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Is deforestation needed for growth? Testing the EKC hypothesis for Latin America

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A B S T R A C T

The current climate change debate puts forest conservation and halting deforestation at the forefront of the social and political agenda. This paper analyzes the relationship between forested area and economic growth for a sample of 19 Latin American countries. The selected region has extensive forested areas, but also high rates of deforestation, which makes it a crucial area for reversing deforestation trends. The Environmental Kuznets Curve hypothesis for deforestation is tested for the period 1991–2014, taking environmental damage to the forest cover as an indicator, measured through two variables: the forested area per capita and a comparison to the country's total area. The methodology used applied regressions by panel data, using a semiparametric technique, as well as the generalized method of moments quantile-regression. Obtained results support the hypothesis, although the positive effects of economic growth on forestation tends to disappear, as the income levels become higher. More specifically, the quantile regression shows a positive, growing relationship between forested area per capita and economic growth (from a threshold point) that tends to be softer in more forested areas. Meanwhile, the U-shaped relationship supported when the forested area is compared to the total area tends to reach the maximum value. Therefore, the positive effects of economic growth on forestation tend to disappear, this being more especially observed in the most forested areas.

1. Introduction

Deforestation is currently one of the most serious environmental issues in the world, and has become particularly relevant for tackling climate change (Dobson et al., 1997; Brook et al., 2003; Sodhi et al., 2004). According to the Sustainable Development Goals Report (United Nations, 2019), between 2000 and 2015, forested areas, measured as a proportion of total land area, decreased from 31.1% to 30.7%. In absolute terms, this means a loss of >58 million hectares of forest. Most of this loss occurred in Latin America and sub-Saharan Africa.

The importance of the damage caused by the destruction of tropical forests was originally pointed out by experts in the natural sciences (Myers, 1979). They highlighted the damage caused at various levels, from the modification of indigenous ways of life, to biodiversity. At the regional level, the reduction in the number of trees destabilizes the water cycle, resulting in a drier climate, infertile soils, and a greater probability of flooding (Walker, 1993).

On the other hand, preventing such harm has an impact on the economy. This is particularly true for developing countries, where the countryside is the main factor of production (Kamanga et al., 2009; Barbier and Hochard, 2018). In this sense, the conversion of forested land for agricultural use, such as crops and livestock, is considered a key factor in the process. Countries such as Brazil and Indonesia, which have the largest forests in the world, are leaders in the export of soybeans, biofuel and palm oil, the growing plantation of which implies a boost to deforestation (Özdemir et al., 2009). For non-industrialized economies, conservation programs represent a huge loss of potential income from exports (Verburg et al., 2014). This impedes the conservation of forested areas.

Latin America, understood as the countries of South America, Central America and the Caribbean, is a very representative scenario of this conflict. The many developing economies in the region tend to specialize in environmentally damaging economic activities, causing deforestation. On the one hand, 49% of the total surface area of Latin America is covered with forests, which represents approximately 23% of the existing forested area in the world (Food and Agriculture Organization of the United Nations - FAO, 2018). On the other hand, these countries also have high rates of deforestation. Between 1990 and 2015, 97

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million hectares have been lost in this part of the world, which corresponds to 60% of world losses. This corresponds to an annual deforestation rate equal to −0.40%, while the world rate equated to −0.13% (Bárcena et al., 2020; FAO, 2016). Likewise, as stated by Ritchie and Roser (2021), Latin America is the world zone where most net deforestation has been occurring in recent years, mostly directly associated (66%) with human activities. Therefore, studying the relationship between the economic activities and deforestation in this region is of special interest.

Such studies cover a wide sample of countries. Some of them focus on Latin America, but none of these refer to a recent period (see Table 1). In fact, the most recent period considered refers to 2007 (Joshi and Beck, 2016). However, considering recent periods is interesting, since the rate of deforestation has tended to stabilize in the world generally and in Latin America. Thus, as noted in Ritchie and Roser (2021), deforestation has declined globally from 78 million hectares in the 1990s, to 52 million in the early 2000s, and to 47 million in the last decade. Also, as indicated in FAO (2016), the rate of forest loss in Latin America has decreased substantially in the period 2010–2015.

The aim of this current study is to analyze the relationship between economic growth and deforestation in Latin American countries, considering the most recent period available. To this end, the EKC hypothesis for deforestation is tested for Latin American countries, during the period 1991 to 2014. This hypothesis, which suggests an inverted U relationship between deforestation and economic growth, is tested by using semiparametric and parametric panel data models; the parametric modeling presenting some novelties that allow advances to be made on the previous knowledge.

Firstly, the method proposed by Hasanov et al. (2021) is followed to determine the order of the polynomial that, according to the data, best defines the nonlinear relationship between deforestation and economic growth. This method, which to our knowledge has not been used in the previous literature, allows us not to determine, a priori, the nonlinear relationship of the variables to be tested. On the contrary, it establishes a criterion to determine when it is more appropriate to use the GDP and its squared value as independent variables, and when it is more appropriate to also include the GDP cubed and/or the quadratic value. This flexibility makes it possible to verify the EKC hypothesis as to its validity for all income levels, or only for certain levels. Secondly, quantile regressions have been performed to test the parametric model, which have not previously been used for Latin American countries. This method allows us to consider the heterogeneity between countries. This is interesting for Latin America since, according to FAO data (2016), some Latin American countries, such as Chile, the Dominican Republic and Uruguay, have positive cumulative forest area change rates between 1990 and 2015, while others, such as Honduras and Paraguay, have very negative rates.

This study is structured into seven sections. After the introduction, Section 2 presents the review of the literature related to the subject of study. Section 3 details the database and model used. Section 4 presents a descriptive analysis of variables and Section 5 details the econometric procedure, while Section 6 comments on the results of the applied model. The final Section gives the conclusions drawn from the study.

2. Literature review

2.1. *The Environmental Kuznets Curve hypothesis for deforestation and the Forest Transition Theory*

Two methodologies can be highlighted in the analysis of world deforestation processes linked to the economic growth process: the Forest Transition Theory (or FTT) and the EKC hypothesis applied to this

Table 1
Previous studies on the EKC for deforestation for Latin America.

Article	Period	Countries	Method	Dependent variable	Explanatory variables	EKC for LatAm
Cropper and Griffiths (1994)	1961–1988	Three models: Africa, Asia & LatAm	FE	Deforestation rate	GDPpc, GDPpc^2, GDP change, tropical log price, population change, rural population density, time trend	Yes
Antle and Heidebrink (1995)	1980–1984	82-country model (n.a. LatAm)	OLS	Protected parks & Reforestation	GNIpc, GNIpc^2, forested area, total area, population	Yes
Koop and Tole (1999)	1961–1992	Three models: Africa, Asia & LatAm	OLS, RE, FE, RC	Deforestation rate	GDPpc, GDPpc^2, GDP change, population density, population change	Yes
Barbier and Burgess (2001)	1961–1994	Three models: Africa, Asia & LatAm	OLS, FE, RE	Cropland expansion	GDPpc, GDPpc^2, GDP change, population growth, cereal yield, cropland, agricultural export, arable land per capita	Yes
Bhattarai and Hammig (2001)	1972–1991	Three models: Africa, Asia & LatAm	FGLS	Deforestation rate	GDP, GDP^2, GDP^3, institutions, foreign exchange black market, debt, population, cereal yield change	Yes
Ehrhardt-Martinez et al. (2002)	1980–1995	74-country model (21 from LatAm)	OLS	Deforestation rate (in logs)	GDP (log), forest stock, migration, service work, secondary education, protected areas, governance, democracy, debt, forest export, forest import, import/export	Yes
Barbier (2004)	1960–1999	“Tropical countries” model (n.a. LatAm)	RE	Expansion of arable & cropland	GDPpc, GDPpc^2, terms of trade, agricultural export, agricultural value added, grain yield, rural population, agricultural land, corruption control, political stability, law enforcement	No
Culas (2007)	1972–1994	Three models: Africa, Asia & LatAm	OLS, FE, RE	Deforestation rate	GDPpc, GDPpc^2, contract compliance, forested area (absolute & relative), population, agricultural production, export price	Yes
Scrieciu (2007)	1980–1997	50-country model (17 from LatAm)	FE	Cropland	(Logarithmic equation) GNIpc, export and import deflators, cereal yields, population	n.a.
Motel et al. (2009)	1970–2005	48-country model (13 from LatAm)	FE (time series)	Deforestation rate	(Logarithmic equation) GDPpc, GDPpc^2, GDP change, initial forested area, cultivation, growth & population density, agricultural export, instability of agricultural export	Yes
Culas (2012)	1970–1994	Three models: Africa, Asia & LatAm	RE	Deforestation rate	GDPpc, GDPpc^2, GDP change, forested area (absolute & relative), population, agricultural production, foreign debt, export price, time trend	Yes
Galinato and Galinato (2012)	1990–2003	22-country model (n.a. LatAm)	OLS, FE, RE	Harvested area	(Logarithmic equation) GDPpc, crop prices, Foreign Direct Investment, political stability, corruption control, trade opening, unpaved roads, investment price	No
Joshi and Beck (2016)	1990–2007	Four models: OECD, Africa, Asia & LatAm	GMM	Forested area	GDPpc, GDPpc^2, population, terms of trade, urban population, agricultural land, cereal yield	No

Note: LatAm: Latin America, OLS: Ordinary Least Squares, RE: Random Effects, FE: Fixed Effects, FGLS: Feasible Generalized Least Squares, RC: Random Coefficients, GMM: Generalized Method of Moments, n.a.: not available.

field.

FTT considers that the evolution of the forested area with respect to economic growth is U-shaped. In the early stages of development, forest area decreases. Beyond a certain level of development, however, forest area begins to increase (Klooster, 2003). Based on the analysis by Rudel et al. (2005), Lambin and Meyfroidt (2010) identified five different pathways of the FTT. Firstly, the Forest Scarcity Pathway stands out. According to this process, governments only react with reforestation policies when economic damage, caused by deforestation, occurs. Secondly, the State Forest Policy Pathway is cited. This category highlights the role of government policies in reversing deforestation. These policies may be motivated by the damage mentioned in the previous case, or by reasons unrelated to forest development (for example, tourism). The third pathway is the Economic Development Pathway. According to this, the appearance of economic opportunities, outside agriculture, encourages farmers to abandon their activity, leaving space for forest regeneration. Fourth, the Globalization Pathway is a version of the previous one. In this case, globalization is the agent that induces these changes in farmers' activity. Finally, the Smallholder, Tree-based, Land Use Intensification Pathway. This consists of relating reforestation with the diversification of agricultural activity of small farmers, who seek to reduce risk and preserve their sources of subsistence.

