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Revisiting the deforestation-induced EKC hypothesis: the role of democracy in Bangladesh

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Abstract This paper aimed at evaluating the validity of the deforestation-induced Environmental Kuznets Curve hypothesis controlling for the democracy between 1971 and 2018 in Bangladesh. The cointegration results provide statistical evidence of long-run associations between economic growth, deforestation propensities and the quality of democracy. The elasticity estimates certify the validity of the EKC hypothesis for all the three indicators of deforestation used in this paper: forest area coverage, deforestation rate and net forest depletion rate. Moreover, controlling for democracy lowers the threshold level of growth beyond which the marginal impact of growth results in environmental betterment by reducing the deforestation propensities in Bangladesh. Moreover, democracy and economic growth are also seen to exert a combined impact on the growth-deforestation nexus. The estimated growth thresholds are above the current real GDP level of Bangladesh which reasons the nation's deforestation woes. Finally, the causality results also affirm causal associations between economic growth, deforestation and the quality of democracy. Thus, these findings impose key policy implications keeping into cognizance the sustainable economic and environmental development goals of Bangladesh.

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Introduction

In the past, economic development was always prioritized over environmental well-being which often resulted in a trade-off between economic and environmental welfares. In the quest for rapid industrialization of the traditional agrarian economies, world output levels have surged over the years which simultaneously jeopardized the harmony of the global environment (Gorus and Aslan 2019). A particular reason behind this phenomenon could largely be attributed to the widespread combustion of fossil fuels to source energy for production of the national outputs. As a consequence, environmental pollution, in multifaceted forms, has aggravated with time to trigger climate change adversities worldwide (Graven 2015). Although the economic development-environment welfare trade-off did receive acceptance in the past, the modern-day development strategies often aim at achieving economic development without axing the environmental attributes, particularly through the integration of environmental policies into the global sustainable development strategies (Emas 2015). Hence, keeping the associated adversities into cognizance, economic development in the contemporary era is appropriately envisioned to simultaneously cater to environmental welfare as well (Odum 1996).

The adverse environmental impacts of economic growth can be broadly classified into three major forms, namely deterioration in the quality of air (Sulemana et al. 2017), water (Zhang et al. 2017) and land (Esposito et al. 2016). Although the negative impacts on air and water qualities have attracted a significant amount of interest amidst the ecological researchers, the economic growth effects on the quality of forest lands, particularly in the form of deforestation, has received relatively less emphasis in the existing literature. It is critically important to probe into the dynamic nature of the growth-deforestation nexus since forests endowments are believed to be a source of natural capital that ensures the livelihoods for humans (Lee et al. 2009) while providing a natural habitat for animals as well (Ewel et al.1998). Besides, forests also attribute to economic growth via providing land for agriculture (Kant et al. 1996), generating government revenue (Mason and Lippke 2007) and supplying industrial inputs in the form of timber and non-timber products (Psaltopoulos and Thomson 1993). Moreover, it is often hypothesized that economies with higher natural forest endowments are likely to account for relatively higher growth rates than economies with relatively less natural forest reserves (Naidoo 2004). Most importantly, forests mitigate climate change adversities through naturally absorbing carbon dioxide from the atmosphere (Bonan 2008). Forests also portray key roles in preventing natural calamities such as floods and soil erosion. Despite such advantageous features, tropical deforestation has been a global phenomenon which, from the perspective of environmental sustainability, is a matter of deep concern.

Although during the initial phases of growth, the associated trade-off between the economy and the environment does implicate towards a positive association between economic growth and deforestation rates, the relationship could well be reversed in the long-run. Hence, a non-linear growth-deforestation nexus can be hypothesized which can be explained in light of the Environmental Kuznets Curve (EKC) hypothesis.[1] The EKC hypothesis postulates in favor of growth initially attributing to environmental degradation and later on improving the environment beyond a threshold level of economic growth. Thus, economic growth is referred to as both the cause and the possible solution to the environmental adversities (Gill et al. 2019). Against this backdrop, this paper aims to shed light on the validity of the deforestation-induced EKC hypothesis in the context of Bangladesh, an emerging South Asian economy that has traditionally faced deforestation issues.

Bangladesh is an appropriate country of choice for exploring the growth-deforestation nexus, particularly due to the nation's historical susceptibility to climate changes and other adverse environmental concerns (Pouliotte et al. 2009). On the other hand, the fact that Bangladesh is a tropical country with acute inequality in the living standards of the people, especially between the urban and rural areas, makes it a frontier of deforestation. The nation shares the geographical forest land covered by the Sundarban mangrove forest with India. However, deforestation within the portion of the Sundarban forest governed by Bangladesh has persistently risen over the years (Rahman et al. 2010). As a result, the nation's deforestation woes have often been alleged to have played a critical role in disharmonizing the local environment (Islam and Sato 2012) which, in turn, is believed to impose macroeconomic adversities within the overall economy as well. According to the World Bank estimates, total forest areas in Bangladesh shrunk by almost 700 square kilometers between 1990 and 2016, which sums up to be a loss in the nation's total forest areas by more than 4.5% within the last two and a half decades (World Bank 2018). Although the recent occurrences of deforestation in Bangladesh can largely be accredited to the razing of the forests in Cox's Bazar regions to shelter the latest influx of the Rohingya refugees (UNICEF 2018), deforestation in Bangladesh is primarily attributable to the lack of arable lands, firewood extraction, harvesting for industrial raw materials, transitions in the patterns of land-use and, most importantly, to the surging incidences of the associated ministerial corruption in the country (Gossman 2017).

However, it is to be noted that Bangladesh in comparison to the leading global economies, that are much more developed, emits lower volumes of carbon dioxide per capita (Ahiduzzaman and Islam 2011). The per capita Carbon dioxide Emissions (CO2e) of

[1] For more information on the EKC hypothesis see Grossman and Krueger (2011).

Bangladesh is below that of the regional average within South Asia (World Bank 2018). According to the World Bank estimates, the nation's CO2e per capita in 2014 stood at 0.46 metric tonnes while the corresponding figures for India, Pakistan and Sri Lanka were around 1.73, 0.90 and 0.89 metric tonnes, respectively (World Bank 2018). On the other hand, despite accounting for low per capita CO2e levels, the nation's deforestation woes have persistently aggravated over the years, thus, marginalizing the per capita forestlands as well (Iftekhar and Hoque 2005). Moreover, taking the rapid population growth rate of Bangladesh into consideration, it can be anticipated that the demand for the existing forestlands, particularly for non-forest activities, is likely to surge in the future which, in turn, could reverse the nation's lower per capita CO2e trends amidst higher deforestation propensities. Thus, identifying the factors responsible for widespread deforestation practices across Bangladesh is key to managing its CO2e emissions in the future, as well.

Against this milieu, the main objective of this paper is to empirically investigate the growth-deforestation nexus in light of the deforestation-induced EKC hypothesis in Bangladesh. This paper contributes to the literature by conducting an empirical study on the impacts of economic growth on the deforestation propensities in Bangladesh. To the best of knowledge, apart from a theoretical study by Miah et al. (2011) on the growth-deforestation nexus in Bangladesh, there has not been an empirical study exploring this issue. This paper addresses this gap in the literature using annual time series data from 1971 to 2018 to perform relevant econometric analyses that are robust in handling structural breaks in the dataset. Besides, underscoring the potential impacts of Bangladesh's democratic environment on the growth-deforestation nexus, this paper also controls for the level of democracy within the economy to evaluate whether the quality of the public institutions plays a defining role in affecting the growth-deforestation nexus. The following questions in the context of Bangladesh are specifically addressed in this paper:

Does the deforestation-induced EKC hypothesis have statistical validity?

Are there any long-run associations between deforestation, economic growth and the state of governance?

Is the growth-deforestation nexus conditional on the level of democracy in the economy? Does it affect the curvature and the turning point of the EKC for deforestation?

What are the possible causal associations between growth, democracy and deforestation?

The remainder of the paper is structured as follows. "Literature Review" section reviews the existing literature documenting theoretical and empirical investigations of the EKC hypothesis for deforestation. The econometric models and the attributes of the dataset used are put forward in "Empirical models and data" section while "Methodology" section explains the methodology of research. "Results and discussion" section discusses the findings from the econometric analyses while "Conclusion and policy implications" section provides the concluding remarks and the policy implications.

Literature review

The literature review section is classified into two subsections, respectively discussing the theoretical framework engulfing the growth-deforestation nexus in light of the EKC hypothesis, and the empirical evidence documented in this regard.

Theoretical framework

Expressing deforestation as an indicator of the level of environmental degradation, the movements in the deforestation propensities across Bangladesh along its economic growth cycle can be explained in light of the EKC hypothesis. This hypothesis is a variant of the Kuznets curve hypothesis originally put forward in the seminal paper by Simon Kuznets (1955) who postulated a non-linear inverted-U shaped association between growth and income inequality. Keeping the non-linearity aspect into consideration, the EKC hypothesis asserts that economic growth, during the initial stages, attributes to environmental degradation, following structural changes within the economy, and results in a trade-off between economic and environmental welfares. However, beyond a certain level of growth, which is termed as the threshold growth level, the relationship can be expected to reverse to stimulate environmental betterment.

