An Evaluation of Bioenergy Industry Sustainability Impacts on Forest Degradation in the EU 28 Region

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Abstract

Bioenergy industry is a proven option to replace fossil fuels in the heat supply and partly in the transport sector and generation of electricity. The aim of this study is to investigate the empirical model pertaining whether bioenergy use and institutional quality impact forestry destruction in European Union countries. To achieve this, a selection of 28 European countries covering 1990–2018 was employed. Also, the Pooled OLS, Fixed Effect, Random Effect and Least Square Dummy Variable Corrected approaches were applied to regress the developed model. The findings referred that bioenergy use within institutional framework significantly participated to reduce forest degradation in the European Union countries. In developed countries, institutional quality indicator was negatively pertained to forest degradation. This shows that efficient institutions and governments can add to reducing forest degradation in the developed countries in European Union. The reduction of forest degradation in European Union countries can be achieved by interacting bioenergy use and government effectiveness indicators. Thus, policy makers should (1) stimulate

the sustainability criteria of bioenergy application end-uses (2) intensify the quality of institutions, and (3) ensure the bioenergy use under effective governance.

Keywords: Bioenergy use; institutional quality; forest degradation; sustainability

Introduction

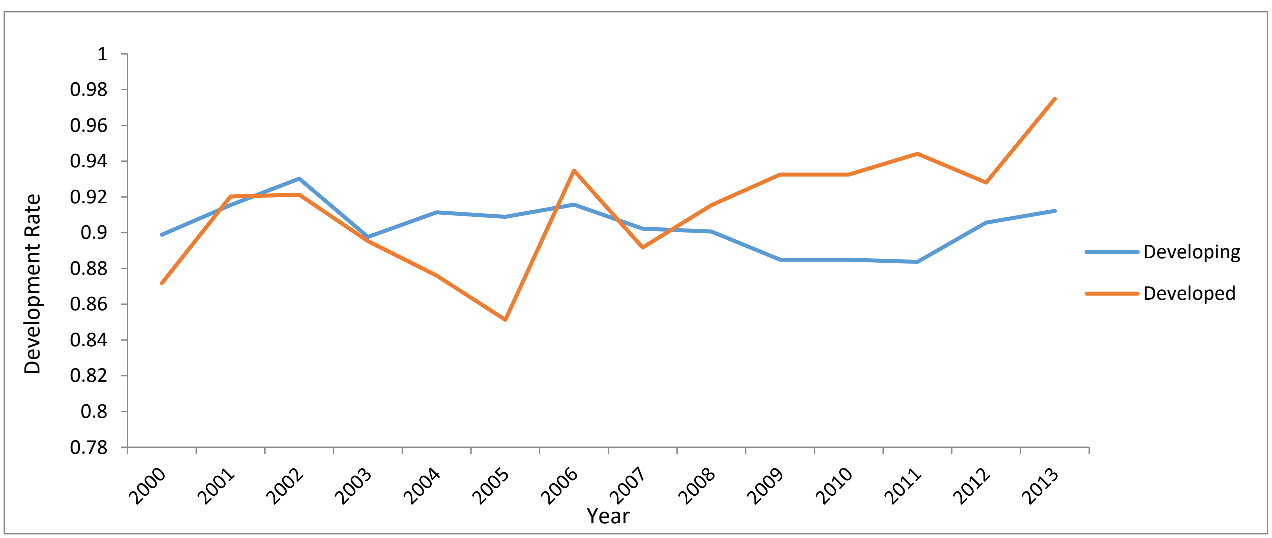
Forestry degradation is a major driver of global warming and biodiversity loss. Forests are home to 80% of the world's terrestrial biodiversity. Activities related to forestry and other land use, primarily deforestation, were responsible for 12% of greenhouse gas emissions between 2000 and 2009, and based on the International Panel on Climate Change, which makes them the second major cause of climate change after the burning of fossil fuels. Protecting forests is thus essential to meet the objectives of the Paris Agreement and the 2030 Agenda for Sustainable Development. Forests provide subsistence and income to about 1.5 billion people in the world, many of them indigenous peoples. Deforestation threatens their livelihoods and their traditional way of life. Very often, their collective property rights are violated (see Appendix A). Activists defending forests and trying to enforce their rights are often threatened and sometimes killed (Lavelle et al., 2011).

