposed by Pesaran [30] is presented in Table 3. The null hypothesis of cross-section independence is rejected at 1% significance level. Thus, the CD test confirms the presence of cross-section dependence. As a requirement of the Kao residual cointegration tests, the variables under investigation should be integrated of order one. As such, the study employs the second generational unit root tests (CIPS and CADF) that control for heterogeneity and cross-section dependence. The results of CIPS [31] and CADF [31] unit root tests presented in Table 3 reject the null hypothesis of non-stationarity for all the data series. Meaning that all the data series are integrated of order one, thus fulfilling the conditions of FMOLS and DOLS estimation techniques.

Table 3. Panel Cross-section Dependence and Unit Root Test.

Variable	CD	CIPS Level	CIPS 1st Diff	CADF Level	CADF 1st Diff
lnCO_2	7.470 †	−1.864	−5.973 ***	0.438	−4.795 ***
lnPEC	8.200 †	−1.290	−5.790 ***	1.593	−3.486 ***
lnGDP	8.840 †	−1.896	−4.754 ***	−0.175	−3.966 ***
lnPOP	8.880 †	−0.037	−3.960 ***	6.110	−2.507 ***

Notes: CD denotes Cross-section Dependence test, † represents the rejection of the null hypothesis of cross-section independence CD~N(0,1), ***,**,* denote rejection of the null hypothesis of unit root at confidence interval 99, 95, 90%.

To examine the validity of the EKC hypothesis in Kenya, Senegal and Eswatini, the study employs the fully modified ordinary least square (FMOLS) and the dynamic ordinary least squares (DOLS) regression as the estimation technique. The results of the Kao residual cointegration test are presented in Table 4. As a requirement of the FMOLS and DOLS, the cointegration between the response and predictor variables should be validated. Table 3 reveals that out of the five tests conducted, four tests confirm the validity of the panel cointegration test at 1%, 5% and 10% significance levels.

Table 4. Residual Cointegration Tests.

Panel	A	B	C	D
Modified Dickey–Fuller t	−3.129 ***	−3.129 ***	−5.236 ***	−1.286 *
Dickey–Fuller t	−2.644 ***	−2.644 ***	−5.913 ***	−1.501 *
Augmented Dickey–Fuller t	−1.006	−1.006	−1.963 **	−0.939
Unadjusted modified Dickey–Fuller t	−5.486 ***	−5.486 ***	−14.642 ***	−4.018 ***
Unadjusted Dickey–Fuller t	−3.253 ***	−3.253 ***	−8.035 ***	−2.575 ***

Notes: Panel A = lnCO_2~f(lnGDP, lnGDP^2, lnPEC, lnPOP), Panel B = lnCO_2~f(lnGDP, lnPEC, lnPOP), Panel C = lnPEC~f(lnGDP, lnCO_2, lnPOP), and Panel D = lnGDP~f(lnPEC, lnCO_2, lnPOP). ***,**,* denote the rejection of the null hypothesis of no cointegration at 99, 95 and 90% confidence interval.

After confirming that the data series are cointegrated in all four models, the study progresses to test the validity of the EKC hypothesis in Kenya, Senegal and Eswatini. Evidence from Table 5 shows that both DOLS and FMOLS shows similar outcome based on the sign and significance. The goodness of fit test (R-squared) in DOLS and FMOLS shows that the independent data series (GDP, GDP^2, PEC) predicts 92% of the response variable (CO_2). Table 5 reveals that a 1% increase in total primary energy consumption increases CO_2 emission by 0.6% in both DOLS and FMOLS. Moreover, a 1% increase in economic growth increases CO_2 emissions by 0.6% (i.e., GDP/2*GDP^2) and reduces thereafter, thus, confirming the validity of the EKC hypothesis in Kenya, Senegal and Eswatini.

Table 5. DOLS and FMOLS Regression Analysis.

DOLS				FMOLS			
Variable	Coefficient	t-Statistic	Prob.	Variable	Coefficient	t-Statistic	Prob.
GDP	1.3013 (0.3408)	3.8185	0.0002 ***	GDP	1.5527 (0.3211)	4.8358	0.0000 ***
GDP^2	−1.0459 (0.2682)	−3.9003	0.0002 ***	GDP^2	−1.2476 (0.2524)	−4.9428	0.0000 ***
PEC	0.6162 (0.1270)	4.8504	0.0000 ***	PEC	0.5621 (0.1200)	4.6826	0.0000 ***
R^2	0.9239			R^2	0.9216		

Notes: [.] denotes the standard error, *** represents statistical significance at 1% level.