The second methodology used to analyze the deforestation process is based on the EKC hypothesis. Grossman and Krueger (1991) were the first authors to test this hypothesis. In their study they related environmental degradation to economic growth resulting from the NAFTA trade agreement. The result was an inverted U-shaped pattern. Later, Panayotou (1993) replicated this study, coining the name Environmental Kuznets Curve.

Based on these studies, which initially used air pollution as an environmental indicator, numerous research projects have been developed and applied to other specific fields. For example, biodiversity (Mills and Waite, 2009) and water quality (Paudel et al., 2005). The EKC hypothesis has also been applied to the field of deforestation, with Cropper and Griffiths (1994) being one of the first studies in this topic. The EKC hypothesis for deforestation states that, at the beginning of a country's economic expansion, there are high standards of natural forest conservation. Nevertheless, when the country starts growing, forests participate as engines of development, and the deforested area increases rapidly to obtain resources and free up land for carrying out other economic activities. This stage lasts until a threshold level of income is reached, when the country becomes interested in avoiding the consequences of deforested soil (fires, erosion, deterioration of river basins, etc.) and on taking benefits from the forest. From that threshold level, deforestation tends to decrease. The result is an increasing deforestation curve during the initial economic expansion, and a decreasing movement from a certain level of income, which is an inverted U-shaped relationship between economic growth and deforestation (Joshi and Beck, 2016).

Both approaches (FTT and the EKC for deforestation) consider the problem of deforestation from a different perspective. However, Perz and Skole (2003) point out that both theories are related, as there is an inverse relationship between the pattern of the Environmental Curve, in the form of an inverted U, and the evolution explained by the FTT, in the form of a U. In any case, testing one or other hypothesis implies testing the non-linearity relationship between forest, or deforestation, and economic growth.

2.2. Previous research on the EKC hypothesis for deforestation

The results of previous studies which test the EKC hypothesis for deforestation are wide and very heterogeneous. This heterogeneity is found in the pioneering studies. For example, Bhattarai and Hammig (2001) obtained an inverted U pattern for the relationship between income and deforestation in Africa, Latin America and Asia. Cropper and Griffiths (1994) found it only for Latin America and Africa, and not for Asia. Culas (2007) corroborated it for Latin America, Barbier and Burgess (2001) for Asia and Barbier (2004) did not support it for tropical countries. The study by Motel et al. (2009) analyzed this heterogeneity of results, concluding that the more recent the publication of the study, the lower the probability of confirming the EKC hypothesis. More recent studies have also shown this heterogeneity of results. Thus, while Tang and Tan (2015), Yin et al. (2015), and Gill et al. (2018) have proven the existence of the EKC for deforestation, Ozturk and Al-Mulali (2015), Polomé and Trotignon (2016) and Katircioğlu and Katircioğlu (2018) have not found such evidence. In this regard, the recent literature review on this topic by Ajanaku and Collins (2021) shows that these mixed results depended on the type of ecological indicator chosen, the country or group of countries selected, the use of other explanatory variables, and the period of the research.

Regarding the indicators of deforestation in the recent study by Murshed (2022), three deforestation indices in logarithmic form were used: the total forest cover, the deforestation rate, and the net forest depletion rate. In this study, two indices are used with similar characteristics to those in the previous literature.

Regarding the explanatory variables included in previous models, Bhattarai and Hammig (2001) highlight the importance of demographic variables in prior research. In their article, it was argued that many authors had explained deforestation as a function of population variables, largely due to the difficulty in finding reliable statistics for certain countries, especially for developing economies. Therefore, the population variable is also included in the current study. Furthermore, recent studies have used additional explanatory variables. Some of them have been repeatedly applied, as for example political institutions or institutional quality (Ehrhardt-Martinez et al., 2002; Apergis and Ozturk, 2015; Murshed, 2022), trade openness (Onafowora and Owoye, 2014; Ahmed et al., 2015; Azam and Khan, 2016), technological development (Barbier, 2004; Joshi and Beck, 2016), energy consumption (Ang, 2007; Al-Mulali et al., 2015), education levels (Jewel et al., 2018), and Direct Foreign Investment (Galinato and Galinato, 2012; Shahbaz et al., 2013; Bakirtas and Cetin, 2017). In addition, an indicator of agricultural land use, found in Byerlee et al. (2014), is among the control variables used in these studies to understand the relevance of the duality between crop land and deforestation. In this paper, variables for population, exports, energy consumption and crop land are included in the model.

The econometric method employed has also been cited as the possible cause of different results, because sometimes the econometric method did not consider several data characteristics. In this sense, the study by Scrieciu (2007) argued that previous research did not consider autocorrelation problems, thereby conditioning the obtained results. The study by Ajanaku and Collins (2021) shows that different econometric procedures have been used to test the EKC for deforestation. Nevertheless, Ordinary Least Squares-Fixed Effects (OLS-FE) and Ordinary Least Squares-Random Effects (OLS-RE) have frequently been used. However, the application of these techniques can cause bias due to the strong heterogeneity of deforestation factors. Therefore, it is necessary to take this heterogeneity into account. Despite this, to our knowledge, only the study by Damette and Delacote (2012) for the period 1972–1994 used quantile regressions to account for heterogeneity, with no paper using this technique for Latin American countries, nor for a recent period.

The country selection approach for the sample is another aspect that may explain the differences observed among the results of previous studies. Some studies, for instance Caravaggio (2020), test the EKC hypothesis for deforestation from a worldwide perspective. Nevertheless, numerous studies have analyzed only regions or groups of countries. For example, Ajanaku and Collins (2021) tested the EKC hypothesis for deforestation for Africa, while Zambrano-Monserrate et al. (2018) compared it for five European countries. Others have analyzed countries with common characteristics. For example, the study by Cary and Bekun (2021) classified countries by institutional features, such as democracy, while the study by Gokmenoglu et al. (2019) selected the sample based on forest cover.

There is substantial previous research related to Latin America. However, there have been no recent advances in research in this field covering all countries in the region. As shown in Table 1, 13 studies have been carried out to date that take the spatial scope of Latin America as a reference. In the last column of Table 1, it can be observed that a total of nine studies support the EKC hypothesis, while three do not, and one shows no evidence. It should also be noted that most of these studies refer to past periods, the most recent being from 1990 to 2007. Additionally, it is worth noting that most of the studies use OLS (FE or RE), one uses Feasible General Least Squares, and another uses the Generalized Method of Moments. None of these studies use quantile regressions to account for heterogeneity.

This study tests the EKC hypothesis for deforestation for Latin America in a more recent period, for which there is no previous research. Carrying out an analysis during the current period is interesting as, in recent years, the deforestation rate has tended to decrease which could not have been included in previous studies. It also provides original methodological aspects. This study tests two models based on different forested area indicators, by using semiparametric and quantile regressions to account for heterogeneity, which is not found in the previous literature for Latin American countries. Heterogeneity is considered relevant, since Latin American countries show positive and negative deforestation rates in the study period, from 1990 to 2014, indicating differences that should be studied. Finally, it is worth noting that the polynomial order to test the EKC by the quantile method is determined by using the method proposed by Hasanov et al. (2021) which, as far as we know, has not been used previously in the literature.

3. Model justification and database

In this study, the relationship between economic growth and deforestation is analyzed through two different equations' estimates, based on the dependent variable used. In Eq. 1, the dependent variable is the forested area per capita. In Eq. 2, it is the forested area to total area of the country. The explanatory variables used in both equations are the same, as follows:

$$ABSFApc_{it} = f\,(GDPpc_{it}, RURPOP_{it}, EXPORT_{it}, ECpc_{it}, CYpc_{it}) \quad [1]$$

$$RELFA_{it} = f\,(GDPpc_{it}, RURPOP_{it}, EXPORT_{it}, ECpc_{it}, CYpc_{it}) \quad [2]$$

The dependent and independent variables of these equations are defined in Table 2. Meanwhile, i refers to the countries of the sample and t to the years. The sample covers 19 countries within Latin America and the Caribbean, for the period 1991 to 2014. These countries are Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, Guatemala, Honduras, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Paraguay, El Salvador and Uruguay. All data used are from the World Bank database (World Bank, 2020).

Table 2
Model variables.

Variable	Description	Unit	Expected sign
ABSFApc	Forested area per capita	Square kilometers per capita (in logs)	
RELFA	Forested area in relation to the total area of the country	Percentage	
GDPpc	GDP per capita	Constant 2010 US$ (in logs)	Negative
$GDPpc^2$	GDP per capita squared	Constant 2010 US$ (in logs)	Positive
$GDPpc^3$	GDP per capita cubed	Constant 2010 US$ (in logs)	No Prediction
RURPOP	Rural population rate	Percentage	Negative
ECpc	Energy consumption per capita	Kilotonnes of oil equivalent per capita (in logs)	Negative
EXPORT	Export volume index compared to year 2000	Percentage	Negative
CYpc	Cereal Yield	Kilograms of cereal per hectare per capita (in logs)	No Prediction

The first dependent variable is the total area occupied by forest. It is measured in terms of square kilometers in per capita terms, converted into logarithms. This transformation was already applied by Koirala and Mysami (2015). The second dependent variable is the forested area, measured as the country's forested area compared to the total area, an index that can be found in the study from Joshi and Beck (2016). In order to measure the forested area, all types of tree vegetation were included. More recent papers, such as that by Benedek and Fertő (2020), combine qualitative and quantitative techniques to produce a Forest Recovery Index that can account for dissimilar forest management regimes which could impact on forest recovery. In this study, although considering the quality of forests is interesting, only available quantitative data have been used. Additionally, we consider it interesting to compare and analyze direct reforestation, due to investment from abroad or from internal pressures, especially in view of the momentum of reforestation in Latin America since the launching of the 20 × 20 Initiative at COP 20 in Lima in 2014. However, there is insufficient data available to perform such an analysis which therefore poses a limitation on this analysis.

The effects of the economic growth on these variables were studied by including a production variable in previous equations. It is measured as GDP per capita, expressed in constant 2010 US Dollars, converted to per capita terms as a logarithm. In line with previous studies (Bhattarai and Hammig, 2001), the relationships between GDP and the forest variables may be non-linear. Parametric and non-parametric techniques have been previously used to analyze this non-linear relationship (for example, Koop and Tole, 1999; List and Gallet, 1999; Dijkgraaf and Vollebergh, 2005; Nguyen Van and Azomahou, 2007, among others). In this study, a semiparametric estimate was initially obtained and, depending on these results, a parametric function, including squared, cubed and/or a quadratic GDP variable, was also estimated to compare and check the robustness of the results. To choose the most appropriate parametric estimate function (that is, the order of the GDPpc polynomial included in the parametric function), the method proposed by Hasanov et al. (2021), was followed.