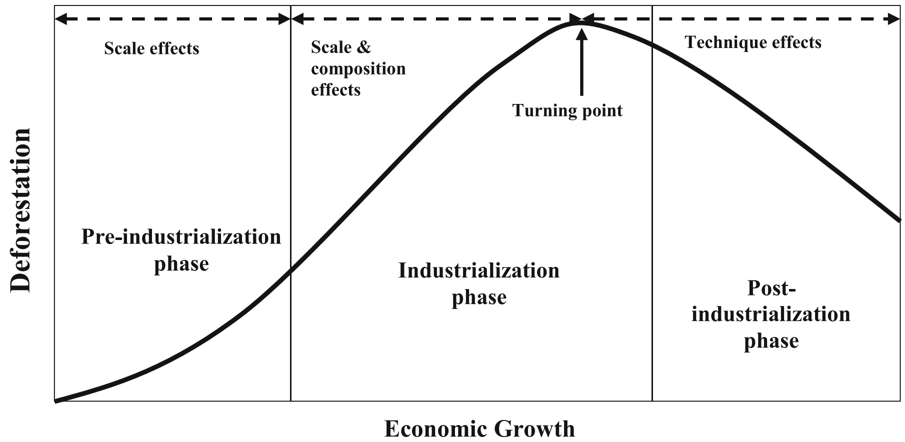

Fig. 1 The deforestation-induced Environmental Kuznets Curve Source: Author's own

The deforestation-induced EKC, as illustrated in Fig. 1, can be described in terms of the scale, composition and technique effects stemming from the growth of the economy. In the early stages, which can be referred to as the pre-industrial phase, economic growth is likely to degrade the environment through promoting deforestation activities stemming from the need for clearing forest lands to source agricultural land, housing and firewood in particular. Then, as the economy makes a transition to the industrialization phase, the scale effect can further trigger deforestation since forests can be key sources of industrial inputs in the form of timber and non-timber products. In the quest for rapid industrialization of the conventional agrarian economy, the composition effect, in addition to the scale effect, can further attribute to environmental pollution since production processes in the industrialization phase are more likely to be intensive in the utilization of the fossil fuels. However, towards the latter end of the industrialization phase and throughout the post-industrialization period, betterment of the environmental quality can be anticipated. This phenomenon can be referred to as the technique effect which results from technological advancement to facilitate renewable energy transition within the economy.[2] Therefore, technological innovation could be key to bending the EKC at a comparatively lower level of economic growth, thus, expediting the reforestation activities within the economy. Moreover, during the later phases of industrialization and throughout the post-industrialization era, there could also be a rise in the awareness to restore environmental harmony for tackling the climate change adversities. This, in turn, could be expected to reduce the deforestation propensities and could also go on to stimulate reforestation practices as well. Therefore, it can be said that the technique effect reduces the trade-off between economic and environmental welfare in the long-run by curbing deforestation rates.

Now shifting the focus towards the impacts of the democracy on the EKC for deforestation, it can be said that the democratization of the economy is likely to affect the deforestation practices as well. Figure 2 in the appendix illustrates the dissimilar impacts of democracy on the deforestation-induced EKC. The democratic impacts on environmental quality are, in general, inconclusive since democracies could either facilitate environmental betterment or could even attribute to environmental damage (Shafik and Bandyopadhyay 1992). For instance, quoting environment as a public good, Deacon and Mueller (2004) stated that inappropriate democratic governance within the economy leads to misallocation of environmental resources following high rent-seeking behavior amidst the authorized public officials. Thus, in line with this view, it can be claimed that a better democratic environment within the economy is likely to result in lower deforestation rates which, in turn, could account for a faster turning point on the EKC for deforestation. This can be interpreted as the movement in the turning point from point A to point B in Fig. 2. This implies that more democratic nations would have a relatively lower trade-off between economic growth and environment welfare during the initial phases of growth

[2] For more information regarding renewable energy transition see Murshed (2019) and Murshed and Tanha (2020).

whereby the threshold growth or income level can be also expected to be comparatively low (as shown in Fig. 2, GDP_1 is lower than GDP_0). In such cases, the curvature of the deforestation-induced EKC could also be flatter, thus, denoting a lower environmental cost of economic growth (as shown in Fig. 2, the upward-sloping portion of EKC_1 is flatter than that of EKC_0).

In contrast, the critics of political democracy proactively voice in favor of more democratic economies having greater environmental concerns (Chang and Cho 2005). This could be due to the fact that in young democracies, the government could well fall prey to prioritizing the interests of the societal elites rather than serving the broader interests of the common people. Linking this to deforestation, a more democratic economy can at times exhibit greater deforestation propensities among the elite businessmen who are likely to be privileged from the favorable treatment by the government. Under such circumstances, democracy can lead to delaying of the turning point of the EKC for deforestation. This can be interpreted as the movement in the turning point from point A to point C in Fig. 2. As a result, the threshold level of growth or national income would go up as well (as shown in Fig. 2, GDP_2 is higher than GDP_0). Moreover, the upward-sloping part of the deforestation-induced EKC could become relatively steeper (as shown in Fig. 2, the upward-sloping part of EKC_2 is steeper than that of EKC_0) which would implicate higher environmental cost of economic growth and a relatively greater trade-off between the economic and environmental welfares during the initial stages of economic growth.

Empirical evidence on the EKC hypothesis

Empirical studies on the EKC hypothesis was pioneered by Grossman and Krueger (2011) in which the authors analyzed the environmental impacts, in terms of sulfur dioxide and smoke emissions, of growth stemming from the implementation of the execution of the North American Free Trade Agreement (NAFTA). Since then, a plethora of studies has gone on check the validity of the EKC hypothesis using diverse indicators of environmental deterioration. Although environmental deterioration can take several forms, the associated literature has primarily documented the environmental impacts in terms of carbon emissions. Dogan and Turkekul (2016), in this regard, found the statistical validity of the EKC hypothesis for CO2e in the context of the United States of America. The authors concluded in favor of bidirectional causation between real output levels and CO2e. However, equivocal evidence regarding the EKC hypothesis for CO2e in the literature suggests the ambiguity of the overall growth-environmental quality nexus. In a recent study on Kazakhstan, Hasanov et al. (2019) found that CO2e increases all along the growth cycle which condemns the inverted-U EKC hypothesis. Besides CO2e, relevant studies have also used other indicators of environmental deterioration including total greenhouse emissions (Cho et al. 2014), sulfur dioxide emissions (Zhou et al. 2017), methane emissions (Benavides et al. 2017), nitrogen dioxide emissions (Sinha and Sengupta 2019), water pollution (Lee et al. 2010) and land degradation (Bimonte and Stabile 2017).

Likewise, several studies have examined the deforestation impacts of economic growth to check the cogency of the EKC hypothesis. However, the empirical findings in this regard also depict mixed findings, thus, highlighting the ambiguous nature of the growth-deforestation nexus. The seminal work by Shafik and Bandyopadhyay (1992) laid the foundation for the successive studies that were conducted to test the EKC hypothesis using deforestation to proxy for environmental degradation. Among the country-specific analyses, Ahmed et al. (2015) found statistical evidence regarding the existence of the deforestation-induced EKC hypothesis in the context of Pakistan. Moreover, the authors also emphasized the long-run association between economic growth and deforestation propensities in Pakistan. In a similar study, Kumar and Aggarwal (2003) used annual data from 1963–64 to 1995–96 to investigate the deforestation-induced EKC hypothesis for India. The authors claimed that the EKC hypothesis holds for the Indian economy and the threshold income level was estimated to be 811 Indian rupees in constant 1970–71 prices. In a similar study using annual data from 1962 to 2007 for Indonesia, Waluyo and Terawaki (2016) predicted the deforestation-induced EKC to turn at a national per capita income level of 990 US dollars. In contrast to the aforementioned studies that supported the EKC hypothesis for deforestation, Tsiantikoudis et al. (2019) reported statistical evidence to disprove it. Rather, the authors postulated the nexus between greenhouse emissions from deforestation and the growth of the Bulgarian economy to exhibit an N-shaped relationship, thus, implicating a cubic economic growth-deforestation nexus to contradict the quadratic association as per the EKC hypothesis.

Among the relevant studies probing into the provincial growth-deforestation nexus, Naito and Traesupap (2014) found strong statistical evidence regarding the validity of the deforestation-induced EKC hypothesis in the context of 23 Thai provinces. The author's considered the provincial mangrove forest coverage, as a measure of environmental quality, for assessing the growth-deforestation nexus across Thailand. The expansion of the Thai shrimp farming industry was alleged to be the major factor attributing to the loss of provincial mangrove forest lands during the initial growth phase. Similarly, in the recent study on 30 Chinese provinces, Hao et al. (2019) advocated in favor of economic growth, in the long run, ultimately stimulating afforestation activities in China, thus, increasing its forest coverage and correcting for the rising deforestation propensities during the early stages of development within the Chinese economy. Conversely, Lantz (2002) opposed to the EKC hypothesis for deforestation for five major Canadian regions. Rather, the author found statistical support to validate a U-shaped association between the regional per capita GDP and forest areas.