We examine the long-run and short-run equilibrium relationship between CO_2 emission, energy consumption, economic growth and population using the mean-group (MG) and pooled mean-group

(PMG) estimation models. The MG and PMG models are capable of estimating panel data with problems of non-stationary series (i.e., POP) as evidenced in the unit root test. The mean group results in Table 6 reveal that the effect of energy consumption on CO_2 emission is not significant in the long run. However, a 1% increase in economic growth and population, increases CO_2 emissions by 0.21% and 1.37% in the long run. The results of the pooled mean-group estimation in Table 6 shows that the error correction speed of adjustment is negative and significant at 5% level in the three countries under investigation. Thus, the speed of adjusting the previous disequilibria in CO_2 emission in Kenya, Senegal and Eswatini is 40%, 52% and 23%, respectively. Table 6 reveals that, in holding all data series constant, CO_2 emission declines immensely in Kenya, Senegal and Eswatini in the short run.

Table 6. Long-run and Short-run Relationship Analysis.

$\ln CO_2$	Coef.	Std. Err.	z	P > z
LR				
lnPEC	−0.2855	0.2694	-1.0600	0.2890
lnGDP	0.2145	0.1143	1.8800	0.0610 *
lnPOP	1.3672	0.3802	3.6000	0.0000 ***
SR				
Kenya				
ECT(-1)	−0.4028	0.1059	−3.8000	0.0000 ***
lnPEC	0.0517	0.2309	0.2200	0.8230
lnGDP	−0.0447	0.1240	−0.3600	0.7190
lnPOP	−131.6134	63.2806	−2.0800	0.0380 **
_cons	−8.1012	2.6299	−3.0800	0.0020 ***
Senegal				
ECT(-1)	−0.5178	0.1286	−4.0300	0.0000 ***
lnPEC	0.4385	0.1577	2.7800	0.0050 ***
lnGDP	0.0201	0.1032	0.1900	0.8460
lnPOP	58.3176	32.4960	1.7900	0.0730 *
_cons	−9.9219	3.6142	−2.7500	0.0060 ***
Eswatini				
ECT(-1)	−0.2325	0.1106	−2.1000	0.0360 **
lnPEC	1.2801	0.3097	4.1300	0.0000 ***
lnGDP	0.5122	0.2329	2.2000	0.0280 **
lnPOP	22.6474	16.0772	1.4100	0.1590
_cons	−4.1624	2.3686	−1.7600	0.0790 *

Notes: ECT(-1) means the error correction term, LR denotes the long-run elasticities while SR denotes the short-run elasticities; *,**,*** represent statistical significance at 10, 5 and 1% level.

Next, we apply the Kernel-based Regularized Least Squares to predict CO_2 emissions, economic growth and energy consumption by controlling for heterogeneity effects across mean and quantiles contrary to the DOLS, FMOLS, mean-group and pooled mean-group estimators. The panel-estimated models show the goodness of fit test (R-squared) between 0.92-0.97 and statistical significance at 1% level. Thus, the Kernel-based Regularized Least Squares estimator reveals that the regressors predict 95% of variations in CO_2 emissions (Panel A–B), 97% of variations in energy consumption, and 92% of variations in income level across Kenya, Swaziland and Eswatini. The estimated parameters presented in Table 7 reveal that an average increase in energy consumption spurs CO_2 emissions by 0.26-0.30% on average. The average population growth by 1% increases CO_2 emissions by 0.13-0.14% in Panel A-B. This confirms the results of the long-run elasticities and the short-run results for Senegal and Eswatini in Table 6. Contrary to the results of the EKC presented in Table 5, we find a positive coefficient for both GDP and squared GDP when population growth is controlled. Panel C in Table 7 reveals that an average increase in CO_2 emissions, income level and population by 1% drives energy consumption by 0.24%, ~0.24% and ~0.32%, respectively. Panel D in Table 7 shows that an average increase in energy consumption, CO_2 emissions, and population leads to economic expansion by 0.52%, 0.41% and ~0.12%, respectively. The estimated model is validated using the panel quantile-based

Kernel-based Regularized Least Squares presented in Table 8. In Panel A-B (Table 8), we observe a negative coefficient on energy consumption, GDP, Square GDP and population at the 5th percentile, but turns positive at both the median and 95th percentiles. In Panel C (Table 8), the initial coefficient is negative for CO_2 emissions and income level at the 5th percentile but turns positive at the 50th and 95th percentiles, However, the coefficient of population in Panel C (Table 8) remains unchanged from the 5th to 95th percentiles. In contrast, the coefficient on CO_2 emissions, energy consumption and population in Panel D (Table 8) is negative at the 5th percentile but turns positive across the median and 95th percentiles; thus, confirming the presence of heterogeneous distribution across quantiles.

Table 7. Average panel Kernel-based Regularized Least Squares.

