Testing the Environmental Kuznets Curve Hypothesis: The Role of Deforestation

Korhan K. Gokmenoglu, Godwin Oluseye Olasehinde-Williams and Nigar Taspinar

Abstract This study examines the validity of the environmental Kuznets curve (EKC) hypothesis by augmenting the model with renewable energy consumption, fossil fuel energy consumption, urbanization, and deforestation. The ten countries that jointly own two-thirds of the global forest area are studied over the period of 2000–2015. This study fills the gap in the environmental economics literature by introducing deforestation for the first time as a variable affecting environmental degradation, instead of as a measure of environmental degradation. The long-run equilibrium relationship between the variables was confirmed by Kao (J Econ 90(1):1–44, [40])and Pedroni (Fully modified OLS for heterogeneous cointegrated panels. Emerald Group Publishing Limited, 93–130, [59]) panel cointegration tests. Fully modified ordinary least squares' (FMOLS) results support the validity of the deforestation-induced EKC hypothesis, and the pairwise Dumitrescu and Hurlin Granger causality test suggests the existence of a causal relationship among the variables. The empirical results suggest that policies which induce afforestation—such as afforestation grants, tax exemptions for plantations, and tariffs on imports for forest products—are crucial to reducing the carbon dioxide (CO_2) emissions in host countries.

Keywords Environmental Kuznets curve · Deforestation · FMOLS · Granger causality

JEL Codes C23 · Q53 · Q58

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1 Introduction

The world has seen serious changes in its biosphere. In the 1700s, approximately 50% of the world biosphere was wild, and about 45% was in a semi-natural state. However, these percentages have nearly reversed themselves. By 2000, about 55% of the terrestrial biosphere had been converted into either human settlements or agricultural land, 20% remained in a semi-natural state, and only about 25% was in a purely natural state [29]. This drastic change in the natural order has brought many changes to the environment, the most significant of which is increased greenhouse gas (GHG) emissions. The negative effect of GHGs on the environment is well-established in the environmental economics literature.

Many human-induced factors, such as burning fossil fuel for electricity, transportation, heat, and industry, are major causes of GHG emissions. Approximately one-quarter of the total amount of human-induced GHG emissions is attributable to the agriculture, forest, and other land-use sectors, with deforestation being the biggest contributor [73]. Deforestation is, in fact, the second highest human-induced cause of carbon emissions, even higher than the entire world transportation sector emissions and only lower than the emissions from the global energy sector [79]. The forest biomass absorbs carbon dioxide (CO_2) emissions from the atmosphere, and about 300 billion ton (approximately 30 times the per annum emissions from burning fossil fuels) are stored up in this biomass [21]. About three billion tons of carbon is estimated to be released yearly into the air as a result of deforestation [10, 36]. A possible cost-effective policy option for carbon emission control that is often overlooked is deforestation management. Stern [75] claims that a single hectare of forest is valued at approximately 25,000 USD in terms of its carbon sequestration ability, whereas each ton of CO_2 emissions released into the atmosphere is valued at about 85 USD in terms of its negative impact on the world economy.

The Kuznets curve concept was first introduced by Kuznets [47] when he asserted that there was a relationship between per capita income and income inequality. He further claimed that the relationship produces an inverted U-shaped curve, suggesting that income inequality rises to a maximum and then begins to decline as per capita income increases over time. His idea was eventually adopted by the environmental policy literature in the 1990s as a means for studying the relationship between environmental quality and per capita income. Grossman and Krueger [33] were the first to uncover the existence of an inverted U-shaped association between pollution and per capita income. Not long afterward, Shafik and Bandyopadhyay [69] also put forward evidence in support of an inverted U-shaped association between the quality of the environment and economic growth by tracing the environmental transformation patterns of nations at various levels of national income. Panayotou [58] similarly investigated the growth-environmental quality relationship and, like others before him, also found an inverted U-shaped relationship between the variables. It was he who named the environmental Kuznets curve (EKC). Following the precedent set by these pioneering empirical studies, a generation of EKC empirical studies also examined the income-environmental quality nexus with a focus on only these two variables [34, 67, 68]. Figure 1 graphically represents the main idea of the EKC hypothesis.

Over time, several patterns of augmentation of the traditional EKC model have emerged. The first set of researchers augmented the EKC model with energy consumption. The argument for this is that energy consumption, economic growth, and pollution are intricately intertwined and therefore should be studied within an integrated framework. Most of these studies focused primarily on total fossil fuel energy consumption as the most significant measure of energy consumption [1, 6, 17, 20, 44, 66, 76, 80]. Others have used specific forms of energy consumption in their studies, such as coal consumption [78], natural gas consumption [74], and electricity consumption [49, 65].