A wide array of studies have also probed into panel data analysis of the deforestation-induced EKC hypothesis. Among the relevant studies validating this hypothesis, Barbier and Burgess (2001) found evidence to support the EKC hypothesis for tropical deforestation in the context of 90 countries from Africa, Asia and the Pacific, and the Latin America and Caribbean regions. Similarly, Chiu (2012) conducted a study using data from 52 developing countries and also found statistical evidence to validate the EKC hypothesis for deforestation. In a more recent study on a panel of 10 nations, collectively accounting for two-thirds of the global forest areas, Gokmenoglu et al. (2019) opined in favor of the validity of the deforestation-induced EKC hypothesis. This study made a novel attempt by considering deforestation as a contributor rather than an indicator of environmental degradation.

On the other hand, in a comparison between non-member and member countries of the Organization for Economic Cooperation and Development (OECD), Joshi and Beck (2016) found an N-shaped association between economic growth and deforestation which invalidated the deforestation-induced EKC hypotheses. However, only for the African non-OECD countries, the EKC hypothesis for deforestation was held to be true. Using deforestation as an indicator of environmental degradation, Zambrano-Monserrate et al. (2018) supported the inverted-U shaped growth-deforestation nexus in the context of France, Germany, Greece, Portugal and Turkey. In contrast, Ogundari, Ademuwagun and Ajao (2017) concluded that economic growth initially reduces deforestation rates across the Sub-Saharan African region, but, beyond a threshold level of growth, the propensity of deforestation practices tends to rise which denounces the EKC hypothesis for deforestation. The invalidity of the deforestation-induced EKC hypothesis has also been highlighted in the study by Choumert, Motel and Dakpo (2013).

Controlling for the level of democracy with the econometric analysis, some of the existing studies attempted to evaluate its impacts on the growth-deforestation nexus. In a study concerning the deforestation practices within 66 countries across Latin America, Africa, and Asia, Bhattarai and Hammig (2001) found statistical validity of the EKC hypothesis for deforestation. The authors also concluded that better political institutions and good governance, although exerting heterogeneous effects across regions, attribute to lower rates of deforestation. The linkage between democracy and environmental degradation via deforestation was also put forward by Buitenzorgy and Mol (2011). The authors concluded that democratization, although triggering deforestation in the initial periods of democratic transition, ultimately accounts for environmental betterment by reducing deforestation rates in the long run across a panel of 177 countries. Thus, the authors, keeping environmental sustainability into cognizance, recommended the need for promoting democracy alongside strategies aimed at achieving economic growth. Similarly, McCarthy and Tacconi (2011) asserted that improving electoral democracy, along with the other factors enhancing the quality of the political institutions, can play a key role in reducing deforestation propensities to a large extent. In contrast, Ogundari et al. (2017) alleged greater political liberty, using it as an indicator of the state of the political economy, to be responsible for higher rates of deforestation across the Sub-Saharan African region.

The literature on the EKC hypothesis in the context of Bangladesh

The existing studies focusing on the EKC hypothesis in the context of Bangladesh predominantly used CO2e to quantify environmental degradation (Murshed 2020). For instance, Islam et al. (2013) explored the non-linear association between economic growth and per capita CO2e in Bangladesh between 1971 and 2010. The results from the cointegration test revealed long-run associations between these variables. Moreover, the statistical estimates supported the EKC hypothesis for Bangladesh both in the short and the long runs. Besides, unidirectional causations were found to be running from trade openness and urbanization to CO2e per capita. In a similar study by Shahbaz et al. (2014), the authors modeled the non-linear dynamics engulfing industrial value-added and CO2e in Bangladesh, controlling for electricity consumption, financial development and international trade flows. The results provided statistical validity to the EKC hypothesis for Bangladesh between 1975 and 2010. Besides, all the three control variables were found to exert adverse impacts on the environment via attributing to higher CO2e in Bangladesh. Likewise, Rabbi et al. (2015) found evidence of long-run associations between CO2e, economic growth, energy use and trade openness. Using annual data from 1971 to 2012, the results from the error-correction model approach did not support the EKC hypothesis since the estimated coefficients revealed a U-shaped association between GDP and CO2e. On the other hand, using deforestation as a measure of environmental quality, Miah et al. (2011) advocated in favor of the validity of the deforestation-induced EKC hypothesis in Bangladesh. The authors concluded that Bangladesh was far off the turning point level of economic growth beyond which the marginal growth impacts would stimulate reforestation activities within the economy.

Among the other relevant studies that have probed into the macroeconomic factors responsible for stimulating CO2e in Bangladesh, Banerjee and Rahman (2012) opined that industrial output and population size stimulated CO2e between 1972 and 2008. However, no statistical evidence regarding the impacts of foreign direct investment on CO2e could be ascertained. Kashem and Rahman (2019) probed into the causal dynamics between CO2e and its determinants in the context of Bangladesh over the period 1972–2015. The results indicated that there are bidirectional causations between CO2e and urbanization and between CO2e and per capita economic growth while no causal association between population density and CO2e could be established. In another study by Rahman and Kashem (2017), the authors referred industrial growth and consumption of energy resources to dampen environmental quality in Bangladesh. The study used annual data from 1972 to 2011 to perform the econometric analyses. Moreover, the results from the causality analysis reveal unidirectional causalities stemming from industrial growth and energy use to CO2e. In a recent study by Ahmed et al. (2020), the authors considered the effects of democratic institutions and energy consumption on CO2e in Bangladesh. The results suggested that the quality of democratic institutions and CO2e are influenced by each other. Besides, better democratic institutions were also said to positively influence economic growth in Bangladesh.

Empirical models and data

Firstly, the deforestation-induced EKC hypothesis in the context of Bangladesh is assessed using non-linear econometric models in which three alternate indicators of deforestation are expressed as separate functions of economic growth and other key macroeconomic factors influencing the deforestation-growth nexus. In the first model, the forest area coverage is used as a measure of deforestation practices within the economy of Bangladesh. In simple terminology, a reduction in the total area occupied by forest lands can be referred to as a rise in deforestation propensities within the economy and vice versa. This underlying model can be shown as:

$$\mathbf{ln}\boldsymbol{farea_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 lnGDP_t} + \boldsymbol{\beta_2 lnGDP_t^2} + \boldsymbol{\beta_3 lnagri_t} + \boldsymbol{\beta_4 lnpopg_t} + \varepsilon_t \tag{1}$$

where the subscript t denotes the time period, β_i (i = 0, 1, …, 4) represents the parameters to be estimated, and ε is the random error term. The variable *farea* abbreviates for the total area of forest lands in the country. The level of economic growth is proxied by the real Gross Domestic Product (GDP) figures of Bangladesh. The predicted signs of the elasticity parameters attached to GDP (β_1) and its squared term

(β_2) are expected to provide statistical evidence regarding the existence of the deforestation-induced EKC hypothesis in the country. The econometric model is controlled for the coverage of land utilized for agriculture, denoted as *agri*, The inclusion of the agricultural land area in the model can be rationalized from the understanding that forest areas are often razed for agricultural purposes, especially across the rural regions (Barbier 2004). Thus, a substitution effect between forest and agricultural lands can be expected. Finally, population growth rate, denoted by *popg*, accounts for the impacts of population size on the deforestation activities in Bangladesh. The inclusion of population size in the analysis is based on the hypothesis that a rise in the population growth rate is likely to exert pressures to clear forests for housing purposes and firewood supplies in particular.

For robustness check of the deforestation-growth nexus across diverse indicators of deforestation, two additional indicators of deforestation are considered in the econometric analyses which can be shown as:

$$\ln deforest_t = \beta_5 + \beta_6 lnGDP_t + \beta_7 lnGDP_t^2 + \beta_8 lnagri_t + \beta_9 lnpopg_t + \varepsilon_t \quad (2)$$

$$\ln nf\,dep_t = \beta_{10} + \beta_{11} lnGDP_t + \beta_{12} lnGDP_t^2 + \beta_{13} lnagri_t + \beta_{14} lnpopg_t + \varepsilon_t \quad (3)$$

where *deforest* and *nfdep* respectively symbolize the deforestation and net forest depletion rates. The deforestation and net forest depletion rates are calculated using current and previous year's figures for forest area coverage and the value of net forest depletion, respectively. All the variables have been transformed into their natural logarithms for the ease of the elasticity estimations.

The predicted signs and the statistical significance of the elasticity parameters attached to lnGDP and $\ln GDP^2$ would provide statistical support to the validity of the deforestation-induced EKC hypothesis for the respective deforestation indicators. Thus, in the context of model (1), the threshold level of real GDP at the turning point can be calculated as:

$$TurningpointlevelofRealGDP = \frac{\beta_1}{2\beta_2}$$

The turning point levels of real GDP for model (2) and (3) can also be estimated the same way using the corresponding elasticity estimates.

