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Environmental Kuznets curve for deforestation in Eastern Europe: a panel cointegration analysis

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Abstract

Deforestation, a major cause of climate change, in Eastern European countries has been an activity coupled with agricultural expansion mainly within the time period of political transition. The present study examines the environmental impact of deforestation and its association with agricultural income as synopsized in environmental Kuznets curve. More specifically, carbon emissions generated by deforestation per hectare (COD)–agricultural income relationship as reflected by the net value added (NVA) per capita of the rural population are studied with the assistance of three panel data models, namely the fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS) and Poold Mean Group autoregressive distributed lag (PMG-ARDL) cointegration technique. The research findings do not validate the environmental Kuznets curve (EKC) in its traditional form, but they verify the inverse N-shaped trajectory (FMOLS, DOLS), or N-shaped trajectory (PMG–ARDL methodology). The results provide policy makers with motivation to focus on agro-economic expansion based on productivity or use of marginal lands and not on land-use change based on deforestation.

Keywords Deforestation · Agriculture · Environmental Kuznets curve · Policy · Economic growth · Land-use land-cover change · Fully modified ordinary least squares (FMOLS) · Autoregressive distributed lag (ARDL)

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1 Introduction

Deforestation is the loss of forests and the degradation of their land to non-forest uses, while forest degradation refers to the loss of the forests' capacity to provide their valuable goods and services (European Commission, 2019). Forests are certainly considered global carbon sinks, but during the last decade, deforestation has severely affected the relationship between carbon emissions and the net positive value from agriculture. Subsequently, deforestation is regarded as a threat to the carrying capacity of forestry sources to store carbon, keep the balance of the natural carbon cycle and maintain the biodiversity of forests in a sustainable manner (Call et al., 2017).

Generally, land-use change and therefore forest loss are strongly affected by economic and other factors. The identification of these factors could provide a useful database in policy planning at the national, regional, or even global levels and help policy makers improve decision efficacy (Geist et al. 2002; Meyer et al., 2003; Lambin & Meyfroidt, 2010).

However, there are different causes of deforestation across countries. Windbreak renovations of forest, agricultural expansions, the type of land ownership, the unsustainable clear cutting on lands or the land restitution are a few of them worth to be mentioned (Hais et al., 2008; Kuemmerle et al., 2015; Taff, 2005).

Historically, Eastern European countries have experienced multiple socio-economic transitions and institutional shocks, especially during the twentieth century (Kuemmerle et.al, 2015). Furthermore, for those countries the issue of deforestation is characterized by two significant events, namely the Fall of Communism and the Accession of a number of those countries in EU. As regards the Fall of Communism is worth mentioning that the occurrence of numerous transformations affected the forest cover total area. Adaptation of forestry to open market principles and resettlement of private ownership on forests are the changes needed to take place within the transition process to an open market economy (Živojinović et al, 2015). Moreover, socio-economic phenomena of corruption and disruption in forest management have led to numerous public debates (Scriban et.al, 2019) making forest restitution a problem difficult to be solved. Furthermore, the accession of some countries in EU—including Slovakia, Poland and Romania—has caused a number of unavoidable struggles lasting almost 10–15 years to adapting to the existing environmental legislation as synopsized in the Community Environment Action (Feranec et al., 2017). What's more the oscillations of net value added (NVA) growth rate are significantly related to marginal economic development, while new value chains support the opening of new markets for agricultural products, a stylized fact that may explain the connectivity between deforestation and the economic growth in agriculture (Leblois et al., 2017).

In this respect, deforestation and afforestation are considered two reversed processes that determine the total forest area. To get an insight to the extent of deforestation in those countries and the changes recorded due to those events, we provide a table (Table 1) that presents the areas of afforestation and deforestation for two different time periods. According to those data, in the initial post-communist period 1990–2000, afforestation outperformed deforestation, while in the period 2000–2006, deforestation outperformed afforestation among the countries that became members of the European Union (Feranec et al., 2017). More specifically, in Eastern and Central Europe, the land-use change cover (LUCC) area was estimated to be approximately 21,970 km^2 in 1990–2000 and approximately 13,860 km^2 in 2000–2006 among 17 Central European countries (Hosonuma et al., 2012). In Eastern Europe, for the period 1990–2006, both afforestation and deforestation were reported as the most common land-cover changes. More specifically, deforestation

Table 1 Areas of afforestation, deforestation, and LUCC in Eastern Europe. Source: Adapted from Feranec et al. (2017, p. 27)

LUCC type	1990–2000a			2000–2006b		
	Total area (km^2)	Mean annual increase over the period 1990–2000 (km^2)	Mean annual change in LUCC area (%)	Total area (km^2)	Mean annual increase over the period 2000–2006 (km^2)	Mean annual change in LUCC area (%)
Deforestation	580,318	58.031	26.4	652,29	108,688.2	47.1
Afforestation	619,346	61,934.6	28.1	344.569	57,428.2	24.9
Total LUCC area	2,197.023	219,702.3	–	1,385.739	230,956.5	–
Total study area	122,375.321	–		134,022.612	–	

corresponded to 54.5% of the total LUCC area for the 1990–2000 period and 72.0% of the total LUCC area for the 2000–2006 period, as illustrated in Table 1.

1 Notes: a) Regarding the period of 1990–2000, the LUCC data are available for the countries such as Bulgaria (BG), Czech Republic (CZ), Estonia (EE), Croatia (HR), Hungary (HU), Lithuania (LT), Latvia (LV), Montenegro (ME), Poland (PL), Romania (RO), Serbia (RS), Slovenia (SI), Slovakia (SK); b) regarding the period of 2000–2006, the LUCC data are available for the countries such as Albania (AL), Bosnia and Herzegovina (BA), Bulgaria (BG), Czech Republic (CZ), Estonia (EE), Croatia (HR), Hungary (HU), Kosovo (KV), Lithuania (LT), Latvia (LV), Montenegro (ME), North Macedonia (MK), Poland (PL), Romania (RO), Serbia (RS), Slovenia (SI), Slovakia (SK).