The EKC for deforestation can be tested for production levels by considering the non-linear relationship between forest and GDP variables. However, it should be noted that the dependent variables do not directly represent deforestation, but rather the forested area in relative terms. Therefore, estimate results should be interpreted considering this fact. Thus, an inverted U-shaped relationship between GDP and deforestation will be consistent with a U-shaped relationship between GDP and forested area. As the EKC for deforestation results from previous literature are ambiguous (Bhattarai and Hammig, 2001), there are no clear expected results for Latin American countries during a recent period, thereby justifying this analysis.

To adequately study the relationship between economic growth and deforestation, several control variables were also included in Eqs. [1] and [2]. Firstly, the rural population rate (RURPOP) was included in the model. Increases in population may increase pressure on forests, due to demand for forest products, or alternative uses of forested land. An increase in rural population will be accompanied by an increase in economic activities related to agriculture and livestock, which compete with forests for land use (Jorgenson and Burns, 2007). For this reason, this variable is expected to have a negative effect on the area of forest.

Secondly, energy consumption per capita (ECpc), expressed in kilotonnes of oil equivalent (Ktoe) per capita, was also included in the model. An increase in the population's demand for energy increases the requirements for energy sources, and this generation of energy may come from forest biomass sources (Nepal et al., 2012). Therefore, a negative effect on the dependent variable is expected. Thirdly, an export variable (EXPORT) was also included in the model. In this case, an index from the World Bank was used. This measures the volume of yearly exports as a percentage of the amount reached in the year 2000. For this purpose, an index was extracted with the reference year as 2000. The reference values are expressed as 100% and the percentages of the other periods were established on the basis of these values. Previous studies, such as Ehrhardt-Martinez et al. (2002), have explained that the EKC for deforestation is related to exports. The authors state that the more goods that are exported, the greater is the requirement for domestic resources. Therefore, a positive relationship between exports and deforestation can be expected.

Finally, the cereal yield per capita (CYpc), measured in kilograms per hectare divided by the total population, was considered. The evolution of this variable may be used as an index of the rural technical development. In that sense, the study by Byerlee et al. (2014) observed opposing effects of technological development on deforestation, depending on the context. Thus, it is not expected that the CYpc will have a clear effect on the dependent variable.

Other variables may influence the deforestation-reforestation process in Latin American countries. Some are related to institutional factors specific to each country that change relatively little over time. Their effect can therefore be integrated into individual dummy variables that are constant over the period analyzed. Other variables may be related to the development of projects that are articulated under initiatives, generally of an international nature, which have tried to promote reforestation in the region. These are projects related to the country-led effort Initiative 20 × 20, or those funded by the Forest Investment Program (FIP), the Global Environment Facility (GEF) and the Clean Development Mechanism (CDM). These projects undoubtedly have an important influence on reforestation in the region, and the analysis of their impact on forestry development in Latin America is therefore of great interest. However, this analysis is outside the scope of this study, which is a limitation of the study. There are two reasons for this omission. First, there is insufficient systematic data to generate a variable capable of measuring the amount of all these types of projects, carried out to date, in each Latin American country. Second, and perhaps more importantly, the period of analysis of this study ends in 2014, and it is not until that year that reforestation objectives begin to be developed at the international level. Nevertheless, the individual and temporal dummies may in part capture the effect of previous programs that have been carried out in specific countries or in specific periods in the region.

The main statistics of the variables are shown in Table 3. As can be observed, there is a greater dispersion of data between countries, than over time.

Specifically, the two equations to be estimated are shown below:

$$\ln ABSFApc_{it} = A_i + \delta_t + g\,(\ln GDPpc_{it}) + \beta_4 \ln RURPOP_{it} + \beta_5 \ln EXPORT_{it} + \beta_6 \ln ECpc_{it} + \beta_7 \ln CYpc_{it} + e_{it} \qquad [3]$$

$$\ln RELFApc_{it} = A_i + \delta_t + g\,(\ln GDPpc_{it}) + \beta_4 \ln RURPOP_{it} + \beta_5 \ln EXPORT_{it} + \beta_6 \ln ECpc_{it} + \beta_7 \ln CYpc_{it} + e_{it} \qquad [4]$$

where A represents the individual effects that account for country differences, t represents the temporal effects that account for time varying omitted variables, and g(·) stands for a function of per capita GDP.

4. Econometric procedure

4.1. Non-parametric estimate

In order to estimate Eqs. [3] and [4] adequately, a prior econometric study was undertaken. Initially, a semiparametric approach was undertaken to avoid forcing data into any ex-ante restrictions on the shape of the relationship curve, between forestry variables and the GDP structure, allowing the relationships between the variables to vary flexibly throughout the domain. Based on the Wald heteroscedasticity test (Greene, 2000), and the Hausman fixed effects test results, the Baltagi and Li (2002) semiparametric fixed effects estimator was performed. Thus, a partially linear model is defined to estimate [3] and [4], consisting of two parts: one parametric and the other non-parametric. The parametric part is given by $A_i + \delta_t + \beta_4 \ln RURPOP_{it} + \beta_5 \ln EXPORT_{it} + \beta_6 \ln ECpc_{it} + \beta_7 \ln CYpc_{it}$, while the non-parametric part is the unknown function $g(\ln GDPpc_{it})$. The classic nonparametric estimator, based on an Epanechnikov kernel-weighted local polynomial fit, was used to perform the nonparametric part of the semiparametric model, which is g(lnGDPpcit). Fig. 1 shows the partial fit of GDPpc and the two forestry variables, while Table 4 shows the estimated coefficients of the parametric part of the semiparametric model.

Fig. 1 shows that a non-linear relationship is observed for both forestry variables. Therefore, a linear function between these variables and GDPpc is not adequate. For the forest area in per capita term (ABSFA variable), an increasing relationship is observed from GDPpc equal to 3.5 in logs (3165 constant 2010 US$), while a soft decreasing trend is observed for GDPpc lower values. Additionally, an increasing relationship is observed for the lowest GDPpc values. Therefore, a cubic parametric specification could be appropriate. For the forest area (RELFA

Table 3
Main statistics.

Variable		Mean	Standard deviation	Min	Max	Observations
ABSFApc	Overall	−2.196	0.648	−4.030	−1.050	*N* = 456
	Between		0.748	−4.030	−1.050	n = 239
	Within		0.000	−2.196	−2.196	T-bar = 1.908
RELFA	Overall	37.626	18.819	3.520	70.780	N = 456
	Between		19.082	3.848	63.986	n = 239
	Within		2.909	24.453	53.343	T-bar = 1.908
GDPpc	Overall	3.610	0.324	2.820	4.170	N = 456
	Between		0.294	2.830	4.140	n = 239
	Within		0.180	2.784	4.227	T-bar = 1.908
RURPOP	Overall	−0.059	1.286	−3.620	2.020	N = 456
	Between		1.168	−3.610	1.980	*n* = 239
	Within		0.713	−2.704	2.767	T-bar = 1.908
EXPORT	Overall	140.305	161.073	26.260	1490.290	N = 456
	Between		113.978	27.540	986.443	n = 239
	Within		111.009	−745.648	1102.783	T-bar = 1.908
ECpc	Overall	2.892	0.205	2.280	3.340	N = 456
	Between		0.179	2.280	3.300	n = 239
	Within		0.108	2.448	3.217	T-bar = 1.908
CYpc	Overall	−3.671	0.466	−4.910	−2.870	N = 456
	Between		0.378	−4.910	−2.870	n = 239
	Within		0.292	−4.790	−2.635	T-bar = 1.908

Note: 'overall' refers to the values for the entire sample, 'between' refers to the values between countries for the same period, and 'within' refers to the values between periods for the same country. Min and Max represent the lowest and highest value of each subsample.

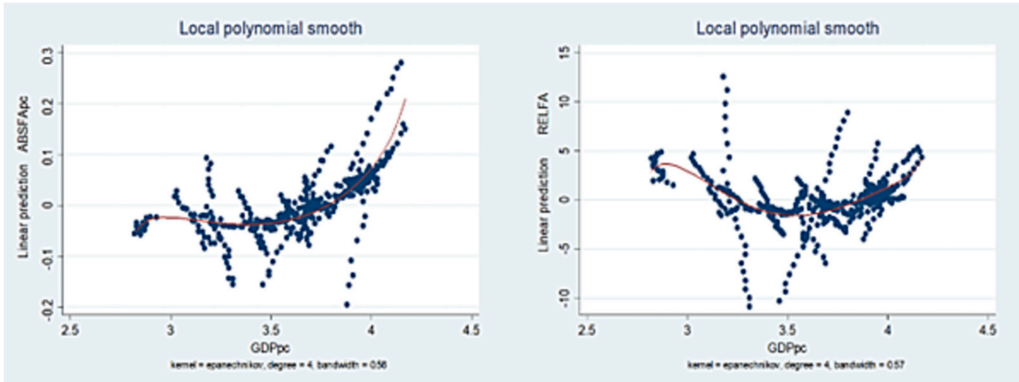

Fig. 1. Partial fit of GDPpc and the two forestry variables: ABSFApc (left) and RELFA (right).

Table 4
Estimates results by using semiparametric fixed effect: linear part.

Variables	ABSFApc	RELFA
RURPOP	−0.003* (0.002)	−0.143* (0.092)
EXPORT	−0.0004*** (0.000)	−0.001** (0.000)
ECpc	−0.036* (0.025)	0.492 (0.963)
CYpc	0.071 (0.063)	−0.522 (0.554)

Note: Standard errors in brackets; ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. All estimates include time dummies.

variable), a soft U shape is appreciated, although for the highest GDPpc values, it can be appreciated that the increasing relationship becomes softer. Therefore, although a squared function could be adequate to test the EKC, a cubic function could be better for its analysis if there is a turning point for higher GDPpc levels. Regarding the linear estimated coefficients, Table 4 shows that rural population and exports have negative coefficients for both per capita and relative area, as expected. The energy consumption is only significant for the ABSFA variable, while the cereal yield variable is not significant in either equation.