Researchers have built expanded significantly on these earlier studies by extending the traditional EKC model with macroeconomic, demographic, and institutional variables. For example, Chang [18] augmented his model with labor and capital. Al-Mulali et al. [5], in addition to labor and capital, also factored in foreign trade. Solarin et al. [74] and Tang and Tan [77] all included foreign direct investment in their studies. Trade openness has also been extensively used in EKC studies (see Jalil and Mahmud [38], Kohler [45], Lau et al. [48], Shahbaz et al. [70]. Examples of studies that model demographic variables in addition to the traditional EKC variables include the following: Ahmed and Long [2], Azam and Khan [9], Kang et al. [39], and Onafowora and Owoye [56]. Also, Apergis and Ozturk [7], Ozturk and Al-Mulali [57], and Yin et al. [82] augmented their models with institutional variables.

Several studies have examined deforestation within the EKC framework. Their approach, however, has mainly been to treat deforestation as a measure of environmental degradation rather than as an explanatory variable. According to Miah et al. [54], the inverted U-shape observed for deforestation is due to the fact that the people

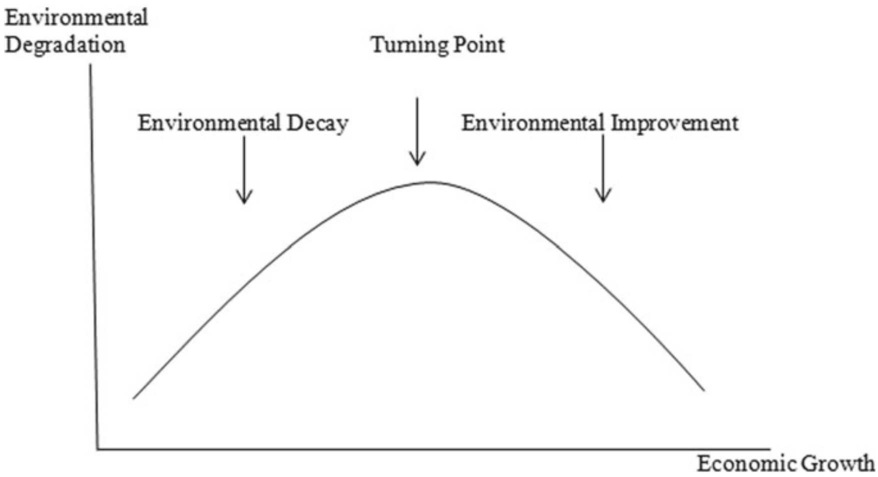

Fig. 1 Environmental Kuznets curve

who depend largely on forest products are at the lower levels of income per capita, but, beyond a certain income level, forest products begin to be replaced with substitutes which have no negative impact on forests. Studies treating deforestation as an environmental degradation indicator include Benedek and Fertő [12], Bhattarai and Hammig [13], Culas [22, 23], Galinato and Galinato [31], Koop and Tole [46], and Polomé and Trotignon [64]. The general consensus of these studies is that deforestation is strongly correlated with economic growth. For example, Ehrhardt-Martinez et al. [28] investigated the sources of EKC for deforestation relative to the economic performance of developing countries from 1980 to 1995; when applying ordinary least squares (OLS) estimation techniques, they found strong evidence in support of the inverted U-shaped EKC. Ahmed et al. [3] examined the EKC hypothesis in Pakistan from 1980 to 2013 by applying time series estimation techniques, such as the autoregressive distributed lag (ARDL) bounds test for the level relationship, and the results suggested a level relationship between growth and deforestation, in addition to a few other variables. Their results also showed that the economic growth Granger-causes deforestation. Table 1 summarizes the literature on the EKC augmentation pattern.

It stands to reason that the traditional EKC model should be augmented with deforestation for two reasons: (1) Deforestation is a major source of carbon emissions, and (2) deforestation is correlated with economic growth. Therefore, not explicitly controlling for the effects of deforestation in a typical EKC model will result in an omitted variable bias and a violation of the zero conditional mean assumption. Our argument is that deforestation, economic growth, and environmental degradation are closely interrelated and, thus, deserve to be studied within a single framework. Consequently, the aim of this study is to test the validity of the EKC hypothesis when the EKC model is augmented with deforestation and other common EKC variables over the period of 2000–2015 for the ten countries that jointly own two-thirds of

Table 1 Summary of EKC augmentation literature

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Ahmed et al. [3]	1980–2013	Pakistan	ARDL, VECM Granger causality	DEF, economic growth, EC, trade openness, population	Yes
Al-mulali et al. [5]	1981–2011	Vietnam	ARDL	CO_2, GDP, fossil fuels EC, renewable EC, capital, labor, export, imports	No