The data provided above contradict the view of Taff (2005), who reported an increase in the overall forest area among all Central and Eastern European countries for the time period 2000–2006. This contradiction could be caused by the utilization of false raw or processed data. Forest area data are commonly obtained from national statistics and summarized by the United Nations Food and Agriculture Organization (UN-FAO) issued in 2006, while land-use/land-cover (LU/LC) changes are based on CORINE land-cover (CLC) data, in alignment with satellite image analyses (Leinenkugel et al. 2019).

In terms of individual countries that participate in the sample of the present study, Latvia, Estonia, and Lithuania do have the highest rate of deforestation, followed by Hungary, Romania and northern Slovakia within the period 2000–2006. In addition, in the Czech Republic, saturation of the deforestation rate was recorded in 2000. However, a high deforestation rate was evident for the period 2000–2006 in Bosnia Herzegovina and north-eastern Albania (Feranec et al., 2017).

The above-mentioned situation unveils the scientific value of a study on deforestation in the aforementioned countries. Furthermore, lack of studies on the EKC for Eastern European countries (the existing literature is referring mainly to Asia, Latin America and Africa), along with the fact that forest cover or land covered by agricultural crops is used as proxies for deforestation without unveiling the real impact of deforestation on climate change, does create a gap in the EKC literature concerning deforestation. The present study is an effort to bridge this scientific gap. It investigates environmental degradation as reflected by deforestation in association with agricultural income. The environmental degradation caused by deforestation is represented by the annual net carbon emissions removal from forestland/hectare (CODd), while the NVA of agriculture per capita of the rural population was associated with economic growth. This relationship is described according to the EKC for a panel data set of sixteen former socialist European countries.

The proxies employed, and the research area with its particularities synopsizes the novelty in the present study. Specifically, we focus on interlinkages of deforestation (environmental degradation) with the expansion of land used for cultivation and in sequence with growth of agricultural income per capita of the rural population. Another significant contribution of this study is the methodological issue since the above relationship is examined with three different methodologies providing in some cases different results concerning the EKC pattern validated. Finally, we consider the evolution of this relationship over time and the policies adopted to increase productivity in agriculture and limit forest loss.

The study is structured as follows: The next section involves the literature review to describe deforestation in the international context and among the former socialist countries in Eastern Europe, as well as the role of the EKC in the case of deforestation with the assistance of different indices. The next section outlines the theoretical background of the analysis. Next, the adopted methodology and the research findings are provided and then discussed, while the last section concludes.

2 Literature review

Deforestation is a form of environmental degradation that leads to an increase in anthropogenic greenhouse gas (GHG) emissions and a decrease in their mitigation (Smith et al., 2014). Previous studies focus on eliminating the detrimental impacts caused by deforestation using governmental policies and initiatives by non-governmental organizations (Köthke et al., 2013). These policies and initiatives should consider varied forestry functions, including food production, watershed protection, erosion control, and natural landscape conservation.

Deforestation and forest degradation have led to a significant increase in CEM during the last decade. According to the World Bank, in the period 2000–2012, the average annual deforestation rate was 0.12%, and over 40% of countries lost a total forested area of 1,036,998 km^2 to deforestation. No changes in forest areas were recorded for one-fourth of the countries considered, while one-third of the countries sustained a net increase in forest area, accounting for 503.6 km^2 of reforestation (Da Silva & Rodgers, 2018).

Countries experiencing forest transition and an increase in forest cover commonly lack comprehensive data on deforestation drivers. Therefore, it is highly significant for decision-makers to ascertain whether the current sociocultural behaviour in the country accelerates forest loss (Pendril et al., 2019). In this context, a land-balance model was used to quantify deforestation with the assistance of the variable production for Agri silvicultural products for the tropical countries (Skoutaras, 2010; Pendril et al., 2019). In the study, the potential to trace embodied deforestation to countries of evident consumption was outlined with the aid of a physical country-to-country trade model (Pendril et al., 2019). From 2005–2013, almost 62% (5.5 Mha yr − 1) of forest loss could be attributed to alternative land uses. A large share of deforestation, accounting for 26%, was attributed to the fact that 87% of demand worldwide was exported to countries being characterized by either decreasing deforestation rates or enhancement in forest cover. These countries are mainly late- or post-forest transition countries in Europe and Asia, namely China, India and Russia. Approximately 30% of the net earnings in countries after changes in forest land were outperformed by imports of commodities, which in turn have led to deforestation elsewhere. In other words, the achievement of forest transition worldwide will be substantially more effective and demanding in terms of efforts compared to national or regional transitions (Pendril et al., 2019).

The increasing demand for agricultural products leads to an accumulated increase in GHG emissions. Since forestry and agriculture are competing land uses, a decrease in forest cover and an increase in the demand for cultivated land are the result (Angelsen & Kaimowitz, 2001). This competitive model among land uses constitutes one of the major reasons leading to forest loss. Accordingly, the loss of forestry wealth represents almost one-third of the accumulated increase in GHG emissions and one-tenth of the current global emissions (IPCC, 2013). Therefore, the tillage of soil could both foster the sustainable management of natural resources and control deforestation (Angelsen & Kaimowitz, 2001; IPCC 2018; Gibbs et al., 2010).

In terms of trade–deforestation linkages, it is noteworthy that the impact of trade is high in countries still endowed with a large proportion of forest cover, while it has less impact in countries with less remaining forest cover (Gibbs et al., 2010). This indicates that trade in forestry and agricultural commodities are important factors of forest clearance (Gibbs et al., 2010).

Hosonuma et al. (2012) suggested that central governments trace the factors of deforestation and forest degradation as a basic guideline for the development of national strategies and action plans, as these are reflected in Reducing Emissions from Deforestation and Degradation (REDD+). Furthermore, Pirard and Belna (2012) investigated the relationship between farming technologies and deforestation in the tropics to determine whether and how the REDD+mechanism may affect farming extension in forests (Skoutaras, 2010). According to their findings, public and private investment should focus on farming technologies to expand agricultural productivity. This strategy may provide even small farmers the opportunity to implement techniques promoting sustainability and eco-efficiency in their land cultivation (Pirard & Belna, 2012).