4.2. Parametric estimate: Stochastic nature of the variables

Considering the previous semiparametric results, a cubic GDPpc specification is initially defined, although the study could later indicate whether a squared or quadratic form is a better specification. Thus, the initial equations to be estimated are the following:

$\mathrm{lnABSFApc}_{it} = A_i + \delta_t + \beta_1\,\mathrm{lnGDPpc}_{it} + \beta_2\,(\mathrm{lnGDPpc}_{it})^2 + \beta_3\,(\mathrm{lnGDPpc}_{it})^3 + \beta_4\,\mathrm{lnRURPOP}_{it} + \beta_5\,\mathrm{lnEXPORT}_{it} + \beta_6\,\mathrm{lnECpc}_{it} + \beta_7\,\mathrm{lnCYpc}_{it} + e_{it}$ [5]

$\mathrm{lnRELFA}_{it} = A_i + \delta_t + \beta_1\,\mathrm{lnGDPpc}_{it} + \beta_2\,(\mathrm{lnGDPpc}_{it})^2 + \beta_3\,(\mathrm{lnGDPpc}_{it})^3 + \beta_4\,\mathrm{lnRURPOP}_{it} + \beta_5\,\mathrm{lnEXPORT}_{it} + \beta_6\,\mathrm{lnECpc}_{it} + \beta_7\,\mathrm{lnCYpc}_{it} + e_{it}$ [6]

where A represents the individual effects, and t the temporal effects. The coefficients to be estimated are β_1, β_2, β_3, β_4, β_5, β_6 and β_7, which will show the effect of the variation of their respective variables on the dependent variable. The β_1, β_2, β_3 coefficients estimate results may inform about the relationship between GDPpc and the level of forestation. According to Pablo-Romero et al. (2021), this shape depends on the value of the mathematical expression $\beta_2^2–3\beta_3\beta_1$ and the β_3 value and sign. Thus, if $\beta_3 > 0$ and $\beta_2^2–3\beta_3\beta_1 > 0$, an N shape is observed, while if $\beta_3 < 0$ and $\beta_2^2–3\beta_3\beta_1 > 0$, an inverted N is obtained. Likewise, if $\beta_3 > 0$ and $\beta_2^2–3\beta_3\beta_1 \leq 0$, an increasing relationship is obtained, while if $\beta_3 < 0$ and $\beta_2^2–3\beta_3\beta_1 \leq 0$, an increasing relationship is observed. Additionally, if $\beta_3 = 0$, $\beta_1 > 0$ and $\beta_2 < 0$, an inverted U shape is obtained, while if $\beta_3 = 0$, $\beta_1 > 0$ and $\beta_2 > 0$, a U-shaped relationship exists. If $\beta_2 = \beta_3 = 0$ and $\beta_1 > 0$ or $\beta_1 < 0$, a monotonic increasing or decreasing linear relationship is observed, respectively.

To estimate Eqs. [5] and [6] adequately, tests were undertaken. Firstly, the multicollinearity of the variables was studied by means of variance inflation factors (VIF). Column 2 in Table 4 shows the results of this analysis. Some VIFs are >10, implying the presence of multicollinearity between certain variables. According to Pablo-Romero et al. (2019), transforming the variables into deviations from the geometric mean of the sample may reduce this collinearity. The VIF results of the transformed variables are shown in Column 3 in Table 5. In this case, all the VIFs offer values lower than 10. Therefore, Eqs. [5] and [6] are now transformed as follows:

$(\mathrm{lnABSFApc}_{it} - \overline{m}_a) = A_i + \delta_t + \beta_1(\mathrm{lnGDPpc}_{it} - \overline{m}) + \beta_2(\mathrm{lnGDPpc}_{it} - \overline{m})^2 + \beta_3(\mathrm{lnGDPpc}_{it} - \overline{m})^3 + \beta_4(\mathrm{lnRURPOP}_{it} - \overline{m}_r) + \beta_5(\mathrm{lnEXPORT}_{it} - \overline{m}_e) + \beta_6(\mathrm{lnECpc}_{it} - \overline{m}_{ec}) + \beta_7(\mathrm{lnCYpc}_{it} - \overline{m}_c) + e_{it}$ [7]

$(\mathrm{lnRELFAit} - \overline{m}_R) = A_i + \delta_t + \beta 1(\mathrm{lnGDPpc}_{it} - \overline{m}) + \beta_2(\mathrm{lnGDPpc}_{it} - \overline{m})^2 + \beta_3(\mathrm{lnGDPpc}_{it} - \overline{m})^3 + \beta_4\,(\mathrm{lnRURPOP}_{it} - \overline{m}_r) + \beta_5(\mathrm{lnEXPORT}_{it} - \overline{m}_e) + \beta_6(\mathrm{lnECpc}_{it} - \overline{m}_{ec}) + \beta_7(\mathrm{lnCYpc}_{it} - \overline{m}_c) + e_{it}$ [8]

where $\overline{m}$, $\overline{m}_a$, $\overline{m}_R$, $\overline{m}_r$, $\overline{m}_e$, $\overline{m}_{ec}$, and $\overline{m}_c$ are the geometric mean of $\mathrm{lnGDPpc}_{it}$, $\mathrm{lnABSFApc}_{it}$, $\mathrm{lnRELFA}_{it}$, $\mathrm{lnRURPOP}_{it}$, $\mathrm{lnEXPORT}_{it}$, lnECpc_{it} and lnCYpc_{it}, respectively.

The variables transformation implies that the β_1 coefficient now represents the ABSFApc and RELFA elasticity, with respect to GDPpc at the point of the sample which makes GDPpc be equal to its geometric mean, that is to say, in the central point of the sample, respectively. The β_4 to β_7 coefficients are interpreted, as in eqs. [5] and [6], as the elasticity with respect to the respective independent variable.

Secondly, the stochastic nature of the variables was analyzed. The first step was to examine the cross-sectional dependence in the panel, by using Pesaran (2004). The results in Table 6 show that the null hypothesis of cross-sectional independence is rejected for all variables, except CYpc.

Once the cross-sectional dependence was studied, the second step undertaken was the unit root analysis. Pesaran's (2007) test for unit roots (CIPS) was applied to the level and first differences variables. As this test analyzes unit roots in heterogeneous panels with cross-sectional dependence, it was applied to all variables except CYpc, according to the results in Table 5. As the null hypothesis of the CIPS test assumes that series are non-stationary, the results shown in Table 7 indicate that all variables are I(1).

For the CYpc variable, the MW test (Maddala and Wu, 1999) for unit

Table 5
Variance Inflation Factors (VIF).

Variables	VIF (variables)	VIF (deviation from the mean)
GDPpc	90,234.560	8.710
GDPpc2	370,611.310	3.090
GDPpc^3	95,958.320	7.460
RURPOP	1.680	1.680
EXPORT	1.170	1.170
ECpc	4.650	4.650
CYpc	1.200	1.200

Table 6
Pesaran's (2004) CD Test.

Variables	Pesaran's CD-test
ABSFApc	37.780 ***
RELFA	17.560***
GDPpc	43.740***
$GDPpc^2$	2.520**
$GDPpc^3$	39.360***
RURPOP	9.500***
EXPORT	38.520***
ECpc	28.370***
CYpc	0.340

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7
Pesaran's (2007) test for unit roots.

Variables	Level		First differences	
	Constant	Constant and trend	Constant	Constant and trend
ABSFApc	−1.597**	−2.286 ***	−17.903***	−16.822***
RELFA	3.347	5.520	−2.073**	−1.532*
GDPpc	−0.733	0.025	−12.361***	−11.295***
$GDPpc^2$	0.067	−0.248	−9.302***	−9.517***
$GDPpc^3$	1.954	2.997	−9.986***	−8.983***
RURPOP	−2.590***	−0.581	−6.964***	−5.058***
EXPORT	2.690	3.172	−11.245***	−10.454***
ECpc	0.365	2.990	−13.500***	−12.698***

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

roots was used, which is more appropriate for variables with cross-sectional independence. The null hypothesis is the non-stationarity of the series, as in the previous test. The results shown in Table 8 support the stationarity of the cereal yield.

Considering the previous results, the last step was to analyze the existence of a long-run structural relationship between the series. To do so, the Westerlund (2007) cointegration test was applied. This test allows cross-sectional dependence to be corrected through the bootstrapping technique. The test was applied alternately to both dependent variables. The results from four tests are reported. Gt and Ga test for cointegration in at least one country, while Pt and Pa test for full panel cointegration. The null hypothesis of the test assumes no cointegration. The results regarding Pt, shown in Tables 9, indicate that the null hypothesis can be rejected in that case. Therefore, it is appropriate to estimate Eqs. [5] and [6] in levels.

4.3. Parametric estimate: Testing the model specification

Bearing in mind the results of the aforementioned tests, Eqs. [7] and [8] have been initially estimated in levels, by using the Fixed Effects Ordinary Least Squares method with Driscoll-Kraay standard errors (DK-OLS). According to Hoechle et al. (2017), this method is robust to autocorrelation, heteroscedasticity and contemporaneous correlation. Nevertheless, once estimated, it is worth noting that several points should be considered. Firstly, it is adequate to analyze potential endogeneity issues. Secondly, it is convenient to analyze the appropriate

Table 8
MW test (Maddala and Wu, 1999) for unit roots.

Variables	Level		First Differences	
	Constant	Constant and trend	Constant	Constant and trend
CYpc	39.797	62.202***	714.284***	579.587***

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 9
Westerlund (2007) tests.

Variable	Independent variables	First differences			
		Gt	Ga	Pt	Pa
ABSFApc	GDPpc, $GDPpc^2$, $GDPpc^3$, ECpc, EXPORT	−1.946	−4.491	−15.481***	−2.098
RELFA	GDPpc, $GDPpc^2$, $GDPpc^3$, ECpc, EXPORT	−2.459	−1.981	−13.154 ***	−3.417

Note: Test regression fitted with constant and trend. Kernel bandwidth set according to the rule 4(T/100)2/9. The *p*-values are for a one-sided test based on 200 bootstrap replications. *** indicates significance at the 1% level.

specification, related to the polynomial order, when testing the EKC. Finally, it is adequate to test the normality of data.