(continued)

Table 1 (continued)

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Ang [6]	1960–2000	France	ARDL, VECM Granger causality	CO_2, GDP, GDP^2, EC	Yes
Apergis and Ozturk [7]	1990–2011	14 Asian countries	GMM	CO_2, GDP, GDP^2, population density, land, industry shares in GDP, quality of institutions indicators	Yes
Atasoy [8]	1960–2010	USA	AMG, CCEMG	CO_2, GDP, GDP^2, EC, population	Yes
Azam and Khan [9]	1975–2014	Tanzania, China, Guatemala, USA	OLS	CO_2, GDP, energy usage, trade openness, trade volume, urbanization growth rate	Yes for low-income countries
Bakirtas and Cetin [11]	1982–2011	MIKTA countries	PVAR, PVAR Granger causality	CO_2, GDP, GDP^2, EC, FDI	No
Benedek and Fertő [12]	1990–2010	67 countries where forest cover increased between 1990 and 2010	OLS, instrumental variables	Forest cover change and DEF index, GDP, GDP^2, trade in forestry, economic freedom, protected area coverage, arable land	Yes

(continued)

Table 1 (continued)

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Bhattarai and Hammig [13]	1972–1991	66 countries of Latin America, Africa, and Asia	FE	DEF, GDP^2, GDP^3, political institution, black market forex, debt, population, change in cereal yield	Yes
Bilgili et al. [14]	1977–2010	17 OECD countries	Panel DOLS, FMOLS	CO_2, GDP, GDP^2, renewable energy	Yes
Chang [18]	2000–2010	G-7, Brazil, Russia, India, China, and South Africa	Data envelopment analysis	CO_2, GDP, labor, capital, energy use	No
Cho et al. [20]	1992–2004	132 developed and developing countries	OLS	CO_2, GDP, GDP^2	Yes
Culas [22]	1972–1994	14 tropical developing countries from Latin America, Africa, and Asia	Pooled regression, FE, RE	DEF, GDPPC, $GDPPC^2$, contract enforceability, absolute forest area, proportion of forest area, population, agricultural production, export price index	Yes
Culas [23]	1970–1994	43 countries from Latin America, Africa, and Asia	Pooled regression, FE, RE	DEF, GDPPC, $GDPPC^2$, GDP growth, absolute forest area, proportion of forest area, population density, agricultural production, foreign debt, export price, time trend	Mixed results

(continued)

Table 1 (continued)

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Dogan and Turkekul [26]	1960–2010	USA	ARDL	CO_2, GDP, GDP^2, EC, trade openness, urbanization, FD	No
Ehrhardt-Martinez et al. [28]	1980–1995	LDCs with available forest cover estimates that experienced net deforestation between 1980 and 1995	OLS	DEF rate, forest stock, population pressure R/U migration, labor in services, secondary education, protected areas, government scope, democracy, debt level/GDP, change in debt, forest exports/GDP, forest export/global forest exports, forest import/global forest imports, imports/export	Yes
Galinato and Galinato [31]	1990–2003	22 countries from Latin America and Asia	OLS, FE, RE	Crop area harvested, GDPPC, crop price index, FDI, political stability, corruption control index, trade openness, unpaved road, investment price	No

(continued)

Table 1 (continued)

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Gill et al. [32]	1970–2011	Malaysia	ARDL	CO_2, GDP, GDP^2, portion of renewable energy in total energy production	Yes
Jalil and Mahmud [38]	1975–2005	China	ARDL, pairwise Granger causality	CO_2, GDP, GDP^2, EC, trade openness	Yes
Katircioğlu and Katircioğlu [44]	1960–2013	Turkey	ARDL, Maki cointegration	CO_2, GDP, GDP^2, EC, urban population	No
Katircioğlu [43]	1971–2010	Singapore	Maki cointegration, DOLS, VECM Granger causality	CO_2, energy use, GDP, GDP^2, total number of international tourists	Yes
Kasman and Duman [42]	1992–2010	New EU member and candidate countries	Panel FMOLS	CO_2, GDP, GDP^2, EC	Yes
Kohler [45]	1960–2009	South Africa	ARDL, Johansen cointegration, VECM, Granger causality	CO_2, GDP, GDP^2, EC, trade openness	Yes
Koop and Tole [46]	1961–1992	76 developing countries	Pooled regression, FE, RE	DEF, GDPPC, $GDPPC^2$, change in GDP, population density, change in population	No
Lau et al. [48]	1970–2008	Malaysia	ARDL, VECM Granger causality	CO_2, GDP, GDP^2, FDI, trade openness	Yes