In another study, REDD is shown to represent rich and developed countries' efforts to find economic motivations regarding forest resources that may contribute to a decrease in the carbon emissions generated by deforestation in developing countries (Mather, 1992). Implicitly, REDD+can motivate developing countries that voluntarily determine to reduce deforestation rates to maintain carbon emissions below a set threshold. These countries could sell carbon units in the international carbon market and thereby support strategic efforts towards climate change mitigation, biodiversity conservation, and ecosystem management while aiming at profitability. These efforts could be enhanced by trading agricultural goods and services, as well as by quantifying carbon emission equivalents that cannot be released into the atmosphere through deforestation (also referred to as the carbon footprint). Indeed, such equivalents could be valued and sold as determined units in a rapidly developing global market (Mather, 1992).

Based on all the aforementioned issues, this study focuses on environmental degradation from the perspective of a) the equivalent carbon emissions generated by deforestation and b) agricultural income. This relationship composes the empirical framework of the environmental Kuznets curve (EKC). Based on Kaika and Zervas (2013a, b), the inverted U-shaped relationship is interpreted by countries' efforts to overcome environmental problems caused in earlier stages of economic growth in the process of economic development. In the literature on deforestation, a disagreement has arisen among scientists who disregard the EKC and those who consider it to be relevant. The latter group considers that the EKC may adequately interpret the forest transition process (Barbier et al., 2010; Mather, 1992; Rudel et al., 2005). In testing the validity of the EKC, a number of issues have arisen, which are related to the statistical analysis, properties of raw data (Stern et al. 2004; Galeotti et al. 2006; Caviglia et al. 2009), and selection process of data mining (Galeotti et al. 2006; Carson, 2009).

Empirical studies on the EKC for deforestation proliferated after 1990, and the most indicative include those of Munasinghe (1999), Panayotou (1993), Shafik (1994), Stern et al. (1996), and Culas (2007), which have proven to represent contradictory results. The inverted U-shaped relationship was confirmed in a few cases (Esmaeili and Nasrnia 2019), while the U-shaped relationship was validated for the case of Asian countries (Bhattarai & Hammig, 2001; Culas, 2007). An N-shaped relationship was observed by Bhattarai and Hammig (2001), who viewed it as a plausible explanation of efforts made by counties to implement forest restoration programs.

In a cross-country study, Ceddia et al. (2013) utilized FAO data for the period 1970–2006 to investigate the effective role of income in deforestation. Few studies have investigated the impact of demand for agricultural products on deforestation among developed countries (Busa, 2013). Therefore, proper measures should be undertaken or conservation programs should be initiated to confront particular environmental problems. The complex nature of this problem requires integrated solutions that presuppose the relative stakeholders' participation in decision-making. In particular, the necessity for multilevel cooperation should be taken into consideration in line with the strategic consensus that environmental and economic growth should be complementary, rather than conflicting, objectives (Indarto & Mutaqin, 2016). The term eco-efficiency should become a motto for environmentally friendly economic growth at both the country scale and the wider EU scale (Zafeiriou et al., 2017).

In a relevant study, Benedek et al. (2020) suggested for the first time a new application for the EKC, including forest recovery or even forest transition. These findings, with the aid of ecological–economic models, validate the existence of an N-shaped curve in the context of forest recovery. This implies the possibility for improvement in the quality and quantity of new forests in middle-income countries (Benedek et al., 2020). The present study focuses on deforestation as an index for environmental degradation and the linkage to the expansion of agricultural income, a novel approach that may well bridge the existing scientific and research gaps. Particularly, the validation of the EKC in the case of deforestation is approached from the perspective of the carbon emissions factor for forest conversion land, and the agricultural income per capita of the rural population.

3 Materials and methods

Many methodologies have been employed to study the EKC, such as time-series Johansen–Juselius cointegration techniques and linear and nonlinear ARDL cointegration techniques (Ghatak & Siddiki, 2001; Zafeiriou & Azam, 2017). In addition, different panel data methods have been applied, including pooled least squares, the fixed effect model, the random effect model, and the Pedroni cointegration methodology, which often yield contradicting results (Germani et al., 2020; Zafeiriou & Azam, 2017). This study uses for first time panel cointegration tests (Kao and Fisher cointegration tests), the ARDL panel cointegration test and the two dynamic cointegration estimation models (FMOLS and DOLS). To the best of authors' knowledge, these tools have not been previously used to support the EKC for deforestation for this particular group of countries. A panel data analysis outperforms the time-series ones, since interrelations attributed to the same institutions and framework can be captured, providing reliability to the model estimation and the results yielded.

The majority of the existing literature focuses on deforestation represented by arable land and its relationship to GDP, taking the GDP per capita as a growth index. In the present study, panel cointegration is employed using selected data from FAOSTAT (2019). Specifically, the variables selected for studying the Kuznets curve involve the equivalent carbon emissions generated by deforestation per hectare (COD) as a proxy for environmental degradation and the net value added generated by agriculture as a proxy for agricultural income (NVA) for 16 Eastern European countries over a period of 25 years (1990–2015), resulting in 416 observations. For the agricultural sector, agricultural income measures the net value added of goods and services generated by farm operations during a given calendar year. The proxy for environmental degradation, which is the annual net COD emission/removal from forestland, consists of the net carbon stock gain/loss in a living biomass pool (aboveground and belowground biomass) associated with forest and net forest conversion. 'the forest conversion for agriculture is the most expansive signature of human occupation on the Earth's surface' (Lopez Carr, 2021). Based on this reason, in alignment with other works (Hoang & Kanemoto, 2021; Tazeen, 2021) that considered agriculture the most significant reason for deforestation, we selected the NVA generated by agriculture as a proxy for agricultural income, aiming to examine the impact of land-use change on the association between agricultural income and carbon emissions. Based on the above, we seek to unveil the significance of deforestation and the consequent expansion of land used for agriculture for agricultural income. In other words, we investigate whether the change in carbon emissions through deforestation compensates the public with a sufficient increase in agricultural income (FAOSTAT, 2019). Regarding the units of the variables, COD is measured in tons of carbon emissions per hectare, and NVA per capita is measured in thousand dollars in 2005 prices per capita (in terms of the rural population), with both indices derived by FAOSTAT (2019). The analysis involves only these two variables since the objective is to validate and quantify their relationship. The addition of more variables would reduce the degrees of freedom and, most importantly, change the appropriate response surface for the cointegration statistic. This would reduce the odds of finding significant cointegrating relationships. Finally, by allowing polynomial terms of the agricultural income term, we obtain a more flexible shape of the EKC (Fosten et al., 2012).