Regarding the endogeneity issues, it should be noted that ordinary least squares (OLS) estimates should be biased if explanatory variables are correlated with the error term. This could happen due to reverse causality between explanatory and explicative variables, and due to omitted variables. Potential double causality could be expected between GDPpc and forestry variables. Therefore, the instrumental variables technique, in the presence of heteroskedasticity and autocorrelation, was then used to account for this possible endogeneity. In order to manage this problem, Eqs. [7] and [8] were estimated by the generalized method of moments (GMM), considering that variables related to GDPpc were endogenous variables and taking the transformed variables of GDPpc, delayed by one and two periods, as instruments. The Kleibergen-Paap rk LM and Kleibergen-Paap rk Wald F tests and the Hansen J statistics were performed to test for underidentification, weak identification and the validity of instruments, respectively. Additionally, the Sargan-Hausman test was used to test whether endogenous regressors could be treated as exogenous. The results reported in Table 10 for both forestry variables indicate that, although the instruments are able to determine the regressions that are valid and not weak, the endogenous regressors can be treated as exogenous. Therefore, the DK-OLS method is considered adequate to estimate Eqs. [7] and [8]. Additionally, and considering that the EXPORT, ECpc and CYpc variables are also potentially endogenous, Eqs. [7] and [8] were re-estimated by using the GMM method, including their delayed values as instruments. No major differences were observed in the coefficient estimated values for forestry dependent variables estimates, the results also indicating that endogenous regressors can be treated as exogenous.

Regarding the best polynomial order to test the EKC, the Hasanov et al. (2021) strategy was adopted. Therefore, a quadratic polynomial was initially performed by using DK-OLS. However, since the quadratic coefficient is not significant for either ABSFApc or RELFA estimates, then Eqs. [7] and [8] were estimated. Results are shown in Table 10. Taking into account that the cubic coefficients are both significant, an N-shape, inverted N-shape, progressively increasing or decreasing relationships may be obtained, depending on the estimated coefficient values. For ABSFApc, $\beta_3 > 0$ and $\beta_2^2–3\beta_3\beta_1 = 0.35$ is obtained. Therefore, the results are compatible with an N shape. Meanwhile, for RELFA, as $\beta_3 < 0$ and $\beta_2^2–3\beta_3\beta_1 = 2860$, the results are compatible with an inverted N shape.

According to the Hasanov et al. (2021) strategy, it is then necessary to study whether the turning points are within a reasonable range. These turning points may be calculated by making the forestry variable elasticity with respect to GDPpc equal to zero. These elasticity values for each country and year, may be obtained by calculating the derivative of the forestry variable with respect to GDPpc. This is calculated as $\beta_1 + 2\beta_2(\text{lnGDPpc-}\overline{m}_{it}) + 3\beta_3(\text{lnGDPpc-}\overline{m}_{it})^2$. Fig. 2 shows the calculated elasticity values for each transformed GVApc level in logs, for both forestry variables.

Regarding the ABSFApc variable, elasticity values for the cubic

Table 10
Equation estimates results by using instrumental variables and DK-OLS.

Variables	ABSFApc	RELFA	ABSFApc	ABSFApc	RELFA
	IV-GMM	IV-GMM	DK-OLS	DK-OLS	DK-OLS
GDPpc	0.246*** (0.071)	19.210*** (5.051)	0.313*** (0.056)	0.353*** (0.061)	22.538*** 4.145
GDPpc^2	0.672*** (0.061)	34.436*** (3.360)	0.674*** (0.037)	0.664*** (0.035)	34.336*** (3.277)
GDPpc^3	0.113 (0.082)	−21.920*** (7.420)	0.111* (0.060)		−22.827*** (6.359)
RURPOP	−0.015*** (0.004)	−0.849*** (0.189)	−0.017*** (0.006)	−0.016** (0.006)	−1.020*** (0.141)
EXPORT	−0.0001*** (0.000)	−0.005*** (0.000)	−0.0001*** (0.000)	−0.0001*** (0.000)	−0.006*** (0.001)
ECpc	−0.053 (0.040)	−3.198 (2.349)	−0.086*** (0.027)	−0.088*** (0.025)	−1.562 (2.230)
CYpc	0.071 (0.063)	−3.937 (2.875)	0.084 (0.105)	0.085 (0.098)	−2.005 (5.110)
Underidentification test					
Kleibergen-Paap-LM-Chi-sq(4)	34.579***	34.579***			
Weak identification test					
Kleibergen-Paap-WaldF Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 12.20	47.532***	47.532***			
Overidentification test of all instruments					
Hansen J Chi-sq(3)	3.048	7.155			
Endogeneity test Chi-sq(3)	5.556	4.778			

Note: Instrumented variables in GMM models: (lnGDPpc$_{it}$ - $\overline{m}$), (lnGDPpc$_{it}$ - $\overline{m}$)^2, (lnGDPpc$_{it}$ - $\overline{m}$)^3. Included instruments in GMM models: (lnRURPOP$_{it}$ - $\overline{m}_r$), (lnEXPORT$_{it}$ - $\overline{m}_e$), (lnECpc$_{it}$ - $\overline{m}_{ec}$), (lnCYpc$_{it}$ - $\overline{m}_c$), dum1-dum19, dut1-dut23.
Standard errors in brackets; ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

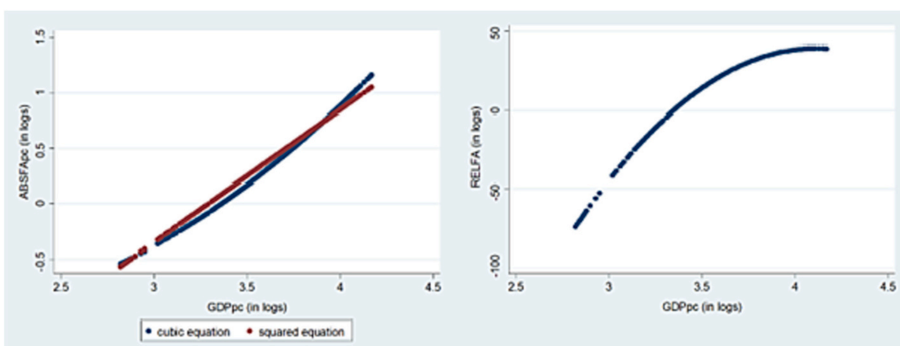

Fig. 2. Forestry variable elasticity with respect to GDPpc, for the two forestry variables: ABSFApc (left) and RELFA (right).

specification show that elasticity becomes zero in the range values, this value being reached from negative to positive values. Therefore, the minimum value of the N shape is reached. Nevertheless, their maximum value is not attained. Thus, the squared function was estimated, and its elasticity calculated. As shown in Fig. 2, no relevant changes are observed showing that both specifications (squared and cubed) offer similar results. Therefore, although the results are compatible with an N-shape in the cubed specification, the sample data only fits a J shape. Regarding the RELFA variable, elasticity values for the cubed specification also show that elasticity becomes zero, within the range values, the minimum value of the inverted-N shape being reached. Nevertheless, a maximum elasticity value is also reached in the range values, so the inflexion point of the inverted N point is reached and the cubed specification may be considered adequate. In this case, the sample data fits into a smooth J shape with a small scroll on top, showing that the growing relationships tend to disappear for higher GDPpc levels.

Finally, normality tests were performed to study whether the data are normally distributed. The Shapiro-Wilk (Royston, 1992) and the Shapiro-Francia (Royston, 1983) normality tests were used in this study. In addition, skewness was also used to study whether variables have normal distribution, while kurtosis was used to analyze the data distortion. Results in Table 11 show that the null hypothesis of normality is rejected at 1% significance level for both Shapiro tests, while differences from zero skewness and kurtosis values, indicate that the variables are not normally distributed and that there is distortion of data.

In addition to these tests, the widely used Quantile–Quantile (Q–Q) normality test was performed to compare the expected normal

Table 11
Test of normal distribution.

Variables	Obs.	Skewness	Kurtosis	Shapiro-Wilk test	Shapiro-Francia test
ABSFApc	456	−0.916	3.728	0.933***	0.935***
RELFA	456	−0.297	1.849	0.938***	0.941***
GDPpc	456	−0.578	2.607	0.954***	0.956***
GDPpc^2	456	2.186	7.999	0.731***	0.731***
GDPpc^3	456	−2.906	11.550	0.635***	
RURPOP	456	−0.901	3.275	0.927***	0.929***
EXPORT	456	5.730	39.885	0.418***	0.414***
ECpc	456	−0.017	2.920	0.973***	0.974***
CYpc	456	−0.648	2.979	0.953***	0.955***

Note: *** indicate significance at the 1%.

distribution (blue line), with respect to variable distribution. As shown in Fig. 3, neither the forestry nor the independent variables fall on the normally distributed blue line, this being more especially observed on the extreme values of several variables. Therefore, the OLS regression may be biased, thus an alternative method should be used.

4.4. The quantile

In this study, a quantile regression was estimated. This type of analysis is usually applied when variables are expected to have different effects along the conditional distribution of the dependent variable. These effects are not captured by traditional regression models (Bitler et al., 2006). This is because such models are based on the mean (Hübler, 2017), whereas quantile regression is based on the median, and is robust to the presence of outliers (Koenker and Hallock, 2001). According to Cade and Noon (2003), the results of these regressions may show the relationship between variables more comprehensively than traditional regression methods, due to their robustness to outliers.

The quantile regression approach originally implemented by Koenker and Bassett (1978) did not take into account unobserved individual heterogeneity. Therefore, based on the Hausman test result, a Fixed Effects model was applied, specifically, the Method of Moments Quantile Regression (MMQR) with fixed effects by Machado and Silva (2019). The advantages of this model are that, in addition to eliminating the distorting effects of outliers, it controls for unobserved individual heterogeneity of the distribution across countries within a panel, through fixed effects. The general form may be expressed as $Q_\tau(\tau|X_{it}) = \alpha_i + \delta_i q(\tau) + X'_{it}\,\beta + Z'_{it}\,\gamma q(\tau)$, where $Q_\tau(\tau|X_{it})$ identifies the forestry variables distribution in quantiles, which depend on the distribution of the independent variables X_{it}, and $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ which are the individual quantile-τ fixed effects.

The quantile regression method has been used previously in environmental research, although its implementations have been scarce and more recent. An example can be found in Ike et al. (2020), for testing the EKC hypothesis. However, to our knowledge, the quantile regression method has not previously been used for testing the EKC hypothesis for deforestation in Latin America. Therefore, it is a novelty of this study, whereby this method allows discovery of whether the explanatory variables have different impacts across the quantiles of forested areas. The results may provide a broader picture of the relationship between dependent and explanatory variables.

5. Results and discussion

Considering the results of previous estimates and tests, Eqs. [7] and [8] are estimated by applying the MMQR, eliminating the cubed coefficient for Eq. [7], while keeping it for Eq. [8]. Table 12 provides the regression results for Eq. [7] when estimating by the MMQR. Additionally, Table 13 shows Eq. [8] estimates by this method.