Likewise, it must be noticed that indicators increasing biodiversity also synchronize with those boost other perspectives of sustainable forestry and related to ecological system interests. For instance, removing deadwood, branches, twigs, etc. For example, extracting forestry residues. Also extract a source of soil humus and nutrients, while continual interactions (for bio-wood removal) also increase to degradation of forest soil coverage, enhancing the risk of soil attrition particularly

in mounds and heights parts of Europe. Residues removal from forests for bioenergy production by 70 percent of wood wastes and 25 percent of branches contributes to a significant decrease in CO2 fluxes and pertaining humus into the soil especially in coniferous forests (Thran et al., 2017).

Solid biomass is mainly originating from forestry resources and wood manufacturing sectors. Feedstocks output utilized recently in generating transport bio-fuels or bio-liquids employed in bioelectricity and bio-heat and bio-cool sectors (Lavelle et al., 2011). Precisely, European Union countries committed to supply 20 percent of EU's total energy from sustainable sources on December 31, 2020 and obligated to produce a minimum 27 percent on December 31, 2030. Bioenergy is presently an important contributor of the plan to achieve the related 2020 and 2030 goals, and more than 50 percent of sustainable energy in European Union region presently produces from bioenergy industry. Almost 40 percent of the yearly extraction from European Union forests is eventually utilized in bioenergy industry (see Figure 1).

Figure 1 Comparisons of Bioenergy Industry Growth in Underdeveloped and Developed Countries in EU Countries



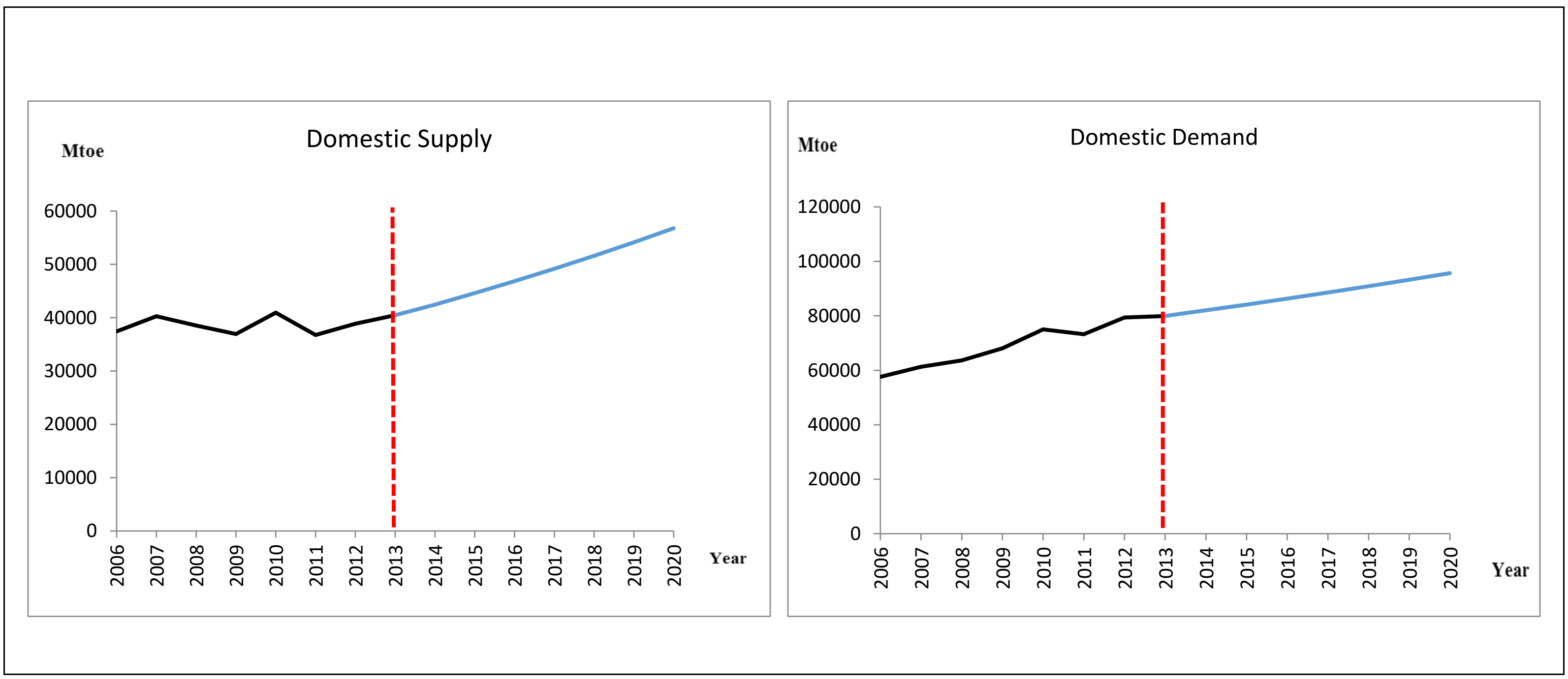
Source: Alsaleh et al. (2017a)