Secondly, all these three models are then controlled for the level of democracy within the Bangladesh economy. Thus, augmenting a democratic indicator into the models (1), (2) and (3) can respectively be shown as:

$$\ln lnfarea_t = \beta_{15} + \beta_{16} lnGDP_t + \beta_{17} lnGDP_t^2 + \beta_{18} lnGDP * DEM_t + \beta_{19} DEM_t + \beta_{20} lnagri_t + \beta_{21} lnpopg_t + \varepsilon_t \quad (4)$$

$$\ln deforest_t = \beta_{22} + \beta_{23} lnGDP_t + \beta_{24} lnGDP_t^2 + \beta_{25} GDP * DEM_t + \beta_{26} DEM_t + \beta_{27} lnagri_t + \beta_{28} lnpopg_t + \varepsilon_t \quad (5)$$

$$\ln nfdep_t = \beta_{29} + \beta_{30} lnGDP_t + \beta_{31} lnGDP_t^2 + \beta_{32} GDP * DEM_t + \beta_{33} DEM_t + \beta_{34} lnagri_t + \beta_{35} lnpopg_t + \varepsilon_t \quad (6)$$

where *DEM* refers to the aggregate democracy index that proxies for the state of democracy within the economy. The variable DEM is calculated as an aggregate of five high-level democracy indices reported in the database of the Varieties of Democracy (V-Dem) Project of the University of Gothenburg (Coppedge et al. 2018). The five democracy indices include electoral, liberal, participatory, deliberative and egalitarian democracy indices. Each of these democracy indices ranges from 0 (lowest level of democracy) to 1 (highest level of democracy). Thus, upon the aggregation, the variable DEM takes a minimum value of 0 (lowest level of democracy) and a maximum value of 5 (highest level of democracy). Moreover, the democracy index is also interacted with the real GDP level to investigate the combined impacts of economic growth and democracy, as well. The turning point level of real GDP, controlling for democracy, in the context of model (4), can be calculated as:

$$TurningpointlevelofRealGDP = \frac{\beta_{16} + \beta_{18} DEM_t}{2\beta_{17}}$$

The same can be repeated for models (5) and (6) using the respective elasticity estimates.

Annual time series data for all the variables covering from 1971 to 2018 is compiled to perform the econometric analyses. Table 1 in the appendix outlines the units of measurements of the different variables used in the analyses and also reports the corresponding data sources.

Methodology

Unit root analysis

The econometric analysis starts off by checking the stationarity properties of the variables. It is pertinent to test for the existence of unit root in the data since non-stationary data is likely to result in spurious regression outputs with an extremely high goodness of fit and statistically significant estimates (Murshed 2018). Moreover, the order of integration among the variables is also understood from the stationarity analysis which, in turn, determines the appropriate cointegration and causality estimation techniques to be applied. The unit root analysis basically denotes whether the variables are mean-reverting or not. However, although the conventional time series unit root evaluating techniques like the Augmented Dickey–Fuller (ADF) and the Phillips–Perron (PP) tests proposed by Dickey and Fuller 1979 and Phillips and Perron 1988, respectively, have been popularly used in the relevant literature, these tests are said to produce biased estimates of the stationarity properties in the presence of potential Structural Break (SB) issues in the data (Perron 1989, 1990). Consideration of SB within the econometric analysis is said to account for the estimation errors involving the traditional techniques that overlook this issue (Vaona 2012). Hence, considering the possibility of SB existing within the data, the Perron-Vogelsang (PV) with one endogenous SB (Perron and Vogelsang 1992a; 1992b) and the Clemente-Monantes-Reyes (CMR) with two endogenous SBs (Clemente et al.1998) unit root tests are employed to predict the stationarity properties. Both these tests, in addition to identifying the break dates, estimate the stationarity properties under the null hypothesis of non-stationarity in the data against the alternative hypothesis of otherwise. This paper considers the Additive Outliers (AO) model within the PV approach which accounts for a sudden shift in the mean of the data. The null hypothesis of non-stationarity under the AO model, as suggested by Perron and Vogelsang (1992a), can be specified as:

$$\boldsymbol{y_t} = \beta \boldsymbol{D}(\boldsymbol{TB})_{\boldsymbol{t}} + \boldsymbol{y_{t-1}} + \boldsymbol{e_t}, \boldsymbol{t} - \boldsymbol{2}, \ldots, \boldsymbol{T} \tag{7}$$

where for a given series y at the break year T_b ranging from 1 to T (i.e. $1 < T_b < T$). $D(BY)_t = 1$ if $t = T_b + 1$ and 0 if T_b is less than 1. The error sequence e_t is a finite-order stationary and invertible Autoregressive Moving Average (ARMA(p,q)) process. The alternative hypothesis of stationarity can be shown as:

$$\boldsymbol{y_t} = \partial + \beta \boldsymbol{DU_t} + \boldsymbol{v_t} \tag{8}$$

where v_t is also a finite-order stationary and invertible ARMA(p + 1, q) process and $DU_t = 1$ if $t > T_b$ and $DU_t = 0$ if t is less than or equal to T_b. Hence, the statistical significance of the t-statistic for testing the null hypothesis would reject the null hypothesis to confirm the stationarity of the series at its level of first difference form. Although the AO model considers a sudden shift in the mean value of the series, this paper also uses the Innovational Outliers (IO) model which considers the shift in the mean in a gradual manner. The IO model also tests the null hypothesis of non-stationarity of the series against the alternative hypothesis of stationarity. However, despite generating outcomes robust to the existence of SB in the data, the major limitation of the PV unit root test is that it can account for a single break in the data. Hence, the CMR approach is also tapped into the unit root analysis for the robustness check of the stationarity properties amidst the SB issues.

The null and alternative hypothesis of non-stationarity and stationarity, respectively, under the CMR test for unit root with two SBs in the series can be specified as:

$$\boldsymbol{y_t} = \boldsymbol{y_{t-1}} + \delta_{\boldsymbol{1}} \boldsymbol{D}(\boldsymbol{TB})_{\boldsymbol{1t}} + \delta_{\boldsymbol{2}} \boldsymbol{D}(\boldsymbol{TB})_{\boldsymbol{2t}} + \mu_{\boldsymbol{t}} \tag{9}$$

$$\boldsymbol{y_t} = \theta + v_{\boldsymbol{1}} \boldsymbol{DU_{1t}} + v_{\boldsymbol{2}} \boldsymbol{D}(\boldsymbol{TB})_{\boldsymbol{2t}} + \mu_{\boldsymbol{t}} \tag{10}$$

The CMR approach is an extension of the PV approach, thus the mechanism of the unit root estimation procedure is almost identical with the only exception being the two SBs in the series instead of one. Moreover, the CMR approach also involves the AO and the IO models assuming the mean shift to be sudden and gradual, respectively.[3]

[3] For more information on the CMR approach see Clemente, Monantes and Reyes (1998).

Cointegration analysis

Once the order of integration among the variables is ascertained from the unit root analyses, it is important to evaluate the cointegrating relationship between them. In other words, the cointegration technique helps to understand whether there is any long-run association between the variables included within the respective models. Moreover, cointegration among the variables is also said to be a pre-requisite to estimating the long-run causal associations. While the traditional time series cointegration techniques developed by Engle and Granger (1987), Johansen (1991) and Johansen and Juselius (1990) are popularly tapped in the existing studies, these methods do not take into account the SB issues. All these techniques are based on the incorrect assumption of the cointegrating associations being time-invariant. However, SB in the data nullifies this erroneous assumption which makes their application inappropriate. Thus, this paper uses the Gregory-Hansen (GH), with single SB (Gregory and Hansen 1996), and the Maki (2012), which can account for multiple SBs, cointegration techniques.

The GH test assumes one endogenous determined SB within the data for each of the models which can generally be specified as:

$$\begin{aligned} y_t = \partial_o + \partial_{1Dt} + \theta_1 T + \sum\nolimits_{i=1}^{a} \varphi_{1i} x_{it} \\ + \sum\nolimits_{i=1}^{a} \varphi_{2i} D_{2i} x_{it} + \varepsilon_t \end{aligned} \tag{11}$$

where y is the dependent variable and x is a vector of a_i number of dependent variables (i = 1, …, a). ε_t is the error term and t is the time period. D_t is the dummy variable used to capture the SB in the constant or in both the constant and trend. D_t takes a value of 1, denoting the presence of the SB at a particular year T_b, if $t > T_b$ (interpreted as the year t is after the break year T_b) and a value of 0, denoting no SB at a particular year T_b, if $t < T_b$ (interpreted as the year t is before the break year T_b). In the GH approach, the statistical significance of any one of the three test statistics, ADF*, Zα and Zt, rejects the null hypothesis of no cointegration to affirm the long-run cointegrating relationships between y and x_i. The ability of the GH cointegration technique is limited to accommodating a single SB in the data. However, SBs in the data may occur quite abruptly and repeated whereby accommodating a sing SB in the data may not be sufficient in estimating the cointegrating properties (Ike et al. 2020). Hence, the Maki cointegration approach is also employed in which can account for as many as five SBs in the data.