The results obtained by the quantile-based Method of Moments provide different insights, depending on the dependent variable used. For forested area per capita, positive and significant coefficients are

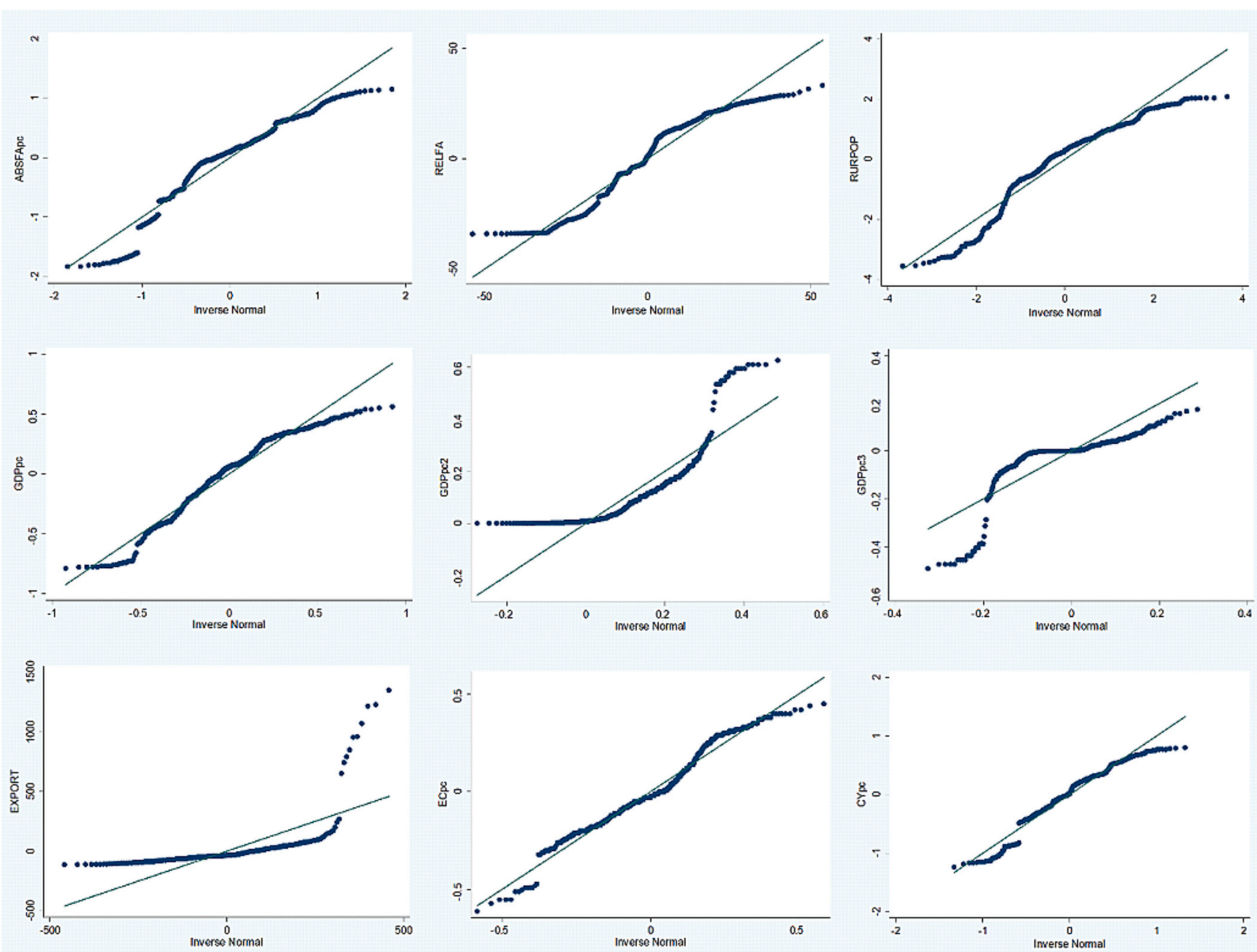

Fig. 3. Normal Q-Q plots (transformed variables).

Table 12
Quantile regression by the method of moments for eq. [7].

Variables	Eq.[7]	Eq.[7]	Eq.[7]	Eq.[7]	Eq.[7]	Eq.[7]	Eq.[7]	Eq.[7]	Eq.[7]
	q (0.1)	q (0.2)	q (0.3)	q (0.4)	q (0.5)	q (0.6)	q (0.7)	q (0.8)	q (0.9)
GDPpc	0.235**	0.264**	0.289***	0.306***	0.327***	0.348***	0.365***	0.381***	0.411***
	(0.126)	(0.097)	(0.077)	(0.067)	(0.061)	(0.064)	(0.072)	(0.084)	(0.111)
GDPpc^2	0.681***	0.674***	0.668***	0.664***	0.660***	0.6565***	0.651***	0.647***	0.640***
	(0.130)	(0.100)	(0.079)	(0.068)	(0.062)	(0.065)	(0.074)	(0.086)	(0.114)
RURPOP	−0.030***	−0.025***	−0.022***	−0.019***	−0.016***	−0.013**	−0.010*	−0.008	−0.003
	(0.011)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)
EXPORT	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)
ECpc	0.029 (0.100)	−0.009	−0.040	−0.062	−0.089*	−0.116**	−0.138**	−0.158**	−0.198**
		(0.077)	(0.062)	(0.053)	(0.0049)	(0.051)	(0.058)	(0.067)	(0.089)
CYpc	0.121 (0.135)	0.110 (0.104)	0.1002 (0.183)	0.096 (0.072)	0.088 (0.065)	0.081 (0.068)	0.074 (0.078)	0.069 (0.090)	0.058 (0.119)

Note: Standard errors in brackets; ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 13
Quantile regression by the method of moments for eq. [8].

Variables	Eq.[8]	Eq.[8]	Eq.[8]	Eq.[8]	Eq.[8]	Eq.[8]	Eq.[8]	Eq.[8]	Eq.[8]
	q (0.1)	q (0.2)	q (0.3)	q (0.4)	q (0.5)	q (0.6)	q (0.7)	q (0.8)	q (0.9)
GDPpc	16.410**	17.567***	18.518***	19.529***	20.512***	21.385***	22.121***	22.919***	24.152***
	(7.861)	(6.315)	(5.210)	(4.347)	(4.009)	(4.228)	(4.747)	(5.558)	(7.104)
GDPpc^2	34.740***	34.562***	34.417***	34.262***	34.111***	33.978***	33.865***	33.742***	33.554***
	(5.511)	(4.424)	(3.648)	(3.041)	(2.804)	(2.959)	(3.326)	(3.894)	(4.978)
GDPpc^3	−13.899	−16.082*	−17.879**	−19.789***	−21.645***	−23.293***	−24.683***	−26.191***	−28.519***
	(11.567)	(9.295)	(7.671)	(6.405)	(5.907)	(6.227)	(6.988)	(8.182)	(10.457)
RURPOP	−1.059***	−1.057***	−1.056***	−1.054***	−1.053***	−1.051***	−1.050***	−1.049***	−1.047***
	(0.421)	(0.3376)	(0.2784)	(0.2320)	(0.2140)	(0.2258)	(0.2538)	(0.297)	(0.3798)
EXPORT	−0.0069***	−0.0065***	−0.0062***	−0.0058***	−0.0055***	−0.0052***	−0.0049***	−0.0046***	−0.0042***
	(0.0017)	(0.0014)	(0.0011)	(0.0010)	(0.0009)	(0.0009)	(0.0010)	(0.0012)	(0.0016)
ECpc	4.124 (4.663)	2.437 (3.757)	1.049 (3.106)	−0.426	−1.860	−3.132	−4.206	−5.371*	−7.168*
				(2.604)	(2.402)	(2.525)	(2.825)	(3.307)	(4.226)
CYpc	−5.230	−4.212	−3.375	−2.485	−1.620	−0.8522	−0.2048	0.4980 (3.853)	1.583 (4.924)
	(5.447)	(4.377)	(3.613)	(3.017)	(2.782)	(2.933)	(3.291)		

Note: Standard errors in brackets; ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

found for GDP per capita, in its linear and squared form. For forested area, these two coefficients are also positive and significant, but now the cubed GDPpc coefficient is negative and significant.

The results obtained by using the forested area per capita variable, indicate that there is a U-shaped relationship between variables. Therefore, the EKC hypothesis for deforestation is supported. In fact, there is a positive and growing relationship between forest area (in per capita terms) and GDPpc from a threshold point, which is within the sample range. These results are in line with some previous research related to Latin America, as in Bhattarai and Hammig (2001), who consider that the positive relationship between variables, when GDPpc levels are higher, could be explained by lower fuelwood energy consumption and higher forest investments. Additionally, the GDPpc coefficient, which represents the income elasticity at the central point of the sample, presents an increasing behavior as quantiles move up (from 0.235 in the first quantile, to 0.411 in the ninth quantile). Additionally, the squared GDPpc coefficient decreases as quantiles become higher. Therefore, a soft lower increasing effect of GDP on per capita forested area is observed as quantiles progress.

The obtained results, when using the relative forested area as the dependent variable, show positive coefficients for GDPpc and its squared value, but negative for its cubed form. Thus, the curve representing the relationship between forested area (in relation to total area) and economic growth takes the form of an inverted N shape. This implies, contrarily to what was discussed for ABSFApc, that the increase in GDPpc negatively affects the growth of relative forested area from a threshold point. That is, there is a progressively growing N-shaped relationship, from the inflexion point onwards, between GDP and deforestation. Therefore, the EKC for deforestation can only be supported for lower GDP levels, with the positive effect of GDP increases on deforestation disappearing when GDP reaches a threshold. Joshi and Beck (2016) observed this same shape for OECD countries. It can be justified by the fact that more valuable forest products and land will imply a more intense deforestation as GDP continues to grow. Nevertheless, it is worth noting that the range values of the sample do not include the maximum value of the inverted N-shaped relationship. However, this range of values does include the inflexion point of the decreasing part of this N. This implies that the advantages of increasing GDPpc to reduce deforestation tends to disappear, or at least be lower, for the highest GDPpc levels.

It is also worth noting that GDP coefficient values increase as quantiles become higher, while those coefficients for the square and cubic forms reduce their values as quantiles increase. To facilitate the observation of these differences, Fig. 4 shows the values of the coefficients of the GDP variables by quantiles and their respective confidence intervals (CI1 and CI2). Considering the sample range values and these coefficient values trends as a quantile increase, the GDPpc increase is going to have decreasing positive effects on forestation for high GDPpc levels in those zones with greater relative forested area. Thus, the positive effects of increasing GDPpc tends to disappear when forest areas are larger.