The descriptive statistics of the variables employed in the model are provided in Table 2.

Furthermore, Figs. 1 and 2 illustrate the evolution of the variables employed. The numbers used in Figs. 1 and 2 correspond to the countries examined.

The second variable employed, that is, the carbon emissions generated by deforestation, is illustrated in Fig. 2.The patterns of each individual country is characterized by specific behavior within the time period studied.

In the following subsections, the stages of the methodology employed in the data sample are outlined.

3.1 Panel unit root tests

In the first stage, we employed Im et al.'s (2003) and Breitung and Das' (2005) panel unit root tests. The first test is a first-generation one, with the main feature of independent cross sections, while the central limit theorem allows us to derive the asymptotic normality and is described by Eq. (1):

$$\Delta y_{\mathrm{it}} = a_i + \rho_i y_{i,t-1} + \sum_{z=1}^{\rho_i} \beta_{i,z} \Delta y_{i,t-z} + \varepsilon_{\mathrm{it}} \tag{1}$$

Table 2 Descriptive statistics of the variables in logarithmic form (common sample)

	lnCOD	lnNVA
Mean	2.629877	0.254840
Median	0.1200000	0.227122
Maximum	6.185426	0.419388
Minimum	0.0120000	0.145092
Std. Dev	2.787174	0.074435
Skewness	0.129503	0.465413
Kurtosis	1.047822	2.002032
Jarque–Bera	67.22009	32.28120
Probability	0.000000	0.000000
Observations	416	416

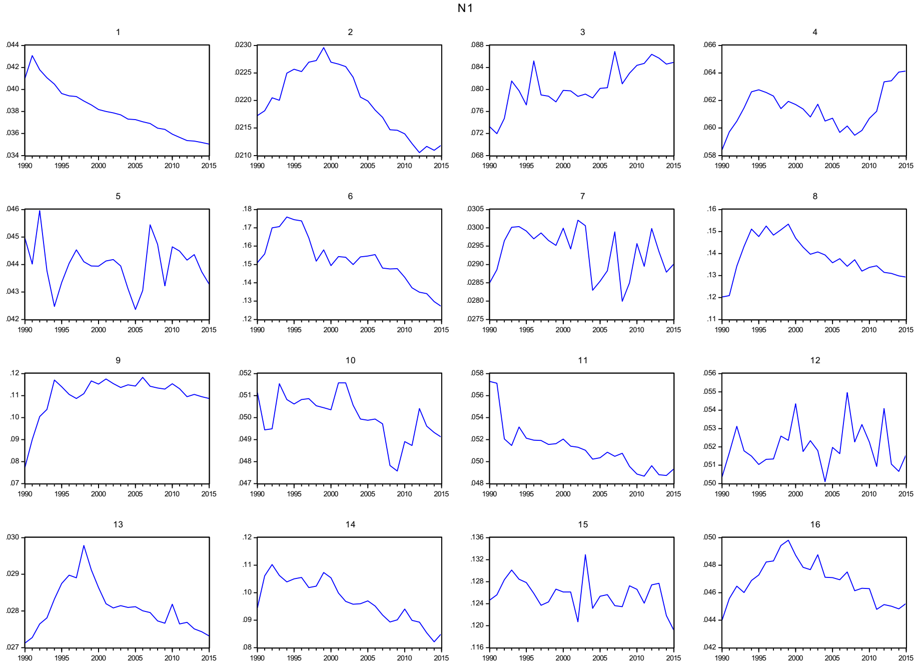

Fig. 1 Illustration of the ln(NVA/cap) of the rural population for the panel data of the studied countries

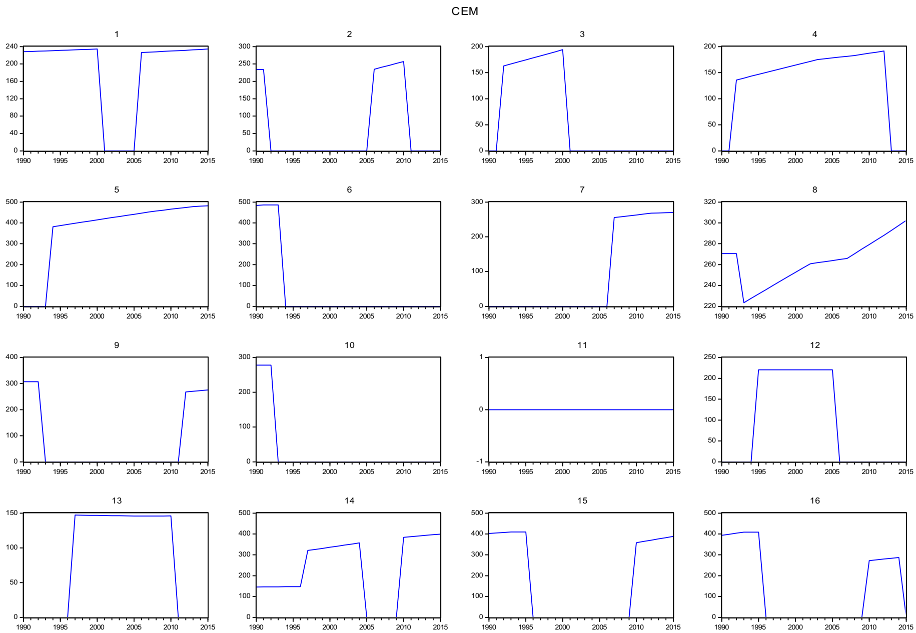

Fig. 2 Evidently in Fig.1 the patterns of agricultural income differ among different countries due to particularities of the sector of agriculture in each individual country. The evolution of ln(COD/hec) for the sample countries

Testing the null hypothesis of $H_0 = \rho_i = 0$, where $i = 1, 2, 3, \ldots.., N$ for each individual group, the statistic employed is the average of the augmented Dickey–Fuller (ADF) test provided by Eq. (2):

$$t_{\mathrm{IPS}} = \frac{1}{N}\sum_{i=1}^{N} t_{\mathrm{iT}}\left(p_i, \beta_i\right) \tag{2}$$

where $t_{iT}(p_i, \beta_i)$ denotes the unit root t statistic estimated for each cross-section item (each country, in our case).