(continued)

Table 1 (continued)

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Lean and Smyth [49]	1980–2006	ASEAN	Johansen-Fisher panel cointegration, DOLS, VECM Granger causality	CO_2, GDP, GDP^2, electricity consumption	Yes
Liu et al. [52]	1970–2013	ASEAN	Pedroni, Kao cointegration, OLS, DOLS, FMOLS, VECM Granger causality	CO_2, GDP, GDP^2, renewable energy, agriculture	No
Onafowora and Owoye [56]	1970–2010	Brazil, China, Egypt, Japan, Mexico, Nigeria, South Korea, and South Africa	ARDL, VECM Granger causality	CO_2, GDP, GDP^2, EC, trade openness, population	Yes for Japan and South Korea
Ozturk and Al-mulali [57]	1996–2012	Cambodia	GMM, TSLS	GDP, urbanization, trade openness, control of corruption, governance	No
Polomé and Trotignon [64]	1975–2014	Brazil	VECM	DEF, GDPPC, $GDPPC^2$	No
Saboori and Sulaiman [65]	1980–2009	Malaysia	ARDL, Johansen cointegration, VECM Granger causality	CO_2, GDP, GDP^2, total energy, coal, gas, electricity, oil consumption	No
Shahbaz et al. [71]	1980–2010	Romania	ARDL	CO_2, GDP, GDP^2, EC	Yes
Shahbaz et al. [70]	1971–2009	Pakistan	ARDL, Gregory–Hansen cointegration, VECM Granger causality	CO_2, GDP, GDP^2, EC, trade openness	Yes

(continued)

Table 1 (continued)

Author	Period	Country/region	Methodology	Variables	EKC hypothesis
Shahbaz et al. [72]	1971–2011	Malaysia	ARDL, VECM Granger causality	CO_2, EC, FD, FD square, trade openness, FDI	Yes
Tan et al. [76]	1975–2011	Singapore	Johansen cointegration, VAR Granger causality	CO_2, GDP, GDP^2, EC	No
Tang and Tan [77]	1976–2009	Vietnam	Johansen cointegration, VECM Granger causality	CO_2, GDP, GDP^2, EC, FDI	Yes
Tiwari et al. [78]	1966–2011	India	ARDL, Johansen cointegration, VECM Granger causality	CO_2, GDP, GDP^2, coal consumption, trade openness	Yes
Wang et al. [80]	1995–2007	China	Pedroni cointegration test, VECM Granger causality	CO_2, GDP, GDP^2, EC	Yes
Yin et al. [82]	1980–2012	China	Pooled regression, FE, RE	CO_2, GDPPC, $GDPPC^2$, regulation, technological progress, population, energy efficiency, energy structure, industrial structure, trade, FDI	Yes

the global forest area. Other variables included for control are renewable energy consumption, fossil fuel energy consumption, and urbanization. To the best of our knowledge, this is the first instance in the EKC literature that deforestation has been introduced as an independent variable affecting environmental degradation, instead of as a measure of environmental degradation.

The remainder of this study is organized as follows: Sect. 2 provides information about data, model specification, and methodology; Sect. 3 summarizes the empirical results of the study; and the conclusion and policy implications are discussed in Sect. 4.

2 Data, Model Specification, and Methodology

The ten countries (Australia, Brazil, Canada, China, Congo, India, Indonesia, Peru, Russia, and the USA) that jointly account for two-thirds of the world's forest area, based on Food and Agriculture Organization (FAO) statistics, were chosen as the sample for this study. Annual data from these ten countries, covering the years 2000–2015, were obtained for seven variables and were dependent on their availability. In our model, in addition to CO_2 emissions, gross domestic product (GDP), the square of GDP, we included deforestation, urbanization, renewable energy consumption, and fossil fuel energy consumption, which are generally accepted as determinants of pollution and extensively used in EKC literature. The EKC literature has established that both urbanization and energy consumption cause increases in carbon emissions [51, 81], while increased use of renewable energy forms lowers the level of carbon emissions [55, 83]. Table 2 represents the variables, measures, and expected impacts of the independent variables on the dependent variable.