There are four specific models: A (considering the breaks in the intercept only), B (considering the breaks in the intercepts and coefficients without the trend, C (considering the breaks only in the intercept and coefficients but the model is assumed to have a trend) and D (considering the breaks in the intercepts, coefficients and trend), within the Maki cointegration analysis which can respectively be expressed as:

Model A:

$$y_t = \partial + \sum_{i=1}^{m} \partial_i D_{i,t} + \beta' x_t + u_t \tag{12}$$

Model B:

$$y_t = \partial + \sum_{i=1}^{m} \partial_i D_{i,t} + \beta' x_t + \sum_{i=1}^{m} \beta_i' x_t D_{i,t} + u_t \tag{13}$$

Model C:

$$y_t = \partial + \sum_{i=1}^{m} \partial_i D_{i,t} + \gamma t + \beta' x_t + \sum_{i=1}^{m} \beta_i' x_t D_{i,t} + u_t \tag{14}$$

Model D:

$$\begin{aligned} y_t = \partial + \sum_{i=1}^{m} \partial_i D_{i,t} + \gamma t + \sum_{i=1}^{m} \gamma_i t D_{i,t} + \beta' x_t \\ + \sum_{i=1}^{m} \beta_i' x_t D_{i,t} + u_t \end{aligned} \tag{15}$$

where y is the dependent variable and x is a vector of the independent variables. t denotes the time period, m denotes the highest number of breaks in the model which can take a maximum value of 5 and u denotes the error term. $D_{i,t}$ is the dummy variable that is used to signal the presence of a break in the data. $D_{i,t}$ takes a value of 1, denoting the existence of the SBs at specific break years T_{bi} (i = 1, …, m), if t_i are after the break years T_{bi} (i.e. $t_i > T_{bi}$) and a value of 0, denoting no SB at the specific break years T_{bi} (i = 1, …, m), if t_i are before the break years T_{bi} (i.e. if $t_i < T_{bi}$). Statistical significance of the test statistics in each of the four models (A, B, C and D) rejects the null hypothesis of no cointegration to confirm the presence of cointegrating associations between the variables in the respective models.

Identification of the SB is even more justified in the sense that Bangladesh has achieved its independence in 1971, following the end to a grueling nine months of war against Pakistan. Thus, just after independence, the economy of Bangladesh could not take off in a robust manner which could influence the growth-deforestation nexus being explored. Hence, to account for these issues, the possible SB years identified from the Maki cointegration analysis are used as break year dummies and augmented into the respective regression models to estimate the elasticities taking the presence of SB issues into account.

Regression analysis

The long-run elasticities are estimated using the Fully-Modified Ordinary Least Squares (FMOLS) and the Canonical Cointegration (CC) regression estimators. The FMOLS estimation technique, proposed by Phillips and Hansen (1990), is grounded on a non-parametric approach to regression analysis which provides estimates accounting for potential endogeneity and serial correlation issues in the data. Moreover, the FMOLS estimator is ideally suited for estimations involving series that are integrated at their first differences, I(1) (Amarawickrama and Hunt 2008). The FMOLS estimator ($\hat{\partial}_{FMOLS}$) can be specified as:

$$\left(\hat{\partial}_{\boldsymbol{FMOLS}}\right) = \boldsymbol{N}^{-1} \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \partial_{\widehat{\boldsymbol{FMOLS},\boldsymbol{i}}} \tag{16}$$

The corresponding t-statistic from the FMOLS estimator can be expressed as:

$$\boldsymbol{t}_{\hat{\partial}_{\boldsymbol{FMOLS}}} = \boldsymbol{N}^{-1/2} \sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \boldsymbol{t}_{\hat{\partial}_{\boldsymbol{FMOLS}}} \tag{17}$$

In addition, the robustness of the elasticity estimates from the FMOLS technique is checked using another non-parametric regression approach, referred to as the CC regression method, introduced by Park (1992). The CC regression estimator generates asymptotically efficient estimates using transformed stationary data into the estimation procedure. The transformation of the data is done in such a manner that it keeps the cointegration relationship, as perceived from the cointegrating model, unaltered. This makes the error-term of the cointegrating model uncorrelated with the regressors whereby the elasticity estimates portray asymptotically efficient outcomes (Khan et al. 2018).[4]

Causality analysis

The causal associations between the variables are evaluated using the Hacker and Hatemi-J (HH) causality estimation technique proposed by Hacker and Hatemi-J (2012). This method is modified from the bootstrapped causality test proposed by Hacker and Hatemi-J (2006). According to Hacker and Hatemi-J (2006), bootstrapping the distribution reduces the concerns from small sample size distortions associated with the conventional Wald test introduced by Toda and Yamamoto (TY) (1995), irrespective of the presence of autoregressive conditional heteroscedasticity effects within the model. The modification of the modified Wald test statistic of Hacker and Hatemi-J (2006) is done by endogenizing the optimal lag selection criterion which tends to reduce the small sample size distortions further. The HH technique uses a Vector Autoregressive (VAR) model to calculate the modified Wald test statistics under the null hypothesis of no causality between the dependent and the independent variables against the alternative hypothesis of otherwise. The bootstrapping involves two stages: firstly, estimating the optimal lag structure and secondly predicting the Wald statistic for investing the Granger causality. The VAR model of order k can be specified as:

$$\boldsymbol{y_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 y_{t-1}} + \cdots + \boldsymbol{\beta_k y_{t-k}} + \boldsymbol{u_t} \tag{18}$$

where y_t, β_0 and u_t are vectors with dimension n × 1 and B_i (i > 0) is a parameter matric with a dimension of $n \times n$. The error term u_t has no expected value and presumed to be independent and identically distributed with a non-singular covariance matrix (Hacker and Hatemi-J 2012). In the first stage of the bootstrapping approach under the HH approach, Eq. (18) is estimated without imposing any restriction in terms of the non-causality null hypothesis. The predicted value, y*, can be given by:

$$\boldsymbol{y_t^*} = \hat{\beta}_{\boldsymbol{0}} + \hat{\beta}_{\boldsymbol{1}}\boldsymbol{y_{t-1}} + \cdots + \hat{\beta}_{\boldsymbol{k}}\boldsymbol{y_{t-k}} + \widehat{\boldsymbol{u*}_{\boldsymbol{t}}} \tag{19}$$

[4] For more information on CC regression see Han (1996).

Table 2 The unit root test results

	Perron–Vogelsang				Clemente–Monantes–Reyes			
	Additive outliers		Innovational outliers		Additive outliers		Innovational outliers	
Variable	t-statistic	BY	t-statistic	BY	t-statistic	BY	t-statistic	BY
$Lnfarea_t$	−3.978	1998	−3.137	1997	−3.711	1997; 2008	−3.923	1999; 2000
$Deforest_t$	−2.112	1986	−2.150	1990	−3.585	1990; 2015	−4.223	1991; 2014
$Lnnfdep_t$	−4.989	1982	−4.319	1978	−3.775	1978; 2005	−3.990	1980; 2000
$LnGDP_t$	−2.984	2011	−2.228	2007	−3.313	1994; 2009	−3.819	1998; 2012
$LnGDP^2_t$	−2.679	2011	−2.167	2008	−4.021	2002; 2012	−4.212	2000; 2009
$Popg_t$	–2.746	2012	−2.126	2011	−2.017	1992; 2004	−2.339	1995; 2001
$Lnagri_t$	−1.229	1994	−1.076	1990	−2.187	1986; 1993	−2.981	1990; 1995
$\Delta Lnfarea_t$	−8.293*	1999	−8.336*	1997	6.117**	1987; 1990	6.899**	1990; 1992
$\Delta Deforest_t$	−7.009*	1992	−6.216*	1990	−9.606*	1990; 2013	−10.223*	1992; 2010
$\Delta Nfdep_t$	−8.129*	2005	−7.989*	1978	−6.112**	1978; 1979	−6.391**	1980; 1982
$\Delta LnGDP_t$	−6.715*	2011	−8.690*	2007	−5.553**	2001; 2012	−6.010**	2003; 2008
$\Delta LnGDP^2_t$	−6.819*	2012	−8.889*	2007	−6.893**	2002; 2003	−7.109**	2000; 2005
$\Delta Popg_t$	−6.919*	2013	−6.663*	2011	−5.668**	1981; 1987	−6.102**	1985; 1992
$\Delta Lnagri_t$	−6.881*	1995	−7.209*	1990	−7.114**	1986; 1990	−7.221**	1990; 1993

Selection of the optimal lags is based on Akaike Information Criterion (AIC), Δ denotes first difference I(1), BY denotes break year, * & ** denote statistical significance at 1% and 5% significance levels

where $\widehat{u*_t}$ is a vector of bootstrapped error terms and t (t = 1, …, T) is the time period. The set of T bootstrapped error term vectors is estimated by drawing randomly with replacement from the vectors of the modified residual to ensure that the mean value of the bootstrapped error term vectors is a zero vector. The modified residuals are the raw residuals modified via leverages within the HH approach. This modification is ideal to deal with heteroscedasticity issues within the model and also to account for the ARCH effects (Hacker and Hatemi-J 2012). The bootstrapping mechanism is repeated M times to produce a Wald statistic each time which is based on the TY (2005) methodology. The resulting set of bootstrapped Wald statistics is termed as the bootstrapped Wald distribution which is then used to evaluate the causal properties of the pair of variables. In the case of the predicted Wald –statistic being greater than the corresponding bootstrapped critical value then causality stemming from the independent to the dependent variable is affirmed via rejection of the null hypothesis of non-causality. For comparison purposes, the TY (2005) causality technique is also applied.