For small samples, the standardization of this statistic with the assistance of means and variances is evaluated by simulations, where the null hypothesis is $H_0 : \rho_i = 0$, and the statistic employed is represented by Eq. (3):

$$W_t = \frac{\sqrt{N}\left[t_{\mathrm{IPS}} - N^{-1}\sum_{i=1}^{N}\left[Et_{\mathrm{iT}}\left(p_i, 0\right)|\rho_i = 0\right]\right]}{\sqrt{N^{-1}\sum_{i=1}^{N}\left[\mathrm{Vart}_{\mathrm{iT}}\left(p_i, 0\right)|\rho_i = 0\right]}} \tag{3}$$

$$\rightarrow^{d} N(0, 1)$$
$$t, N \rightarrow \infty$$

The robustness of the results and the potential heterogeneity bias of the alternative hypothesis limit the power to reject the null hypothesis. Therefore, a second panel unit root test, the Breitung test (Das 2014), is employed. The Breitung test is a unit root test for panel data with no need for the employment of bias correction factors since variable transformations are made prior to the test (Breitung & Das, 2005). Because of its pooled data construction, the test is against homogenous alternatives (Hlouskova & Wagner, 2005). Particularly, the data are generated by the following models (4–6):

$$y_{\mathrm{it}} = l_i + k_i t + v_{\mathrm{it}} \tag{4}$$

where $v_{\mathrm{it}} = \rho_{\mathrm{it}} v_{\mathrm{it-1}} + \varepsilon_{\mathrm{it}} \quad \varepsilon_{\mathrm{it}} \sim \mathrm{iid}\left(0, \sigma^2\right)$.

The transformed data on which the test is based are derived by the following formula:

$$\left(\Delta y_{\mathrm{it}}\right)^{*} = \left[s_t \Delta y_{\mathrm{it}} - \frac{1}{T - t}\left(\Delta y_{\mathrm{it+1}} + \cdots + \Delta y_{\mathrm{iT}}\right)\right] \tag{5}$$

$$t = 1, 2, \ldots, T - 1, \text{ where } s_t^2 = {}^{(T - t)}\!/\!_{(T - t + 1)}$$

And

$$y^{*}_{\mathrm{it-1}} = y_{\mathrm{it-1}} - y_{\mathrm{io}} - \frac{t - 1}{T}\left(y_{\mathrm{iT}} - y_{\mathrm{io}}\right) \tag{6}$$

The null hypothesis examined is the following:

$H0 : \rho_i = 0$, while the test suggested by Breitung and Das (2005) and employed in our work is provided by Eq. (7):

$$B_{n.T} = \left(\frac{\hat{\sigma}^2}{nT^2}\sum_{i=1}^{n}\sum_{t=2}^{T-1}\left(y_i^{*} - 1\right)^2\right)^{-1/2}\frac{1}{T\sqrt{n}}\sum_{i=1}^{n}\sum_{t=2}^{T-1}\left(\Delta y_{\mathrm{it}}\right)^{*} y^{*}_{\mathrm{it-1}} = \left(B_{\mathrm{2nT}}\right)^{-1/2} B_{\mathrm{1nT}} \tag{7}$$

3.2 Panel cointegration tests

The next step of our analysis includes Kao residual cointegration test and the Johansen–Fisher test, to examine whether the variables under review are related in the long run. The Kao residual cointegration test is alike to that of Pedroni (2004) in that it adopts an identical elementary approach, but the constants and homogeneous coefficients are also specified. Kao et al. (1999) employed for first time a residual-based test on which the DF- and ADF-type tests are employed.

3.3 Panel estimation models

The next step in our analysis involves the estimation of the cointegrating equations. Two models, the DOLS and the FMOLS, are used to estimate the long-run relationships among the variables. In the FMOLS model, the estimator for the long-run parameters and for the transformed data (necessary for endogeneity correction) is provided by Eqs. (8–9):

$$\theta_{\text{iFMOLS}} = N^{-1} \sum_{i=1}^{N} \left[\sum_{i=1}^{T} \left(x_{\text{it}} - \tilde{x}_{\text{it}} \right)^2 \right]^{-1} \sum_{t=1}^{T} \left(x_{\text{it}} - \tilde{x}_{\text{it}} \right) y_{\text{it}}^* - T\tilde{t}_i \tag{8}$$

where

$$y_{\text{it}}^* = x_{\text{it}} - \tilde{y}_i - \frac{\widetilde{M_{21t}}}{\widetilde{M_{22t}}} \Delta x_{\text{it}} \tag{9}$$

and $t_i^{\sim} = \Gamma_{21} + \Omega_{21i}^{O} - \frac{\widetilde{M_{21t}}}{\widetilde{M_{22t}}} \left(\Gamma_{21} - \Omega_{21i}^{O} \right)$

$$\Omega_i = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}$$

(8) denotes the long variance matrix, while Mi denotes its lower triangular decomposition.