Table 2 List of variables

Variable	Measure	Notation	Expectation
Dependent variable			
Carbon dioxide emissions	CO_2 emissions (metric ton per capita)	CO_2	
Independent variables			
Gross domestic product	GDP per capita	GDPPC	+
Squared gross domestic product	(GDP per capita)^2	GDPPC^2	–
Deforestation	Forest area (% of land area)	DF	–
Fossil fuel energy consumption	Fossil fuel energy consumption (% of total)	FOSS	+
Renewable energy consumption	Renewable energy consumption (% of total)	REN	–
Urbanization	Urban population (% of total)	UR	+

The following econometric model is specified in order to test the augmented EKC hypothesis:

$$\begin{aligned} \mathrm{LCO}_{2it} = \beta_0 + \beta_1 \mathrm{LGDPPC}_{it} + \beta_2 \mathrm{LGDPPC}_{it}^2 + \beta_3 \mathrm{LUR}_{it} \\ + \beta_4 \mathrm{LREN}_{it} + \beta_5 \mathrm{LFOSS}_{it} + \beta_6 \mathrm{LDF}_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where LCO_{2it}, LGDPPC_{it}, LGDPPC_{it}^2, LUR_{it}, LREN_{it}, LFOSS_{it}, and LDF_{it} are the logarithmic forms of CO_2 emissions, GDP per capita, squared GDP per capita, urbanization, renewable energy consumption per capita, fossil fuel energy consumption per capita, and deforestation, respectively.

2.1 Panel Unit Root Tests

The panel unit root tests of Levin–Lin–Chu (LLC) [50], Im, Pesaran and Shin (IPS) [37], and ADF–Fisher chi-square test (ADF–Fisher) are applied to test for the presence of panel stationarity. All these tests have a null hypothesis that there is a unit root against the alternative that variables are stationary. The most widely used of these tests is the one created by Levin et al. [50], given as:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \sum_{j=1}^{p_i} p_i \Delta y_{it-j} + e_{it}, \tag{2}$$

where Δy_{it} is the difference of y_{it} for ith country in time period $t = 1, \ldots, T$. This test is based on the assumption of homogeneity such that $H_0 : \beta = \beta_i = 0$.

The test of Im et al. [37] introduces heterogeneity into Eq. (2) by allowing β_i vary across cross sections; i.e., under the alternative hypothesis, some but not all of the individual series may be non-stationary. The nonparametric, heterogeneous Maddala and Wu [53], Fisher [30] test based on p values is our final panel unit root test. The test statistic is shown as:

$$p = -2 \sum_{i=1}^{N} \ln \beta_i \tag{3}$$

2.2 Panel Cointegration Test

Cointegration tests of Kao [40] and Pedroni [59] are conducted to check the existence of a long-run relationship among variables. The Kao test is a parametric, residual-based test for the null hypothesis of no cointegration. It is founded on LSDV regression equation given as:

$$y_{it} = \alpha_i + \beta X_{it} + e_{it} \tag{4}$$

Dickey-Fuller [24] and augmented Dickey-Fuller [25] tests are applied to the residuals obtained from the estimation of the regression equation. All the five variations of the Kao test slope coefficient (β) are cross-sectional invariant. Pedroni [59]—also a residual-based cointegration test for the null of no cointegration—relaxes the homogeneity assumption of Kao [40]. The underlying Pedroni [59] regression equation is specified thus:

$$y_{it} = \alpha_i + \delta_i t + \beta_i X_{it} + e_{it}, \tag{5}$$

where α_i, δ_i and β_i are free to vary across cross sections. Two types of statistics are considered by Pedroni [59] based on the method of pooling residuals obtained from Eq. (5); the first type pools the obtained residuals on the within dimension (homogenous panel cointegration statistics), and the second type on the other hand pools the obtained residuals along the between dimension (heterogeneous group mean statistics).

2.3 *Estimating the Cointegration Relationship with Weighted FMOLS*

We use fully modified ordinary least squares (FMOLS) to estimate cointegrated panel regressions [19]. FMOLS is a very commonly used panel estimation technique. It is a nonparametric approach that produces optimal cointegrating regression results [63], and it is designed to make adjustments for serial correlation and endogeneity due to the presence of cointegrating relationships [62]. We adopt the Pedroni [60] and Kao and Chiang [41] pooled FMOLS estimators for heterogeneous panels that are cointegrated (weighted FMOLS). The approach allows changes in long-run variances across cross sections. The corresponding estimator and asymptotic covariance are given, respectively, as:

$$\hat{\beta}_{fw} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} X_{it}^{*} X_{it}^{*'} \right]^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it}^{*} y_{it}^{*} - \lambda_{12i}^{*'} \right) \tag{6}$$

$$\widehat{V}_{fw} = \left[\frac{1}{N} \sum_{i=1}^{N} \left[\frac{1}{T^2} \sum_{t=1}^{T} X_{it}^{*} X_{it}^{*'} \right] \right]^{-1} \tag{7}$$