Results and discussion

The results from the unit root analyses, accounting for the presence of SB issues in the data, are reported in Table 2. As per the statistical significance of the estimated t-statistics, from both the PV and the CMR tests, it can be said that all the variables are non-stationary at their level forms. However, they do become stationary at their first differences, thus, implicating a common order of integration, I(1), among them. The results collectively denote that all the variables are mean-reverting at their respective first differences whereby the possibility of spurious regression outcomes is nullified.

The unit root investigations are followed by cointegration exercises. Results from the GH and the Maki cointegration tests are presented in Tables 3 and 4, respectively. The statistical significance of the estimated test statistics from both methods confirms the presence of cointegrating relationships between the concerned variables in all models. Hence, it can be said that economic growth, both with and without controlling for the level of democracy, has long run associations with the three indicators of deforestation considered in this paper. Moreover, the results in the

Table 3 The Gregory–Hansen Cointegration test results

Model	Break (constant)						Break (constant and trend)					
	ADF	BY	Zt	BY	Za	BY	ADF	BY	Zt	BY	Za	BY
1	−9.71*	1997	−11.75*	1999	−22.21	1999	−9.00*	1997	−9.05*	1997	−28.51	1997
2	−9.52*	1978	−10.22*	1990	−66.29**	1990	−9.50*	1991	−10.41*	1990	−66.87**	1990
3	−9.49*	1981	−10.77*	1978	−68.33**	1978	−11.29*	1981	−11.41*	1978	−71.47**	1978
4	−9.42*	1997	−9.79*	1997	−60.82**	1997	−7.28*	1988	−7.31*	1988	−57.02	1988
5	−8.93*	1990	−9.03*	1990	−60.11**	1990	−10.26*	1990	−10.20*	1990	−85.00**	1990
6	−6.84*	1977	−6.36*	1977	−60.40**	1977	−7.52*	1985	−7.61*	1985	−79.61**	1985

The optimal lags are based on AIC, BY denotes Break Year, ADF, Zt and Za denote the modified Augmented Dickey-Fuller and z-statistics respectively, * and ** denote statistical significance at 1% and 5% significance levels

context of models (6), (7) and (8) specifically reveal a cointegrating relationship between democracy and deforestation propensities as well.

Following the confirmation of the stationarity and cointegrating properties, the regression analyses are performed using the FMOLS and the CC regression estimators. The regression results in the context of models (1), (2) and (3), not controlling for democracy within the econometric models, are reported in Table 5. The overall results imply that the predicted signs of the elasticity parameters are parallel across both the estimation techniques which portray the robustness of the estimates across different regression techniques.

The signs and the statistical significance of the estimated elasticity parameters attached to real GDP and its squared term confirm the non-linear relationships between economic growth and all the three variables used to proxy for environmental degradation in terms of deforestation in Bangladesh. It is evident that a 1% rise in Bangladesh's real GDP level and its squared term respectively attribute to a reduction and increment in the national forest area coverage by 0.10–0.42% and 0.01–0.03% on average, *ceteris paribus*. This implies that economic growth does trigger deforestation activities in the early stages while correcting for it beyond a threshold level. Hence, these results validate the deforestation-induced EKC hypothesis in the context of forest area coverage being considered as an indicator of deforestation. However, the growth-deforestation nexus in this particular case exhibits a U-shaped association as opposed to the inverted-U shaped association postulated in the EKC hypothesis. This is primarily because a rise in the forest area can basically be interpreted as a fall in deforestation rates and vice-versa. Thus, the U-shaped EKC in this particular case is in line with the theoretical framework addressing the deforestation-induced EKC hypothesis. The turning point level of real GDP in this regard is calculated to be around 715–720 billion US dollars in constant 2010 prices. The notion of the deforestation-induced EKC hypothesis in the context of Bangladesh was also highlighted by Miah et al. (2011).

Similarly, using the rates of deforestation and net forest depletion as the dependent variables, it is also evidenced that economic growth initially triggers deforestation before reducing it beyond a threshold level. These findings, although suggesting a U-shaped association between growth and the two deforestation indicators, also validate the EKC hypothesis in the sense that a rise in the deforestation and net forest depletion rates can be interpreted as environmental deterioration and vice-versa. These results are parallel to the findings by Kumar and Aggarwal (2003), Ahmed et al. (2015) and Waluyo and Terawaki (2016) for India, Pakistan and Indonesia, respectively. The corresponding threshold levels of real GDP are calculated to be around 330–334 billion US dollars in constant 2010 prices for deforestation rate and 298–309 billion US dollars in constant 2010 prices for net forest depletion rate. All the three predicted turning point levels of real GDP are above the current real GDP level of Bangladesh, which in 2018 was equivalent to almost 195 billion US dollars in constant 2010 prices (World Bank 2018). Thus, the deforestation woes of Bangladesh, to an extent, can be reasoned by these findings. The results imply that Bangladesh is still at the stage where a trade-off between economic growth and environmental degradation through deforestation can be expected. However, keeping the

Table 4 The Maki Cointegration Test Results

Model test	(1) Stat	(1) BY	(2) Stat	(2) BY	(3) Stat	(3) BY
A	−7.89*	1995, 1997, 1999, 2004, 2010	−7.99*	1978, 1982, 1991, 1998, 2007	−6.89**	1978, 1981, 1989, 1997, 2004
B	−7.01**	1995, 1998, 2001, 2005, 2009	−7.29*	1980, 1986, 1991, 1999, 2014	−6.63**	1979, 1985, 1990, 1994, 2006
C	−18.01*	1989, 1995, 1999, 2001, 2009	−18.98*	1978, 1983, 1995, 1999, 2011	−9.01**	1979, 1984, 1991, 1997, 2007
D	−9.05	1980, 1985, 2005, 2009, 2013	−9.02	1980, 1988, 1999, 2001, 2010	−9.30***	1980, 1986, 1991, 1999, 2004
Model test	**(4) Stat**	**(4) BY**	**(5) Stat**	**(5) BY**	**(6) Stat**	**(6) BY**
A	−7.69*	1988, 1997, 2001, 2004, 2009	−7.45*	1976, 1981, 1990, 1998, 2009	−7.89*	1977, 1981, 1985, 1996, 2005
B	−7.43**	1992, 1997, 2001, 2006, 2010	−7.31*	1980, 1986, 1990, 2000, 2010	−7.53*	1974, 1981, 1990, 1995, 2005
C	−21.31*	1990, 1997, 1999, 2003, 2008	−19.99*	1975, 1985, 1990, 1997, 2007	−10.01**	1977, 1987, 1990, 1997, 2009
D	−9.35***	1985, 1990, 1997, 2006, 2012	−9.42***	1984, 1990, 1998, 2001, 2018	−10.30***	1983, 1989, 1993, 2000, 2006

The optimal lags are based on AIC, BY denotes Break Years, *, ** and *** denote statistical significance at 1%, 5% and 10% significance levels

adversities associated with environmental degradation into consideration, the nation should ideally implement policies that enhance growth without jeopardizing the environmental well-being through the implementation of environmental policies that would promote afforestation within the economy.

Besides economic growth, deforestation propensities are found to be triggered by the expansion of agricultural land coverage. The predicted signs, and their statistical significances, of the estimated elasticity parameters attached to *lnagri* affirm this claim regarding the substitution effect resulting in forest areas being cleared for expanding arable lands in Bangladesh. This corroborates to views of Barbier and Burgess (2001) in which the authors referred to the per capita arable land to be one of the major factors attributing to tropical deforestation. On the other hand, the population growth rate is also found to exert negative impacts on the environment through the facilitation of deforestation activities within the Bangladesh economy. Similar results were reported in the study by Maji (2017) for Malawi and also acknowledged by Busch and Ferretti-Gallon (2017).

Table 6 reports the results from the FMOLS and CC regression analyses in the context of models (4), (5) and (6) in which the growth-deforestation nexus is evaluated controlling for the level of democracy within the economy. Once again the overall results are robust across the two different regression techniques, as perceived from the same signs of the elasticity estimates. Moreover, the deforestation-induced EKC hypothesis is also statistically supported even after controlling for democracy within the analyses. However, the alterations in the growth-deforestation nexus following the inclusion of democracy within the econometric models can be expressed in two-folds.