$$y_{\text{it}} = \alpha_i + \beta_i X_{\text{it}} + \sum_{k=l}^{l} c_{\text{ik}} \Delta X_{\text{it}+k} + \xi_{\text{it}} \tag{10}$$

where t = 1,2,…,T and i = 1,2,…,N

Thus, the parameter estimates with this approach are given in Eq. (11):

$$\theta_{\text{iDOLS}} = N^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} Z_{\text{it}} \tilde{Z}_{\text{it}} \tag{11}$$

where Zit is a vector with dimensions (2 k + 1) × 1 and provides the regressors as in Eq. (12):

$$Z_{\text{it}} = x_{\text{it}} - x_m, \Delta x_{\text{it}-k}, \ldots \ldots \Delta x_{\text{it}+k} \tag{12}$$

Finally, the PMG-ARDL technique is an econometric tool that investigates the long-term and short-term cointegration (not provided here) and estimates the error correction model (ECM) to identify the short-term dynamics of the panel data. The panel ARDL is preferred for its advantages over alternative methodologies: it uses an individual short form of equation, while the condition for the variables to be I(1) can be abolished, and the variables can include various lags, which is not possible in other estimation methodologies. The simultaneous estimation of the short-term and long-term coefficients and the non-robust results in the case of limited data are further modelling advantages. The model to be estimated is derived in the next three Eqs. (13–15):

$$Y_{\mathrm{it}} = \propto_{\mathrm{it}} + \beta_{\mathrm{it}}^{'} X_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{13}$$

$$Y_{\mathrm{it}} = \propto_{\mathrm{it}} + \sum_{i=1}^{k} \delta_{\mathrm{ij}} Y_{j,t-1} + \sum_{i=0}^{q} \beta_{\mathrm{ij}}^{'} + \varepsilon_{\mathrm{it}} \tag{14}$$

$$\begin{aligned} \Delta \ln \mathrm{COd} = {} & \beta_1 + \sum_{i=1}^{k} a_{\mathrm{ij}} \Delta \ln \mathrm{COd}_{j,t-1} + \sum_{i=0}^{k} a_{\mathrm{ij}} \Delta \ln \mathrm{NVA}_{j,t-1} + \sum_{i=0}^{k} a_{\mathrm{ij}} \Delta \ln \mathrm{NVA}_{j,t-1}^{2} + \sum_{i=0}^{k} a_{\mathrm{ij}} \Delta \ln \mathrm{NVA}_{j,t-1}^{3} \\ & + \theta_1 \ln \mathrm{COd}_{j,t-1} + \theta_2 \ln \mathrm{NVA}_{j,t-1} + \theta_3 \ln \mathrm{NVA}_{j,t-1}^{2} + \theta_4 \ln \mathrm{NVA}_{j,t-1}^{3} \varepsilon_{\mathrm{jt}} \end{aligned} \tag{15}$$

where $i = 1\ldots$, n denotes the cross-section, $t = 1\ldots$, T denotes the time dimension and εit is the error term. The second equation entails a number of assumptions for the parameters, exogeneity and regressors promoting the selection and estimation of an appropriate panel data model. Regarding the variables employed, it is noteworthy that ln (COD/hec) denotes the carbon emissions generated by deforestation and the agricultural NVA per capita of the rural population. Furthermore, t and i refer to time and the studied country, respectively, while Δ is the lag operator and k denotes the lag length. Regarding the signs of the long-run relationships shown in Eq. (15), environmental degradation due to deforestation is expected to expand with increasing income up to a certain level, beyond of which the variables comove to opposite directions. These two effects are noticed in case $\theta 1 > 0$ and $\theta 2 < 0$ (confirming the inverted U-shaped between COD and NVA relationship. In addition, we can easily test the presence of an N-shaped curve by using a cubic functional form ($\theta 3 > 0$). Finally, if the signs are as follows: $\theta 1 < 0$, $\theta 2 > 0$ and $\theta 3 < 0$, the reverse N-shaped Kuznets curve is confirmed implying the existence of a second turning point on income variable.

To investigate the cointegration in the long run among the variables studied, the conditions are provided below in Eq. (16):

$$\begin{aligned} &\theta_1 = \theta_2 = 0 \text{ (Not Cointegrated)} \\ &\theta_1 \neq \theta_2 \neq 0 \text{ (Cointegrated)} \end{aligned} \tag{16}$$

The null hypothesis is investigated with F distribution within the panel autoregressive distributed lag bounds test (it is not necessary for the variables employed to be only I(0) or I(1)). In this methodology, two groups of main rates are computed, namely I(0) identified with lower restriction and I(1) identified with higher restriction. Under the condition that the F statistic has a higher value than that corresponding to I(1), the null hypothesis cannot be accepted. Therefore, it can be argued that the considered variables are not cointegrated. On the other hand, if the estimated value is lower than the critical value corresponding to I(0), the null hypothesis cannot be rejected. Therefore, if the result lies between I(0) and I(1), no conclusion can be derived. Based on the signs of the long-run relationship estimated, the following conclusions can be reached.

The long-term relationship validates the condition of cointegration, and the long-term relationship is estimated with Eq. 17, while Eq. 18 provides the long- and short-term dynamics simultaneously.

$$\begin{aligned}\ln \mathrm{CO}_{2\mathrm{it}} =& \beta_2 + \sum_{j=1}^{k} a_{i2} \ln \mathrm{CO}_{2,j,t-1} + \sum_{i=0}^{k} \beta_{i2} \ln \mathrm{NVA}_{j,t-1} \\ &+ \sum_{i=0}^{k} \beta_{i3} \ln \mathrm{NVA}^2_{j,t-1} + \sum_{i=0}^{k} \beta_{i4} \ln \mathrm{NVA}^3_{j,t-1} + \varepsilon_{it2}\end{aligned} \tag{17}$$

$$\Delta \ln \mathrm{CO}_{2\mathrm{it}} = \beta_3 + \sum_{j=1}^{k} a_{i3} \Delta \ln \mathrm{CO}_{2,j,t-1} + \sum_{i=0}^{k} \beta_{i3} \ln \mathrm{NVA}_{j,t-1} + \gamma \mathrm{ECT}_{j,t-1} + \varepsilon_{\mathrm{it}3} \tag{18}$$

The structure of the error correction term (ECT) is illustrated in Eq. 19, while in Eq. 18, γ indicates the speed of adjustment, and the negative sign indicates a convergence from the short run to the long run and indicates a causal relationship among the explanatory variables and dependent variable.