2.4 Panel Granger Causality Tests

The presence of cointegration is an indication that causal relationships possibly exist between the variables. To detect the existence and direction of causal relationships, we adopt the Dumitrescu and Hurlin [27] Granger causality test. The general form of the multivariate regressions in panel Granger causality testing is:

$$\begin{aligned} y_{it} &= \alpha_{0i} + \alpha_{1i} y_{it-1} + \cdots + \alpha_{li} y_{it-1} + \beta_{1i} X_{it-1} + \cdots \\ &\quad + \beta_{1i} X_{it-1} + \cdots + \beta_{2i} Z_{it-1} + \cdots \beta_{2i} Z_{it-1} + \varepsilon_{it} \end{aligned} \tag{8}$$

$$\begin{aligned} X_{it} &= \alpha_{0i} + \alpha_{1i} X_{it-1} + \cdots + \alpha_{li} X_{it-1} + \beta_{1i} y_{it-1} + \cdots \\ &\quad + \beta_{1i} y_{it-1} + \cdots + \beta_{2i} Z_{it-1} + \cdots \beta_{2i} Z_{it-1} + \varepsilon_{it} \end{aligned} \tag{9}$$

$$\begin{aligned} Z_{it} &= \alpha_{0i} + \alpha_{1i} Z_{it-1} + \cdots + \alpha_{li} Z_{it-1} + \beta_{1i} X_{it-1} + \cdots \\ &\quad + \beta_{1i} X_{it-1} + \cdots + \beta_{2i} y_{it-1} + \cdots \beta_{2i} y_{it-1} + \varepsilon_{it} \end{aligned} \tag{10}$$

Under the Dumitrescu and Hurlin [27] panel causality test, Granger causality regressions are performed for each of the cross sections from which test statistic averages are generated.

2.5 Cross-Sectional Dependence Test

Asymptotic and finite sample properties of panel unit root and cointegration tests applied in this study are based on the assumption that there is no cross-correlation between the error terms (zero error covariance). A relaxation of the cross-sectional dependence assumption means that the variance–covariance matrix will likely increase with the number of cross sections and consequently, and the test distributions will become invalid [16]. Commonly used cross-sectional dependence tests include Breusch and Pagan [15] LM, Pesaran [61] scaled LM, and Pesaran [61] CD tests. We apply the Pesaran [61] CD test since it deals with the size distortion problem present in the others. The Pesaran CD test is formulated from pairwise correlation coefficient averages for the null of no cross-sectional dependence and is shown as:

$$\mathrm{CD_p} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \hat{\rho}_{ij} \rightarrow N(0,1) \tag{11}$$

3 Empirical Results

Initially, we applied the Pesaran cross-sectional dependence (CD) test, and the insignificant p value (0.13) shows that our data do not suffer from cross-correlated error terms, thus justifying the application of first-generation models. Next, we performed several unit root tests to determine the order of integration of the variables as a precondition for panel cointegration tests. We tested all of the variables both with and without trend and both in level and first differences. Our test results predominantly indicate the presence of unit roots at the level and the absence of unit roots at first difference. Unit root test results are presented in Table 3.

Following the confirmation that all variables were integrated of order one, I(1), we proceeded to the cointegration test to determine the existence of long-run relationships among the variables. Table 4 presents the Kao [40] and Pedroni [59, 60] cointegration test results. Considering first the homogenous panel cointegration tests, two out of four Pedroni tests within dimension-based tests (panel PP-statistic and panel ADF-statistic), and Kao tests, we found that all document the presence of a long-run relationship among the variables. More importantly, the heterogeneous (between dimension-based) cointegration tests are more realistic, and two out of three indicate that the variables are cointegrated. Furthermore, we based our final conclusion that the variables are cointegrated on the result of the group PP-statistic which is both heterogeneous and nonparametric, especially as nonparametric tests are suitable for data that are not normally distributed, and also because it has the most power in the Pedroni and Kao tests [35].

We continued on to estimate the coefficients of long-run relationship with a FMOLS estimator, and the results are shown in Table 5. This is also a nonparametric estimation technique and is valid even when the normality assumption does not hold. The results obtained are interesting. First, in conformity with the EKC hypothesis, GDP per capita and its square have significant positive and negative coefficients, respectively. Based on the results, a percentage increase in these variables will cause carbon emission to increase and decrease by 0.46 and 0.02%, respectively. A coefficient of −0.41 for deforestation suggests that, for each percentage increase in the ratio of forest to land area which indicates less deforestation, CO_2 emissions are expected to decrease by 0.41%. This result is significant at 1% and also in agreement with our a priori expectation. Second, we observed a negative and significant long-run relationship between renewable energy consumption and carbon emission—a percentage rise in renewable energy consumption results in a 0.33% decline in carbon emissions, justifying the argument of Al-Mulali et al. [4] for the inclusion of renewable energy consumption in the EKC framework. It is also in concert with the findings of Myers et al. [55] and Zhai et al. [80]. Third, both fossil fuel consumption and urbanization are also found to positively affect the level of carbon emissions. In the long run, a 1% increase in both variables will cause CO_2 emissions to increase by 1.14 and 1.56%, respectively. This is in consonance with the findings of Li and Yao [51], and Wei et al. [81]. Both fossil fuel consumption and urbanization are shown to be the most powerful influences on carbon emissions within the model.