Firstly, the estimated elasticity parameters attached to lnGDP, in comparison to the corresponding estimates provided in Table 5, are relatively lower in magnitudes which imply that the EKC for deforestation, controlling for democracy, is likely to be flatter in trajectory. This implies that when the level of democracy is considered within the econometric analyses, the initial trade-off between economic and environmental welfare tends to be lower, possibly due to the

Table 5 The FMOLS and CC regression results for models (1), (2) and (3)

Model Dep. var Estimator	(1) $Lnfarea_t$ FMOLS	(1) $Deforest_t$ CC	(2) $Lnnfdep_t$ FMOLS	(2) $Lnfarea_t$ CC	(3) $Deforest_t$ FMOLS	(3) $Lnnfdep_t$ CC
Regressors						
$Lngdp_t$	−0.421* (0.026)	−0.092* (0.029)	4.478* (1.464)	6.217* (2.030)	1.628* (0.129)	1.881* (0.159)
$Lngdp^2{}_t$	0.032* (0.002)	0.007* (0.002)	−0.386* (0.139)	−0.535* (0.177)	−0.142* (0.027)	−0.165* (0.509)
$Lnagri_t$	−0.032* (0.007)	−0.0219* (0.006)	1.274* (0.401)	1.126* (0.398)	2.027*** (1.150)	2.786* (1.172)
$Popg_t$	−0.153* (0.022)	−0.132* (0.026)	2.475** (1.254)	1.665* (0.399)	5.125* (1.098)	4.711* (1.015)
BY1	−0.008* (0.001)	-0.004* (0.001)	0.029* (0.001)	0.015 (0.039)	−0.564* (0.105)	−0.456* (0.112)
BY2	0.010* (0.001)	0.003** (0.001)	0.111** (0.046)	0.104* (0.003)	0.097 (0.133)	0.040 (0.104)
BY3	0.000 (0.001)	0.002** (0.001)	0.028 (0.046)	0.028 (0.047)	−0.302** (0.133)	−0.161 (0.106)
BY4	−0.006* (0.001)	−0.003** (0.001)	0.037* (0.002)	0.014 (0.081)	−0.564* (0.154)	−0.632* (0.241)
BY5	−0.005** (0.003)	−0.002** (0.001)	−0.007 (0.044)	−0.023 (0.080)	0.218 (0.155)	0.454** (0.230)
Constant	8.135* (0.406)	7.195* (0.498)	53.091** (23.062)	31.933* (2.089)	92.101* (15.192)	101.113* (8.119)
Turning point	720.540	714.08	330.301	333.619	308.708	298.109
Adjusted R^2	0.832	0.799	0.660	0.689	0.690	0.719
No. of obvs	46	46	45	45	45	45

The selection of the structural breaks are based on the estimated break points from model A of the Maki cointegration tests for the respective models, are selected; The standard errors are reported within the parentheses; Optimal lag selection is based on the AIC. *, ** and *** denote statistical significance at 1%, 5% and 10% significance levels

relatively lower environmental costs of economic growth. Hence, a plausible explanation behind these findings could be the fact that under a good democratic environment the political institutions operating within Bangladesh are likely to be of better quality whereby deforestation of the forestlands becomes relatively difficult. This resonates with the ideas put forward in the study by Shandra (2007) in which the author, based on statistical evidence in the context of 73 countries, concluded that better democracies ensure that the governments serve the interests of the people better and, therefore, safeguard the environmental resources via reducing the frequency of deforestation. This is also supported by the signs of the estimated elasticities of all the three indicators of deforestation with respect to changes in the level of democracy within the economy of Bangladesh. The estimates reveal that a 1% rise in the aggregate democracy index accounts for 0.02–0.04% increment in the forest area coverage, 0.29–0.55% reduction in deforestation rates and 2.34–2.69% reduction in the net forest depletion rates, on average, *ceteris paribus.* These findings oppose the remarks made by Ehrhardt-Martinez, Crenshaw and Jenkins (2002) claiming political democracy to speed up deforestation rates across the developing countries. Moreover, the statistical significances of the interaction terms further imply that the democratic environment and economic growth jointly impact deforestation propensities in Bangladesh. The results imply that higher values of the aggregate democracy index, implying a better democratic environment, increase forest areas and reduces deforestation and net forest depletion rates.

Secondly, it is seen that upon controlling for democracy the turning point levels of real GDP in Bangladesh tend to decline from 715–720 billion US dollars to 593–602 billion US dollars for forest area coverage, from 330–334 billion US dollars to 266–271 billion US dollars for deforestation rate, and from 298–309 billion US dollars to 291–296 billion US dollars for net forest depletion rate. These collectively denote that a better democratic environment reduces the environmental costs of economic growth. Hence, it can be said that the democratization of the economy leads to the elimination of the initial trade-off between economic growth and environmental deterioration via deforestation, in comparison to a poor democratic environment, which takes place at a faster pace and at a relatively lower level of real GDP. Moreover, the statistical significances of the interaction terms imply that the threshold levels of real GDP are conditional on the level of democracy within the economy. The negative signs of the elasticity parameters attached to the interaction terms suggest that a higher level of the aggregate democracy index, synonymous to an improvement in the democratic environment, is likely to exhibit positive impacts on deforestation by reducing the environmental costs of economic growth, thus, reducing the threshold level of real GDP further. Thus, promoting democracy alongside economic growth could be a credible solution to the deforestation woes of Bangladesh. Therefore, it is pertinent to promote democratic practices in order to simultaneously pursue the economic growth and environmental welfare policies in tandem.

Finally, the results from the causality estimation techniques are reported in Table 7. According to the estimated test statistics from the HH test, it can be seen that economic growth influences all the three indicators of deforestation. The statistical significance of the modified Wald test statistics advocate in favor of unidirectional causations stemming from economic growth to forest area coverage and net forest depletion rate while a bidirectional causal association is revealed

Table 6 The FMOLS and CC regression results for models (4), (5) and (6)

Model Dep. var Estimator	(4) $Lnfarea_t$ FMOLS	(4) $Deforest_t$ CC	(5) $Lnnfdep_t$ FMOLS	(5) $Lnfarea_t$ CC	(6) $Deforest_t$ FMOLS	(6) $Lnnfdep_t$ CC
Regressors						
$Lngdp_t$	−0.166* (0.019)	−0.064* (0.029)	2.419** (1.205)	0.838* (0.489)	1.457** (0.701)	1.238* (0.081)
$Lngdp^2_t$	0.013* (0.002)	0.005* (0.001)	0.216*** (0.111)	−0.075** (0.036)	−0.128* (0.028)	−0.109* (0.009)
$Lngdp_t*lnDEM_t$	−0.009* (0.001)	−0.004* (0.001)	−0.128**(0.051)	−0.074* (0.007)	−0.611* (0.173)	−0.680** (0.311)
$LnDEM_t$	0.040** (0.019)	0.018* (0.005)	−0.549* (0.203)	−0.289* (0.100)	−2.341* (0.692)	−2.675** (1.321)
$Lnagri_t$	0.008 (0.005)	−0.023* (0.006)	1.011** (0.338)	1.034* (0.374)	1.518** (0.751)	1.413* (0.061)
$Popg_t$	0.098* (0.020)	−0.066* (0.009)	2.848** (1.247)	3.112* (1.010)	4.058** (2.030)	4.372* (1.015)
BY1	−0.004* (0.001)	−0.003* (0.001)	0.080** (0.031)	0.004 (0.038)	−0.254** (0.107)	−0.179 (0.109)
BY2	0.005* (0.001)	0.001 (0.001)	0.004 (0.037)	0.038 (0.074)	0.288** (0.127)	0.163 (0.120)
BY3	0.004* (0.001)	0.004* (0.001)	0.041 (0.040)	0.039 (0.064)	−0.064 (0.137)	−0.071 (0.148)
BY4	−0.005** (0.003)	−0.003** (0.001)	0.023 (0.042)	0.207* (0.008)	−0.438* (0.144)	−0.594** (0.232)
BY5	−0.002** (0.001)	−0.001 (0.001)	−0.027 (0.044)	−0.028 (0.068)	0.423* (0.150)	0.576** (0.269)
Constant	11.940* (0.372)	8.367* (0.771)	47.381** (22.782)	50.101* (4.098)	78.209* (14.110)	79.280* (6.112)
Turning point	592.657	601.845	270.426	265.610	295.894	290.949
Adjusted R^2	0.872	0.828	0.651	0.692	0.740	0.751
No. of obvs	46	46	45	45	45	45

The selection of the Break Year (BY) dummies are based on the estimated break points from the Maki cointegration test model in which level shift is considered, for the respective models, are selected; The standard errors are reported within the parentheses; The turning points are calculated at zero scores of the aggregate democracy index; Optimal lag selection is based on the AIC. *, ** and *** denote statistical significance at 1%, 5% and 10% significance levels