Panel	A	B	C	D
$lnCO_2$	—	—	0.242 *** (0.047)	0.411 *** (0.074)
lnPEC	0.262 *** (0.033)	0.295 *** (0.037)	—	0.517 *** (0.051)
lnGDP	0.133 *** (0.024)	0.229 *** (0.045)	0.236 *** (0.041)	—
$lnGDP^2$	0.054 *** (0.015)	—	—	—
lnPOP	0.140 *** (0.024)	0.130 *** (0.028)	0.322 *** (0.030)	0.123 *** (0.040)
Diagnostics				
Number of obs	102	102	102	102
R^2	0.950	0.950	0.968	0.920
Lambda	0.800	0.800	0.800	0.800
Eff. df	8.588	8.098	8.471	7.202
Looloss	8.728	8.602	6.707	14.340

Notes: Panel A = $lnCO_2$~f(lnGDP, $lnGDP^2$, lnPEC, lnPOP), Panel B = $lnCO_2$~f(lnGDP, lnPEC, lnPOP), Panel C = lnPEC~f(lnGDP, $lnCO_2$, lnPOP), and Panel D = lnGDP~f(lnPEC, $lnCO_2$, lnPOP). ***,**,* denote the rejection of the null hypothesis at 99, 95 and 90% confidence interval.

Table 8. Validation using panel quantiles of Kernel-based Regularized Least Squares.

Panel	A	B	C	D
$lnCO_2$				
5th Percentile	—	—	−0.136 *** (0.047)	−0.179 *** (0.074)
50th Percentile	—	—	0.290 *** (0.0470	0.404 *** (0.074)
95th Percentile	—	—	0.466 *** (0.047)	0.852 *** (0.074)
lnPEC				
5th Percentile	−0.034 *** (0.033)	−0.036 *** (0.037)	—	0.136 *** (0.051)
50th Percentile	0.244 *** (0.033)	0.267 *** (0.037)	—	0.529 *** (0.051)
95th Percentile	0.664 *** (0.033)	0.730 *** (0.037)	—	1.037 *** (0.051)
lnGDP				
5th Percentile	−0.206 *** (0.024)	−0.238 *** (0.045)	−0.084 *** (0.041)	—
50th Percentile	0.185 *** (0.024)	0.273 *** (0.045)	0.266 *** (0.041)	—
95th Percentile	0.290 *** (0.024)	0.466 *** (0.045)	0.493 *** (0.041)	—

Table 8. *Cont.*

Panel	A	B	C	D
$lnGDP^2$				
5th Percentile	−0.114 *** (0.015)	—	—	—
50th Percentile	0.054 *** (0.015)	—	—	—
95th Percentile	0.149 *** (0.015)	—	—	—
lnPOP				
5th Percentile	−0.018 *** (0.0240)	−0.027 *** (0.028)	0.072 *** (0.030)	−0.063 *** (0.040)
50th Percentile	0.163 *** (0.024)	0.141 *** (0.028)	0.351 *** (0.030)	0.065 *** (0.040)
95th Percentile	0.304 *** (0.024)	0.289 *** (0.028)	0.540 *** (0.030)	0.483 *** (0.040)
Diagnostics				
Number of obs	102	102	102	102
R^2	0.950	0.950	0.968	0.920
Lambda	0.800	0.800	0.800	0.800
Eff. df	8.588	8.098	8.471	7.202
Looloss	8.728	8.602	6.707	14.340

Notes: Panel A = $lnCO_2$~f(lnGDP, $lnGDP^2$, lnPEC, lnPOP), Panel B = $lnCO_2$~f(lnGDP, lnPEC, lnPOP), Panel C = lnPEC~f(lnGDP, $lnCO_2$, lnPOP), and Panel D = lnGDP~f(lnPEC, $lnCO_2$, lnPOP). ***,**,* denote the rejection of the null hypothesis at 99, 95 and 90% confidence interval.

The estimated models found strong evidence that an average increase in population, income level and energy consumption escalate CO_2 emissions. Meaning that structural change and shocks in energy consumption, economic growth and population would affect environmental pollution. Increasing levels of anthropogenic emissions are attributed to extensive economic activity stemming from fossil fuel energy consumption and surges in energy demand due to the outgrowth of population [32]. Thus, the carbon intensity of the energy systems, acceleration in energy per capita, income level and surge in coal-driven electricity production underpin carbon intensity of economic productivity. Besides, not only are anthropogenic emissions driven by fossil fuel production and consumption but complemented by the expansion in income level, long term population growth, the reversal of declining trends of energy intensity and energy-related carbon intensity [25]. It is also reported that besides population growth, the combination of behavioural, lifestyle and consumption patterns of the population and production technology determines the level of CO_2 emissions released to the environment [33]. Sarkodie and Ozturk [34] argued that higher effect of economic growth on environmental pollution in most countries in Africa, including Kenya, Senegal and Eswatini is due to the exploitation of conventional energy and natural resources for "*industrial purposes to achieve the 2030 development strategy of reaching a middle-income country status of US$1,000 per capita GDP with accelerated economic growth of 6%*" [35]. This finding is in line with Asumadu and Owusu [36] for the case of Ghana. Thus, since Kenya, Senegal and Eswatini are agrarian countries, the initial development of the economy from this (agricultural) pre-industrial sector increases CO_2 emission, due to poor and unsustainable agricultural practices ranging from pre-harvest, harvest and post-harvest activities. In contrast to emissions from agrarian-based economies, high levels of anthropogenic emissions are reported from economies where heavy industrialization and energy products are prevalent [37]. Thus, the level of emissions across countries depends heavily on the economic structure and energy portfolio. Increasing populations in Kenya, Senegal and Eswatini increase the demand for energy and natural resources, which in turn propels CO_2 emission due to low technological advancement and weak environmental policies. Corroborating our estimated results, reduced population growth is reported to decrease anthropogenic emissions due to stabilized or reduced demand for energy services [38]. Contrary to the results of the long-run relationship, an increase in the population decreases CO_2 emissions in