$$\mathrm{ECT}_{j,t} = \ln \mathrm{COd}_{2\mathrm{it}} - \beta_2 - \sum_{j=1}^{k} a_{i2} \ln \mathrm{CO}_{2,j,t-1} - \sum_{i=0}^{k} \beta_{i2} \ln \mathrm{NVA}_{j,t-1} - \sum_{i=0}^{k} \beta_{i3} \ln \mathrm{NVA}^2_{j,t-1} - \sum_{i=0}^{k} \beta_{i4} \ln \mathrm{NVA}^3_{j,t-1} \tag{19}$$

4 Results

4.1 Panel unit root test results

The first step in the study examines the validity of the unit root process of each individual variable for every panel data set. The test employed is the Breitung unit root test commonly used for panel data. The variables employed are confirmed to be stationary in first differences and non-stationary in levels. The particular panel unit root test suggested by Breitung and Das (2005) was preferred due to its smallest size distortion validated by Hlouskova and Wagner (2005). The results of the employed tests are provided in Table 3. Poland is not taken into consideration in the cointegration tests and model estimation due to the unaltered value of COd throughout the time period studied.

Table 3 Panel unit root tests for 16 former socialist countries in the 1990–2015 period

Variables	Levels		First Difference	
	IPS	Breitung	IPS	Breitung
CEM	0.21(0.583)	− 1.137(0.1278)	− 7.71***(0.000)	− 3.272***(0.000)
NVA	− 8.52***(0.00)	− 0.4(0.3423)	− 10.12***(0.000)	− 4.542***(0.00)

***Denotes the rejection of the null hypothesis that the series studied has a unit root (at the 1% level of significance)

According to research findings based on the Breitung panel data unit root test, all the employed variables are I(1), while the IPS test provides conflict results; implicitly, some variables are I(0), while a few others are I(1). The ARDL test allows the model estimation for a mixture of I(1) and I(0) variables, although we employ other cointegration tests based on the fact that the findings based on Breitung test are more reliable.

4.2 Panel cointegration test results

The next procedural step tests the existence of a long-run relationship following two methodologies: the Kao residual cointegration test and the Johansen Fisher panel cointegration test. The results of the tests are provided in Table 4.

According to our findings and based on the results of the panel cointegration test, as illustrated in Table 4, it is confirmed that for the 5% level of significance, there is one cointegrating relation among the variables studied, while no such relation is confirmed based on the maximum eigenvalue test. Despite the conflicting results of the Johansen Fisher panel cointegration test, we employ another test, namely the Kao residual cointegration test, which also validates the cointegration among the variables employed. In addition, the panel ARDL cointegration test supports the cointegration among the variables employed. For the case of deforestation, studies present different results, ranging from no significant correlation (Antle & Heidebrink, 1995; Shafik, 1994; Uusivuori et al., 2002) to significant correlation, with sample areas in Latin America and Africa (Fosten et al., 2012; Culas, 2007; Bhattarai & Hammig, 2001; Cropper & Griffiths, 1994).

4.3 Panel cointegration model estimation results

The final step in our analysis involves the estimation of the cointegrating vector with the ARDL model, panel DOLS and panel nonparametric FMOLS. The results for the data used are provided in Table 5. In this table, the coefficients of the models are estimated, while the values in parentheses denote the p values provided by EViews 11 software.

Based on the aforementioned results, two different EKC patterns are validated by the different models. FMOLS and DOLS validate the reverse N-shaped pattern, implying that emissions are increasing after a second income threshold. The PMG/ARDL estimation model validates an N-shaped pattern and not an inverted N-shaped pattern. The results concerning the existence of the EKC for deforestation support the N-shaped curve

Table 4 Panel cointegration tests for the former socialist countries in the period 1990–2015

	Dependent variable implied carbon emissions generated by net forest conversion per hectare			
Kao residual cointegration test		Johansen fisher panel cointegration test		
ADF (6 lags automatically selected)	−4.181***(0.000)	Null Hypothesis	Trace test	Max eigen test
		None	355.4***(0.000)	177.0(0.000)***
		At most 1	113.2***(0.000)	37.78(0.22)
		At most 2	46.56(0.259)	25.53 (0.7839)
		At most 3	36.59	26.07(0.7607)

***, **, and *Indicate the rejection of the null hypothesis at the 1%, 5% and 10% levels of significance

Table 5 Model estimation results for Eastern European countries during 1990–2015

Variables	FMOLS	DOLS	PMG/ARDL
Dependent Variable COD/he			
NVA	− 101.17***(0.00)	− 243.21***(0.000)	688.8***(0.000)
NVA^2	323.39***(0.00)	797.62****(0.000)	− 4062.4***(0.000)
NVA^3	− 336.0****(0.00)	− 836.156***(0.000)	684.753***(0.0000)

***denotes the rejection of the null hypothesis for the non-significance of coefficients (figures in parentheses are *p* values). All the variables are statistically significant (nva denoted ln(NVA))

(PMG-ARDL model) observed by Bhattarai and Hammig (2001) and the reverse N-shaped curve (FMOLS and DOLS estimation models) that was validated for the case of Bulgaria by Tsiantikoudis et al. (2019).

5 Discussion

Despite the existence of a sole cointegrating relationship, the estimated model (based on the signs of the coefficients) contradicts the EKC in its traditional form with both methodologies employed. In particular, the inverted N-shaped trajectory for the data employed is validated. This shape of the EKC supports the focus of Eastern European countries on the growth of the agricultural sector with little effort to contain the carbon emissions attributed to deforestation. This result was also validated by Tsiantikoudis et al. (2019) for the case of Bulgaria and by Bhattarai and Hammig (2001) for other developing countries. However, recent studies have reached conflicting results, supporting N-shaped, inversed N-shaped or even inverted U-shaped EKCs. The methodology for employing the index or the sample size may explain these conflicting results (Choumert 2013).