Regarding the control variables estimated coefficients, different behaviors are observed. For both rural population and exports, negative coefficients are found, albeit with low values. These imply a moderate reduction in forested area for increases in rural population and exports. This negative relationship is observed for both per capita and relative area, as expected. On the one hand, increases in rural population press for alternative forest land use, as stated in Jorgenson and Burns (2007). On the other hand, as exports increase, more deforestation is expected due to the need to use more resources (Ehrhardt-Martinez et al., 2002).

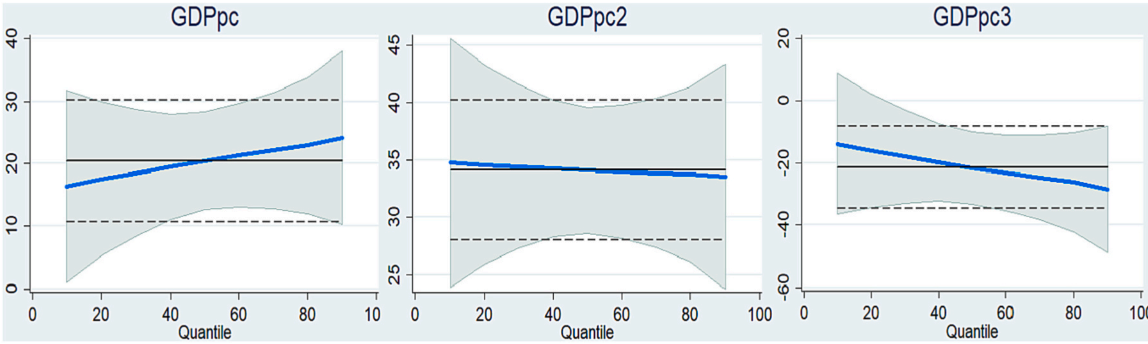

Fig. 4. Estimated GDP coefficients by the method of moments quantile regression.

Additionally, it is worth noting that both variables evolve increasingly as the quantiles advance. Therefore, there is an increased negative effect in countries with greater levels of forestation.

In the case of energy consumption, similar results are reported for the estimates of both equations. For the first quantile, the coefficient takes positive values (0.029 and 4.124, depending on the equation). However, this value decreases as the quantile increases, turning to negative values. Therefore, reductions in forested area are expected when per capita energy consumption increases in those zones with high forestation, even so, it is worth noting the low significance of the coefficient. In Eq. [7], the coefficient does not become significant until quantile 5, while in Eq. [8], it does not occur until the eighth quantile. It can therefore be inferred that the effect of energy consumption in forested areas is only significant for those countries with greater levels of forestation. Therefore, the conclusions in Nepal et al. (2012) may only be valid for those zones.

The cereal yield variable is not significant for any quantile in both equations. This variable represents technological development at the rural level through productivity (Joshi and Beck, 2016). The lack of significance suggests that crop intensification, through new techniques or fertilizer, does not relevantly impact deforestation trends.

6. Conclusions

The current climate change debate puts forest conservation and halting deforestation at the forefront of the social and political agenda. This makes the analysis of the relationship between economic growth and the process of deforestation of utmost interest. In this study, the relationship between deforestation and economic growth has been analyzed by testing the EKC hypothesis for deforestation, specifically by using panel data techniques applied to a sample of Latin American countries in the 1991–2014 period. Two alternative equations have been estimated to test the non-linearity between the variables, based on the dependent variable considered: the forested area per capita and the forested area in relation to the total area. Semiparametric techniques and quantile regressions methods were performed.

The results obtained from the semiparametric and the quantile method support the EKC hypothesis for deforestation when considering forested area per capita (U shape for forestation), while the decreasing trend of the inverted U shape for deforestation (increasing part of the U shape for forestation) tends to disappear when considering the relative forested area. Likewise, when analyzing the GDPpc effect on deforestation by quantiles, the positive effect of GDPpc on forestation tends to reduce for the highest GDPpc level, in those zones with larger forestation. This is more especially observed in terms of relative forested areas, where the elasticity values tend to decrease.

This leads us to think that special attention should be given to those countries with a more advanced economic situation, in order to monitor whether future economic growth in these countries can halt the reduction of deforestation, observed in recent years. This also leads us to think of future lines of research. This article can serve as a basis for studying the relationship between deforestation and economic growth, by grouping countries, according to both their economic characteristics and the size of their forested area. Additionally, it can serve as a basis for studying the relationship between deforestation and economic growth, when considering the quality of the forests.

From the other variables studied, only exports, rural population and, above a certain level of forest cover, energy consumption, have been shown to have a relevant effect on the indicators studied. For all three cases, there is a negative impact on forested areas, which is more relevant for those countries with more forestation.

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CRediT authorship contribution statement

María P. Pablo-Romero: Conceptualization, Methodology, Software, Supervision, Writing – review & editing. **Antonio Sánchez-Braza:** Methodology, Investigation, Supervision, Writing – review & editing. **Jesús Gil-Pérez:** Conceptualization, Methodology, Software, Data curation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Ahmed, K., Shahbaz, M., Qasim, A., Long, W., 2015. The linkages between deforestation, energy and growth for environmental degradation in Pakistan. Ecol. Indic. 49, 95–103.

Ajanaku, B.A., Collins, A.R., 2021. Economic growth and deforestation in African countries: is the Environmental Kuznets Curve hypothesis applicable? Forest Policy Econ. 129, 102488 (11 pp.).

Al-Mulali, U., Saboori, B., Ozturk, I., 2015. Investigating the environmental Kuznets curve hypothesis in Vietnam. Energy Policy 76, 123–131.