Kenya and Senegal in the short-run. In contrast to a previous study [39] in Senegal that found energy consumption to decline CO_2 emissions, our study shows that energy consumption has a positive impact on environmental pollution in Senegal and Eswatini, while an increase in economic growth in Eswatini increases CO_2 emission in the short-run. In contrast to the EKC hypothesis validated by DOLS and FMOLS estimator, the Kernel-based Regularized Least Squares confirm the scale effect hypothesis between income level and CO_2 emissions when the population is controlled. Thus, Kenya, Senegal and Eswatini are in the trajectory of environmental pollution with increasing economic development and population growth. As economic growth and productivity increases to achieve middle-income status, emissions increase due to the reliance on conventional energy and natural resources to meet the growing demand due to the increasing population. Increasing daily requirements of energy and its related services can be traced to population growth and livelihood pressures. The overdependence on fossil fuels—which are carbon-intensive rather than renewables—which has low or zero carbon emissions, can be linked to market failure, cost and technological innovation [2]. Thus, controlling for these challenges, especially in developing economies, will remove the barriers that hamper the patronization of clean and modern energy sources to decline emissions. Though economic development surpasses the levels of anthropogenic emissions, however, it is reported that lower levels of emissions can be achieved with growth in wealth by reducing energy and carbon intensity via efficiency and conservation options in the energy mix [40].

5. Conclusions

The environmental problems in Africa are because of anthropogenic activities from the exploration and exploitation of available natural resources. These environmental issues consist of proximity to safe water, desertification issues, forest encroachment and explosion of population. The African continent is generally driven by primary sectors like agrarian activities, mining and lumbering which have an environmental effect. It is on this premise that we examined the relationship between CO_2 emissions, economic growth, population and energy consumption in Kenya, Senegal and Eswatini by investigating the validity of the EKC hypothesis. We used econometric methods such as DOLS, FMOLS, MG and PMG estimation models to examine the long- and short- run equilibrium relationship. To account for heterogeneous effects across countries, we used Kernel-based Regularized Least Squares (KRLS), a machine learning technique that produces unbiased statistical inferences. The study found that CO_2 emissions, population dynamics and income level escalate energy demand and consumption. This means that variability in weather patterns due to climate change affects temperature, hence, a great deal of energy is required to either contain colder weather (winter) or warmer weather (summer) conditions. This shift in extreme temperature increases energy consumption due to an increase in residential heating and air-conditioning intensity, especially in urban areas. Increase in population dynamics and income level underscore rising levels of energy demand. In developing countries like Kenya, Senegal and Eswatini, the high level of multidimensional poverty propels the exploitation of available resources to meet livelihood pressures. However, our study showed that economic development can be expanded in Kenya, Senegal and Eswatini through improved energy consumption and using its labour force attributed to population growth.

The DOLS and FMOLS estimator confirmed the inversed-U shape relationship between income level and environmental pollution without accounting for population dynamics, hence validating the EKC hypothesis in Kenya, Senegal and Eswatini. In contrast, the Kernel-based Regularized Least Squares approach confirmed the scale effect hypothesis by controlling for population dynamics. Thus, as a requirement to achieve a middle-income status and mitigate climate change and its impacts by 2030, most countries require sustained economic growth and productivity through decarbonization, innovation and creativity, technological advancement, diversification, and value addition to raw materials. The impact of energy consumption and economic growth on environmental pollution can be reduced by improving energy efficiency and decoupling energy use from economic growth.

Our study is limited to the use of immediate drivers of anthropogenic emissions proposed by the IPCC 5th Assessment report, and hence, does not account for underlying factors, policy, and measures related to emissions. Future studies should aim at assessing the role of underlying drivers and policy measures on immediate driver-attributable emissions.

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