Table 3 Panel unit root analysis

Variables		LLC		IPS		ADF–Fisher chi-square	
		No trend	Trend	No trend	Trend	No trend	Trend
Level	LCO2	−1.11242	−0.11169	3.56829	0.52931	8.3737	13.0064
	LDF	−0.34715	-3.1482^{***}	1.71590	−0.32842	15.9776	23.2238
	LGDPPC	-2.933^{***}	4.97634	0.40682	5.25693	13.1271	3.29380
	LGDPPC2	-2.5117^{***}	4.75068	−2.51171	4.9012	11.6324	3.91071
	LFOSS	−1.13918	−0.6818	0.51804	0.61357	18.4436	17.4781
	LREN	−0.7426	3.13589	1.50971	2.01233	14.6255	6.96493
	LUR	2.89047	7.43263	3.50667	7.37388	20.2213	9.34919
1st difference	ΔLCO2	-13.353^{***}	-11.806^{***}	-9.3305^{***}	-7.3396^{***}	98.3720^{***}	80.6701^{***}
	ΔLDF	-1709.1^{***}	-1031.0^{***}	-370.30^{***}	-309.47^{***}	45.7961^{***}	40.1419^{***}
	ΔLGDPPC	2.42980^{***}	-5.3502^{***}	-2.3439^{***}	-1.54191^{*}	33.3142^{**}	29.9079^{*}
	ΔLGDPPC2	-2.5674^{***}	-4.8561^{***}	-2.4386^{***}	−1.14284	34.0972^{**}	27.5231
	ΔLFOSS	-8.1080^{***}	-9.8876^{***}	-6.8682^{***}	-6.2221^{***}	79.1836^{***}	70.2830^{***}
	ΔLREN	-9.2318^{***}	-12.113^{***}	-7.3162^{***}	-7.0152^{***}	82.4323^{***}	77.2796^{***}
	ΔLUR	7.61161	-45.883^{***}	4.88611	-25.362^{***}	6.34362	86.8213^{***}

Notes (1) *, **, and *** mean statistic relationship significant at 10, 5, 1%, respectively; (2) Levin, Lin, and Chu t^* presuppose a common unit root process; (3) Im, Pesaran and Shin W-stat, and ADF–Fisher chi-square presupposes individual unit root process; (4) Δ denotes the first difference

Table 4 Panel cointegration analysis

	Within dimension (homogenous)			Between dimension (heterogeneous)	
No trend	Tests	Statistic	Weighted statistic	Tests	Statistic
Pedroni [59, 60]	Panel v-statistic	−2.538274	−3.462572	Group rho-statistic	4.954619
	Panel rho-statistic	3.749107	3.642602	Group PP-statistic	−13.20545***
	Panel PP-statistic	−1.774534**	−9.746416***	Group ADF-statistic	−2.629404***
	Panel ADF-statistic	−0.456837	−3.002905***		
Kao [40]	ADF t-statistic −4.526694***				
Trend	Tests	Statistic	Weighted statistic	Tests	Statistic
Pedroni [59, 60]	Panel v-statistic	−3.330932	−4.639787	Group rho-statistic	5.473123
	Panel rho-statistic	4.144648	4.270092	Group PP-statistic	−15.26644***
	Panel PP-statistic	−10.40605***	−15.55456***	Group ADF-statistic	−3.560869***
	Panel ADF-statistic	−4.062218***	−4.415027***		

Notes (1) **, and *** mean statistic relationship is significant at 10 and 5%, respectively; (2) 160 observations; (3) automatic lag length based on Schwarz information criterion for lag selection is used

Table 5 FMOLS results

Regressors	Coefficient	Standard error	p value
LDF	−0.413557	0.008891	0.0000
LFOSS	1.138035	0.047426	0.0000
LGDPPC	0.460709	0.020295	0.0000
LGDPPC2	−0.022049	0.010746	0.0430
LREN	−0.332514	0.016707	0.0000
LUR	1.556768	0.000421	0.0000
R-squared	0.99759		
S.E. of regr.	0.07047		
D-W-stat.	1.71623		
Long-run variance	0.00096		