Table 7 Hacker and Hatemi-J Bootstrap and Toda Yamamoto causality test results

Dep. var	Indep. var	Hacker and Hatemi-J bootstrap Modified wald test statistic	Toda and Yamamoto Wald test statistic
$Lnfarea_t$	$Lngdp_t$	6.120**	3.04***
$Lngdp_t$	$Lnfarea_t$	1.989	0.04
$Lnfarea_t$	$LnDEM_t$	8.219*	2.184*
$LnDEM_t$	$Lnfarea_t$	1.691	1.119
$Deforest_t$	$Lngdp_t$	9.128*	3.229**
$Lngdp_t$	$Deforest_t$	8.217*	2.204***
$Deforest_t$	$LnDEM_t$	5.297**	2.229***
$LnDEM_t$	$Deforest_t$	1.605	1.019
$Lnnfdep_t$	$Lngdp_t$	6.002**	2.120***
$Lngdp_t$	$Lnnfdep_t$	2.012	1.814
$Lnnfdep_t$	$LnDEM_t$	4.909**	3.289**
$LnDEM_t$	$Lnnfdep_t$	1.299	1.116
$LnGDP_t$	$LnDEM_t$	9.399*	3.118**
$LnDEM_t$	$LnGDP_t$	8.279*	3.324**

The modified Wald statistics are estimated using bootstrap approach; *, ** & *** denote statistical significance at 1%, 5% and 10% significance levels, respectively

between economic growth and deforestation rate in Bangladesh. Hence, these causal relationships further highlight the fact that environmental welfare, in terms of deforestation and afforestation activities, can largely be attributed to the level of growth of the economy. The results are similar to those found by Ahmed et al. (2015) for Pakistan. Moreover, the other key findings results show that the level of democracy also influences deforestation propensities in Bangladesh. Unidirectional causal relationships running from the aggregate democracy index to all the three proxies for deforestation affirm this claim. This, to a large extent, is in line with the results found in the study by Van Khuc et al. (2018) in which the authors referred good governance, which can be linked to a good democratic environment, to be one of the major drivers of deforestation in Vietnam. Thus, it can be asserted from the causality analyses that both economic growth and democratization of the economy are key factors governing the deforestation activities in Bangladesh. Moreover, the bidirectional causality between economic growth and aggregate democracy index is also unearthed which tends to highlight the interdependency between these two key macroeconomic variables. On the other hand, the causality estimates from the YT causality approach, although corroborating to the findings from the HH test, are found to have comparatively poor levels of statistical significance which validates the superiority of the HH causality approach.

Conclusion and policy implications

This paper contributed to the literature by empirically investigating the validity of the deforestation-induced EKC hypothesis in the context of Bangladesh. Besides, the influences of democratic practices on the economic growth-deforestation nexus are also explored. Using annual time series data from 1971 to 2018, the results indicated long-run associations between economic growth, deforestation, democracy and the other key macroeconomic variables controlled for within the econometric analyses. The results from the regression analyses confirmed the validity of the deforestation-induced EKC hypothesis for all the three indicators of deforestation. Moreover, upon accounting for the level of democracy within the country, the threshold level of growth is evidenced to decline. Hence, it can be recommended that environmental policies are incorporated into Bangladesh's national growth strategies, keeping the prospects of sustainable development into cognizance. Moreover, promoting a better democratic environment within the economy should also be one of the key policy agendas of the government following its capacity to influence both the economic and environmental welfares. Furthermore, causal associations are also revealed to implicate the influences of economic growth and democratic environment on the deforestation propensities in Bangladesh.

The overall results broadly imply that the betterment of institutional quality is essential in reducing deforestation propensities while simultaneously inducing reforestation practices. Therefore, the government is better-off enacting stringent rules and regulations against forest encroachment in Bangladesh. Although there are laws that are envisioned to limit the deforestation rates within the country, poor institutional quality often restrains the implementation of such laws. On the other hand, the expansion of agricultural lands was found to adversely impact the natural forestland coverage in Bangladesh. Hence, it is also pertinent to enhance the agricultural land-productivity to relax the pressures to clear the natural forestlands of Bangladesh. In addition to these forest-conservation strategies, encouraging reforestation initiatives among the stakeholders could be a more comprehensive measure to limit the dampening impacts of deforestation across the nation. Also, taking the negative correlation between population growth and deforestation found from the regression analyses into cognizance, better family planning policies should be adopted to limit the aggravation of food demand which, in turn, is likely to further mitigate the pressures for razing forestlands for agricultural expansion. Moreover, the results also confirmed that the current level of real GDP of Bangladesh is below the predicted growth thresholds which implied that the nation can expect it deforestation woes to sustain for a certain period of time before the threshold real GDP levels are attained. Once again the role of promoting netter democratic environment within the country comes into play since both the regression and the causality analyses confirmed the influences of democracy in affecting deforestation propensities and reducing the threshold growth levels to a large extent. As a result, ensuring proper institutional quality via promoting democracy within Bangladesh has to be emphasized in order to abate the encroachment of the nation's existing natural forest reserves. It is often alleged that ministerial corruption has led to substantial loss of forest reserves in Bangladesh (Reza and Hasan 2019). Thus, improving institutional quality via reducing corruption in this regard can turn out to be an effective policy tool to uphold the exponentially escalating deforestation rates in the country. Apart from these, the government can also subsidize the prices of the modern cooking fuels, like liquefied petroleum gas in particular, to minimize combustion of firewood across the rural vicinities in Bangladesh. Biofuels are still a predominant source of cooking fuel within the poor rural households which, to an extent, does account for higher deforestation propensities in the country. In addition, the government can also support the local non-government bodies that are engaged in enhancing ecological welfare via generating awareness amidst the local communities, in particular, with respect to combating climate change adversities, particularly through conservation of the forest reserves. Simultaneously, the government can also incentivize the private sector to engage in forest conservation campaigns which could turn out to a more compressive means to reducing deforestation in Bangladesh. Finally, it is recommended to the government to undertake afforestation decisions to convert barren unused lands into forests which would also be ideal in limiting the net depletion of the forest reserves in Bangladesh.

As part of the future scope of extending this analysis is concerned, the validity of the impacts of democracy on the curvature and the turning point of the EKC for deforestation can be evaluated using different measures of democracy. Moreover, the EKC hypothesis can also be examined using the carbon emissions from deforestation as a proxy for the deforestation indicator which would provide a different dimension to the deforestation-induced EKC hypothesis in the context of Bangladesh. Besides, this study can be replicated in the context of similar developing economies to check the generality of the results. Finally, panel data analysis in the context of the South Asian region can also be performed for further investigation of the deforestation-induced EKC hypothesis. Furthermore, to assess the potential impacts of technological betterment on the turning point of the deforestation-induced EKC, relevant variables to proxy technological innovation in Bangladesh can be augmented into the model and interacted with economic growth to account for the associated impacts.

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Appendix

See Table 1 and Fig. 2.

Table 1 The units of measurement and data sources

Variable	Unit of measurement	Source
Farea	Square kilometers	World development indicators (World Bank 2018)
Deforest	Percentage	World development indicators (World Bank 2018)
Nfdep	Percentage	World development indicators (World Bank 2018)
GDP/GDP^2	Constant 2010 US dollars	World development indicators (World Bank 2018)
Agri	Square kilometers	World development indicators (World Bank 2018)
Popg	Percentage	World development indicators (World Bank 2018)
DEM	Index	Varieties of democracy (V-Dem) project

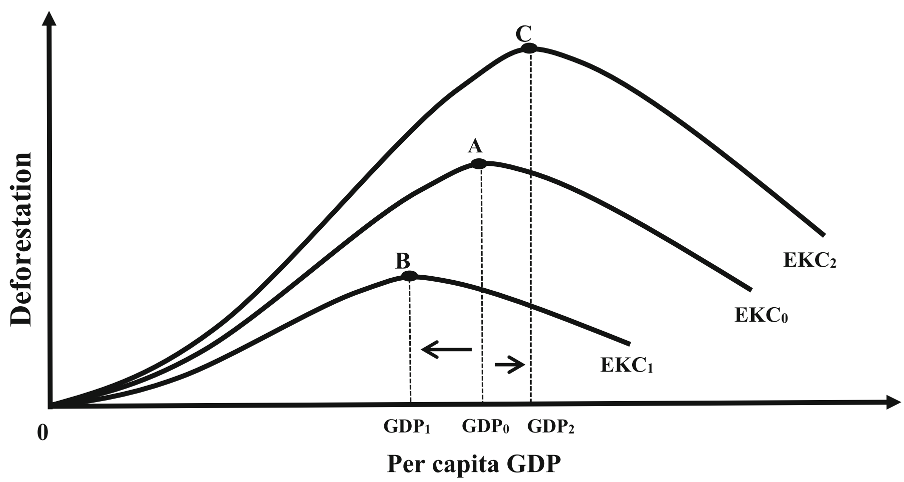

Fig. 2 The impacts of Democracy on the Deforestation-induced EKC Source: Author's own

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