Ang, J.B., 2007. CO_2 emissions, energy consumption, and output in France. Energy Policy 35 (10), 4772–4778.
Antle, J.M., Heidebrink, G., 1995. Environment and development: theory and international evidence. Econ. Dev. Cult. Chang. 43 (3), 603–625.
Apergis, N., Ozturk, I., 2015. Testing environmental Kuznets curve hypothesis in Asian countries. Ecol. Indic. 52, 16–22.
Azam, M., Khan, A.Q., 2016. Testing the Environmental Kuznets Curve hypothesis: a comparative empirical study for low, lower middle, upper middle and high income countries. Renew. Sust. Energ. Rev. 63, 556–567.
Bakirtas, I., Cetin, M.A., 2017. Revisiting the Environmental Kuznets Curve and pollution haven hypotheses: MIKTA sample. Environ. Sci. Pollut. Res. 24 (22), 18273–18283.
Baltagi, B.H., Li, D., 2002. Series estimation of partially linear panel data models with fixed effects. Ann. Econ. Financ. 3, 103–116.
Barbier, E.B., 2004. Explaining agricultural land expansion and deforestation in developing countries. Am. J. Agric. Econ. 86 (5), 1347–1353.
Barbier, E.B., Burgess, J.C., 2001. The economics of tropical deforestation. J. Econ. Surv. 15 (3), 413–433.
Barbier, E.B., Hochard, J.P., 2018. Land degradation and poverty. Nat. Sustain. 1 (11), 623–631.
Bárcena, A., Samaniego, J.L., Peres, W., Alatorre, J.E., 2020. La Emergencia del Cambio Climático en América Latina y el Caribe: ¿Seguimos Esperando la Catástrofe o Pasamos a la Acción?. In: Libros de la CEPAL, n° 160, Comisión Económica para América Latina y el Caribe (CEPAL). Naciones Unidas, Santiago de Chile. Available at: https://repositorio.cepal.org/handle/11362/45677 [accessed 10-december-2021].
Benedek, Z., Fertő, I., 2020. Does economic growth influence forestry trends? An Environmental Kuznets Curve approach based on a composite Forest Recovery Index. Ecol. Indic. 112, 106067.
Bhattarai, M., Hammig, M., 2001. Institutions and the Environmental Kuznets Curve for deforestation: a crosscountry analysis for Latin America, Africa and Asia. World Dev. 29 (6), 995–1010.
Bitler, M.P., Gelbach, J.B., Hoynes, H.W., 2006. What mean impacts miss: distributional effects of welfare reform experiments. Am. Econ. Rev. 96 (4), 988–1012.
Brook, B.W., Sodhi, N.S., Ng, P.K.L., 2003. Catastrophic extinctions follow deforestation in Singapore. Nature 424, 420–423.
Byerlee, D., Stevenson, J., Villoria, N., 2014. Does intensification slow crop land expansion or encourage deforestation? Global Food Securit. 3 (2), 92–98.
Cade, B.S., Noon, B.R., 2003. A gentle introduction to quantile regression for ecologists. Front. Ecol. Environ. 1 (8), 412–420.
Caravaggio, N., 2020. A global empirical re-assessment of the Environmental Kuznets Curve for deforestation. Forest Policy Econ. 119, 102282.
Cary, M., Bekun, F.V., 2021. Democracy and deforestation: the role of spillover effects. Forest Policy Econ. 125, 102398.
Cropper, M., Griffiths, C., 1994. The interaction of population growth and environmental quality. Am. Econ. Rev. 84 (2), 250–254.
Culas, R.J., 2007. Deforestation and the Environmental Kuznets Curve: an institutional perspective. Ecol. Econ. 61 (2–3), 429–437.
Culas, R.J., 2012. REDD and forest transition: tunneling through the Environmental Kuznets Curve. Ecol. Econ. 79, 44–51.
Damette, O., Delacote, P., 2012. On the economic factors of deforestation: what can we learn from quantile analysis? Econ. Model. 29 (6), 2427–2434.
Dijkgraaf, E., Vollebergh, H.R.J., 2005. A test for parameter homogeneity in CO_2 panel EKC estimations. Environ. Resour. Econ. 32 (2), 229–239.
Dobson, A.P., Bradshaw, A.D., Baker, A.J.M., 1997. Hopes for the future: restoration ecology and conservation biology. Science 277 (5325), 515–522.
Ehrhardt-Martinez, K., Crenshaw, E.M., Jenkins, J.C., 2002. Deforestation and the Environmental Kuznets Curve: a cross-national investigation of intervening mechanisms. Soc. Sci. Q. 83 (1), 226–243.
FAO, 2016. Global Forest Resources Assessment 2015. How Are the World's Forests Changing?, Second edition. United Nations, Rome. Available at: https://www.fao.org/publications/card/en/c/770b9ce6-9f65-4a46-a9af-1abbb0f71ab1. accessed 10-december-2021.
FAO, 2018. The State of the world's Forests: Forest Pathways to Sustainable Development. Food and Agriculture Organization of the United Nations. United Nations, Rome. Available at: http://www.fao.org/3/ca0188en/ca0188en.pdf. accessed 08-june-2021.
Galinato, G.I., Galinato, S.P., 2012. The effects of corruption control, political stability and economic growth on deforestation-induced carbon dioxide emissions. Environ. Dev. Econ. 17 (1), 67–90.
Gill, A.R., Viswanathan, K.K., Hassan, S., 2018. A test of Environmental Kuznets Curve (EKC) for carbon emission and potential of renewable energy to reduce green house gases (GHG) in Malaysia. Environ. Dev. Sustain. 20 (3), 1103–1114.
Gokmenoglu, K.K., Olasehinde-Williams, G.O., Taspinar, N., 2019. Testing the Environmental Kuznets Curve hypothesis: the role of deforestation. In: Shahbaz, M., Balsalobre, D. (Eds.), Energy and Environmental Strategies in the Era of Globalization. Springer, Cham, pp. 61–83.
Greene, W.H., 2000. Econometric Analysis, 4th edition. Prentice Hall, Upper Saddle, New Jersey.
Grossman, G.M., Krueger, A.B., 1991. Environmental impacts of a North American free trade agreement. In: NBER Working Papers Series, No. 3914. National Bureau of Economic Research, Cambridge. Available at: https://www.nber.org/papers/w3914. accessed 08-june-2021.
Hasanov, F.J., Hunt, L.C., Mikayilov, J.I., 2021. Estimating different order polynomial logarithmic Environmental Kuznets Curves. Environ. Sci. Pollut. Res. 8, 41965–41987.
Hoechle, D., Ruenzi, S., Schaub, N., Schmid, M., 2017. The impact of financial advice on trade performance and behavioral biases. Rev. Finance 21 (2), 871–910.
Hübler, M., 2017. The inequality-emissions nexus in the context of trade and development: a quantile regression approach. Ecol. Econ. 134, 174–185.
Ike, G.N., Usman, O., Sarkodie, S.A., 2020. Testing the role of oil production in the Environmental Kuznets Curve of oil producing countries: new insights from method of moments quantile regression. Sci. Total Environ. 711, 135208 (10 pp.).
Jewel, A., Chang, J.B., Lee, Y., 2018. Analyzing the effect of socio-economic factors on deforestation using an environmental Kuznets curve model. Kor. J. Agricult. Econ. 59 (3), 169–189.
Jorgenson, A.K., Burns, T.J., 2007. Effects of rural and urban population dynamics and national development on deforestation in less-developed countries, 1990-2000. Sociol. Inq. 77 (3), 460–482.
Joshi, P., Beck, K., 2016. Environmental Kuznets Curve for deforestation: evidence using GMM estimation for OECD and non-OECD regions. iForest-Biogeosci. Forestry 10 (1), 196–203.
Kamanga, P., Vedeld, P., Sjaastad, E., 2009. Forest incomes and rural livelihoods in Chiradzulu District, Malawi. Ecol. Econ. 68 (3), 613–624.
Katircioğlu, S., Katircioğlu, S., 2018. Testing the role of urban development in the conventional Environmental Kuznets Curve: evidence from Turkey. Appl. Econ. Lett. 25 (11), 741–746.
Klooster, D., 2003. Forest transitions in Mexico: institutions and forests in a globalized countryside. Prof. Geogr. 55 (2), 227–237.
Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46 (1), 33–50.
Koenker, R., Hallock, K.F., 2001. Quantile regression. J. Econ. Perspect. 15 (4), 143–156.
Koirala, B.S., Mysami, R.C., 2015. Investigating the effect of forest per capita on explaining the EKC hypothesis for CO2 in the US. J. Environ. Econ. Policy 4 (3), 304–314.
Koop, G., Tole, L., 1999. Is there an Environmental Kuznets Curve for deforestation? J. Dev. Econ. 58 (1), 231–244.
Lambin, E.F., Meyfroidt, P., 2010. Land use transitions: socio-ecological feedback versus socio-economic change. Land Use Policy 27 (2), 108–118.
List, J.A., Gallet, C.A., 1999. The Environmental Kuznets Curve: does one size fit all? Ecol. Econ. 31 (3), 409–423.
Machado, J.A.F., Silva, J.M.C.S., 2019. Quantiles via moments. J. Econ. 213 (1), 145–173.
Maddala, G.S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxf. Bull. Econ. Stat. 61 (S1), 631–652.
Mills, J.H., Waite, T.A., 2009. Economic prosperity, biodiversity conservation, and the Environmental Kuznets Curve. Ecol. Econ. 68 (7), 2087–2095.
Motel, P.C., Pirard, R., Combes, J.L., 2009. A methodology to estimate impacts of domestic policies on deforestation: compensated successful efforts for "avoided deforestation" (REDD). Ecol. Econ. 68 (3), 680–691.
Murshed, M., 2022. Revisiting the deforestation-induced EKC hypothesis: the role of democracy in Bangladesh. GeoJournal 87 (1), 53–74.
Myers, N., 1979. The Sinking Ark. A New Look at the Problem of Disappearing Species. Pergamon Press, Oxford.
Nepal, P., Ince, P.J., Skog, K.E., Chang, S.J., 2012. Projection of U.S. forest sector carbon sequestration under U.S. and global timber market and wood energy consumption scenarios, 2010–2060. Biomass Bioenergy 45, 251–264.
Nguyen Van, P., Azomahou, T., 2007. Nonlinearities and heterogeneity in environmental quality: an empirical analysis of deforestation. J. Dev. Econ. 84 (1), 291–309.
Onafowora, O.A., Owoye, O., 2014. Bounds testing approach to analysis of the Environment Kuznets Curve hypothesis. Energy Econ. 44, 47–62.
Özdemir, E.D., Härdtlein, M., Eltrop, L., 2009. Land substitution effects of biofuel side products and implications on the land area requirement for EU 2020 biofuel targets. Energy Policy 37 (8), 2986–2996.
Ozturk, I., Al-Mulali, U., 2015. Investigating the validity of the Environmental Kuznets Curve hypothesis in Cambodia. Ecol. Indic. 57, 324–330.
Pablo-Romero, M.P., Sánchez-Braza, A., Galyan, A., 2019. Relationship between economic growth and residential energy use in transition economies. Clim. Dev. 11 (4), 338–354.
Pablo-Romero, M.P., Pozo-Barajas, R., Molleda-Jimena, G., 2021. Residential energy Environmental Kuznets Curve extended with non-linear temperature effects: a quantile regression for Andalusian (Spain) municipalities. Environ. Sci. Pollut. Res. 28, 48984–48999.
Panayotou, T., 1993. Empirical tests and policy analysis of environmental degradation at different stages of economic development. In: ILO Working Papers (WEP 2–22/WP 238). International Labour Organization, Geneva. Available at: http://www.ilo.org/public/libdoc/ilo/1993/93B09_31_engl.pdf. accessed 08-june-2021.
Paudel, K.P., Zapata, H., Susanto, D., 2005. An empirical test of Environmental Kuznets Curve for water pollution. Environ. Resour. Econ. 31 (3), 325–348.
Perz, S.G., Skole, D.L., 2003. Secondary forest expansion in the Brazilian Amazon and the refinement of forest transition theory. Soc. Nat. Resour. 16 (4), 277–294.
Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels. In: Cambridge Working Papers WP0435. Faculty of Economics, University of Cambridge, Cambridge. Available at: http://www.econ.cam.ac.uk/research-files/repec/cam/pdf/cwpe0435.pdf. accessed 08-june-2021.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ. 22 (2), 265–312.
Polomé, P., Trotignon, J., 2016. Amazonian deforestation, Environmental Kuznets Curve and deforestation policy: A cointegration approach. In: Groupe d'Analyse et de Théorie Economique Lyon St-Étienne (GATE Lyon St-Étienne). Université de Lyon, Lyon. Available at: https://halshs.archives-ouvertes.fr/halshs-01274854. accessed 08-june-2021.

Ritchie, H., Roser, M., 2021. Forests and Deforestation (published online). Available at: https://ourworldindata.org/forests-and-deforestation. accessed 10-december-2021.
Royston, J.P., 1983. A simple method for evaluating the Shapiro–Francia W′ test of non-normality. J. R. Stat. Soc. Ser. D (The Statistician) 32 (3), 297–300.
Royston, P., 1992. Approximating the Shapiro-Wilk W-test for non-normality. Stat. Comput. 2 (3), 117–119.
Rudel, T.K., Coomes, O.T., Moran, E., Achard, F., Angelsen, A., Xu, J., Lambin, E., 2005. Forest transitions: towards a global understanding of land use change. Glob. Environ. Chang. 15 (1), 23–31.
Scrieciu, S.S., 2007. Can economic causes of tropical deforestation be identified at a global level? Ecol. Econ. 62 (3–4), 603–612.
Shahbaz, M., Solarin, S.A., Mahmood, H., Arouri, M., 2013. Does financial development reduce CO_2 emissions in Malaysian economy? A time series analysis. Econ. Model. 35, 145–152.
Sodhi, N.S., Koh, L.P., Brook, B.W., Ng, P.K.L., 2004. Southeast Asian biodiversity: an impending disaster. Trends Ecol. Evol. 19 (12), 654–660.
Tang, C.F., Tan, B.W., 2015. The impact of energy consumption, income and foreign direct investment on carbon dioxide emissions in Vietnam. Energy 79, 447–454.
United Nations, 2019. The Sustainable Development Goals Report. United Nations, Department of Economic and Social Affairs, Statistics Division. United Nations Publications, New York. Available at: https://www.un.org/sustainabledevelopment/progress-report/. accessed 08-june-2021.
Verburg, R., Filho, S.R., Lindoso, D., Debortoli, N., Litre, G., Bursztyn, M., 2014. The impact of commodity price and conservation policy scenarios on deforestation and agricultural land use in a frontier area within the Amazon. Land Use Policy 37, 14–26.
Walker, R., 1993. Deforestation and economic development. Can. J. Reg. Sci. 16 (3), 481–497.
Westerlund, J., 2007. Testing for error correction in panel data. Oxf. Bull. Econ. Stat. 69 (6), 709–748.
World Bank, 2020. World Bank Database. The World Bank, Washington DC. Available at. https://data.worldbank.org/. accessed 15-december-2020.
Yin, J., Zheng, M., Chen, J., 2015. The effects of environmental regulation and technical progress on CO_2 Kuznets Curve: an evidence from China. Energy Policy 77, 97–108.
Zambrano-Monserrate, M.A., Carvajal-Lara, C., Urgilés-Sanchez, R., Ruano, M.A., 2018. Deforestation as an indicator of environmental degradation: analysis of five European countries. Ecol. Indic. 90, 1–8.