Notes (1) Long-run covariance is estimated via the Bartlett kernel and the Newey–West fixed bandwidth; (2) pooled (weighted) panel estimator for heterogeneous panels is used

Table 6 Pairwise Dumitrescu and Hurlin Granger causality test

	LCO2	LDF	LGDPPC	LGDPPC2	LFOSS	LUR	LREN
LCO2	–	0.8224	0.0613*	0.0499**	0.0174**	0.7756	0.1612
LDF	0.0545*	–	0.2511	0.3276	0.1212	0.5832	0.0601**
LGDPPC	0.0262**	0.4645	–	0.9707	0.5266	0.8624	0.0318**
LGDPPC2	0.0501*	0.3618	0.9136	–	0.5702	0.9215	0.0237**
LFOSS	0.0069***	0.9907	0.0582*	0.0912*	–	0.9403	0.8419
LUR	0.0375**	0.7229	0.3551	0.4037	0.382	–	0.0708*
LREN	0.4613	0.5634	0.0783*	0.0726*	0.3938	0.5519	–

Note *, **, and *** mean statistic relationship significant at 10, 5, 1%, respectively

Furthermore, since the cointegration tests results indicate that the variables are cointegrated, we also carried out Granger causality tests in order to determine causal relationship among the variables; Table 6 presents the test results. We infer bidirectional long-run causality for the following variables: carbon emissions and GDP per capita, carbon emissions and squared GDP per capita, carbon emissions and fossil fuel consumption, renewable energy and GDP per capita, and renewable energy and second power of GDP per capita. The unidirectional causality was found, running from urbanization to carbon emissions, deforestation to renewable energy consumption, fossil fuel consumption to GDP per capita, fossil fuel consumption to GDP per capita, urbanization to renewable energy, and, most importantly, from deforestation to carbon emissions. The unidirectional causality from deforestation to carbon emissions provides additional evidence in support of the results obtained from the FMOLS estimations about the relationship between both variables' consumption.

4 Conclusion

The intent of our study is to explore how deforestation influences pollution, and also to determine if the EKC hypothesis holds. To the best of our knowledge, no previous study has augmented the EKC hypothesis with deforestation as an independent variable. Given the important role played by forests in the carbon cycle, we make a case for its inclusion in the EKC model in order to avoid an omitted variable bias problem.

The results from the unit root tests suggest that the variables are integrated into an order of one. The results of both Kao and Pedroni cointegration tests indicate that the variables are cointegrated. This is an indication that long-run relationship exists among the variables. Furthermore, FMOLS results indicate that less deforestation has a negative and significant impact on air pollution, which is in line with our prior expectation. Moreover, the EKC hypothesis holds when deforestation is included in the main model for the case of the ten countries that jointly own two-thirds of the global forest area. From the results, we find that the level of income has a significant and positive long-run coefficient, while the square of income has a significant and negative coefficient. This means that the level of income contributes to CO_2 emissions, while a higher level of income causes improvements in the air pollution.

Our empirical findings are of great importance, especially for policymakers. Given the negative relationship that exists between deforestation and carbon emissions, a relatively simple, easy, and inexpensive means of addressing the pollution problem is to design and/or enforce forest conservation policies. Examples include the creation of protected areas, provision of payments for ecosystem services, and formulation of concession policies that keep deforestation below a national baseline. Policies that induce afforestation, such as afforestation grants, tax exemptions for plantations, and tariffs on imports, are also crucial to reducing carbon emissions. It is safe to say that the cost of planting trees is relatively minimal when compared to the other options available for controlling emissions.

Also, since renewable energy use reduces pollution and non-renewable energy use aggravates it, a strong case is made for greater use of renewable energy sources as opposed to non-renewable energy sources. Policies that encourage renewable energy use, such as eco-taxes, feed-in tariffs, and renewable energy certificates, will be beneficial. Those that promote non-renewable energy by either lowering fossil fuel prices for consumers or by lowering exploitation and exploration costs for producers should at best be abolished or at least drastically reduced.

Our findings on the impact of urbanization on carbon emissions also call into question the effectiveness of urban planning policies which are supposedly designed to take into consideration environmental issues while addressing the problem of urban development. In spite of such policies, our findings show that urbanization is still responsible for a very large share of emissions. There is a need to revisit such urban planning policies and their implementation, especially those concerned with transportation management, land use, and industrialization, in order to ensure that environmental issues such as pollution and deforestation are taken seriously.

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