Furthermore, in the relevant literature, the rate of deforestation for countries being changed early is attributed to their effort to satisfy the domestic demand. On the other hand, for the rest of the countries almost 25% of the total deforestation took served export purposes, with a significant variability to be recorded for different countries (0–78% for late-transition countries and 0–90% for post-transition countries) (Pendril 2019).

Another subject being investigated involves identification of the differences between economic development, changes in forest cover along with scarcity in forest resources. In case the forest transition is outperformed by forest scarcity, the imports play a facilitating role in forest transition either in local or national level, while the economic development/growth path can lead simultaneously to reforestation and expanded imports (Pendril 2019).

Concerning the causality of the forest transition path, the policies aiming at the climate change mitigation are related to forest transitions when are taking place without taking into consideration procedures that transmit the pressure from forests causing emissions to other GHG sources (known as "hidden emissions"). Therefore, agricultural intensification, wood fuel substitution, and land displacement are generation sources of hidden emissions that may effectively outperform the climate change mitigation effect of forest transitions (Kyriakopoulos et al., 2010, 2015; Gingrich 2019). This issue may well be a limitation of the present study, although two prerequisites are required for the efficient assessment and interpretation of the role of hidden emissions on forest transitions, namely the quantification of full national GHG budgets and the analysis of forest transition policies. The aforementioned approaches are vital for the adequate assessment of the net GHG mitigation effect concerning changes in forest land use during the implementation of effective land-based climate change mitigation policies (Ntanos, Kyriakopoulos, et al., 2018; Ntanos, Skordoulis, et al., 2018) in an effective way.

Therefore, hidden emissions are not taken into consideration in GHG accounting and indicators related to land, while policies do not incorporate potential problem shifts of this type (Kyriakopoulos et al., 2010; Papageorgiou et al., 2015; Skordoulis et al., 2019). Additionally, changes in forest land occur in periods of demographic growth, under the condition that forests do not generate additional emissions. Thus, it is critical to get an insight to these concepts and how they evolve with time and among individuals, in order to become possible to develop forest protection plans. Subsequently, the hidden emissions generated by forest transitions are closely related to quantifications of GHG socio-economic accounts and policy implications. A holistic approach provides robust explanations of forest transitions and improves assessments of their net carbon emissions effects and their impact on attitude of societies towards equality and so on. Furthermore, these well-informed mitigation policies under climate change should consider desirable and effective initiatives climate change mitigation related to land use (Gingrich et al., 2019).

Agriculture and forestland are competing activities with unpredictable impacts on agricultural income. For instance, the expansion of the agricultural sector makes it possible to generate income and employment, while at the same time, food and energy demands are met.

Another possible interpretation of our results is related to the Jevons hypothesis since increasing farming profitability may motivate farmers to extend cultivated land into forests, leading to deforestation and increasing environmental degradation. The rebound effect is another issue, according to which greater efficiency of land might lead to an increase in its use (Angelsen & Kaimowitz, 2001; Hosonuma et al., 2012; Rudel et al., 2005).

Moreover, in the sample countries, land ownership played a significant role in deforestation and even afforestation (Taff, 2005). For instance, the forest changes in Latvia in the post-Soviet period due to unsustainable clear cutting may provide plausible interpretations for our findings (Taff, 2005; Kuemmerle et al. 2009, 2015). Another issue that should be taken into consideration is the need for these countries to comply with EU agricultural policy regarding the prioritization of sustainability and ecoefficiency within a short period (some of them before 2004). However, the protection of multifunctional ecosystems, such as forests, should be accompanied by technological improvements in agricultural production. In consequence, forest resources may be conserved by intensifying agricultural production, which though results to an extra cost to be incorporated in the long-run international agricultural prices. REDD + programs may well provide an efficient solution for achieving forest clearance and in addition to limit agricultural exports or intensifying agriculture (Leblois 2017).

6 Conclusion

Urbanization and agricultural expansion are two major drivers of deforestation. Given that forests through carbon sequestration limit carbon emissions, while at the same time their impact on agricultural income seems to be of great significance. The present study examined the validity of the EKC for sixteen countries in Eastern Europe, for which the carbon emissions generated by deforestation were employed as a proxy of environmental degradation, while the agricultural NVA per capita was used as a proxy for economic growth.

Therefore, this study focused on the deforestation–agricultural income association and, in particular, adopted different panel unit root and cointegration tests to investigate how land-use change aimed at the expansion of agricultural production affects agricultural income. According to our findings, the EKC takes an inverted N-shape for our data. Small changes in agricultural productivity or technological improvement could explain this result, since significant changes in the aforementioned issues should lead to forest restoration or afforestation and confine the carbon emissions generated by the related human activity. A further interpretation of the inverse N-shaped trajectory validated for this panel data sample is the focus of policy makers on agroeconomic growth, the detriment of environmental issues related to deforestation, as well as the Jevons hypothesis described in the previous section.

Deforestation may explain the degradation of forest services and the direct and indirect impacts on rural and urban societies. Within this framework, the understanding and awareness of the local society of the causes and socio-economic impacts of deforestation and afforestation are necessary for the achievement of eco-efficiency in terms of deforestation rates and economic development.

Finally, policymakers in these countries should take initiatives to increase the productivity of the existing cultivated land or to expand agriculture to less fertile soils (marginal lands) rather than replacing forests. Proper institutional performance is fundamental for the reduction of carbon emissions worldwide.

Major limitations of the present study include potential data mining issues of FAOSTAT, potential nonlinearity in the behaviour of variables, and unobserved factors that may have an important impact on the evolution of the studied relationship. These issues should be addressed in future studies.

Appendix

The countries included in the sample are the following;

Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Latvia, Lithuania, North Macedonia, Poland, Romania, Russian Federation, Slovakia, Slovenia and Ukraine. Table 2 illustrates the descriptive statistics of the variables employed in the present study.

Author Contributions EZ has conceptualized the research theme and employed the methodologies used. GLK has undertaken the literature review and V.A. did the data mining and assessment. GA conducted the validation of the analysis findings. All authors contributed in the writing—review and editing process. All authors have read and agreed to the published version of the manuscript.

Declarations

Conflict of interest The authors declare no conflict of interest.

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