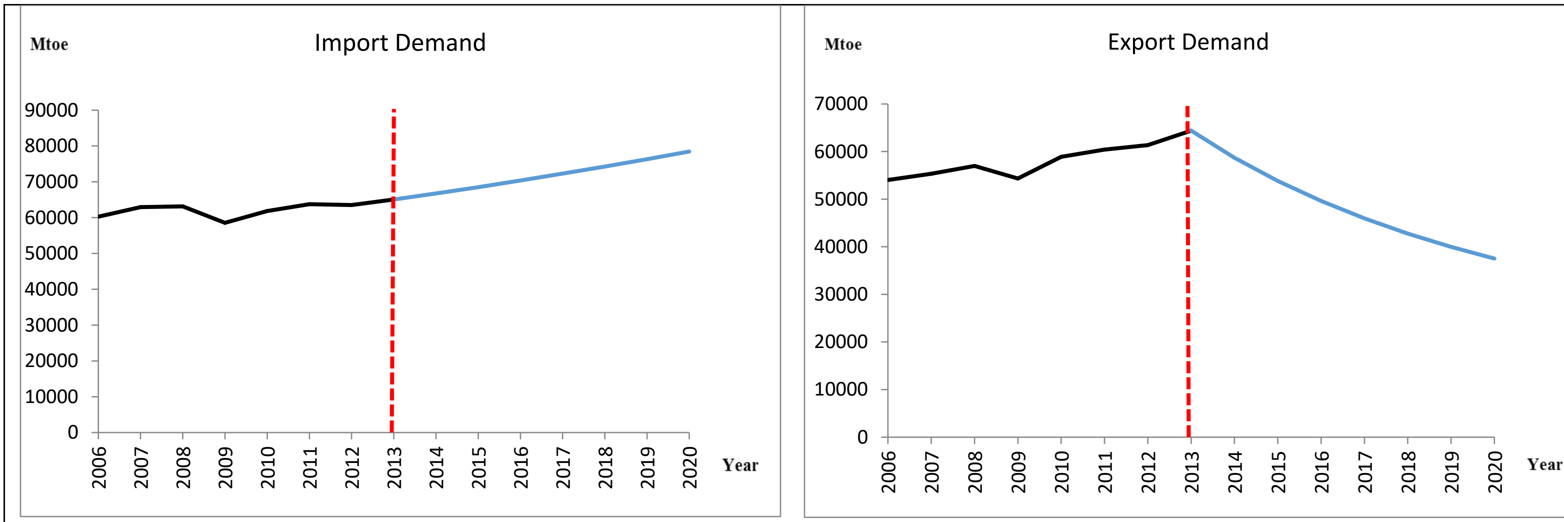
Biomass demand raise up to 318 m³ RWE (= round wood equivalent) from natural forests resource for the 2010-2020 period was computed, based on recent estimation to change primary conventional energy output into bio-wood quantities. According to insufficient database of the National Renewable Energy Action Plans (NREAPs), it is ambiguous to which level this increasing consumption will be supplied from EU28 forests resources and which segment could be supplied from imported forestry biomass in EU28 countries. The EU Commission points that the majority of bioenergy output will be produced form extracted wood pellets from forestry resource, with acceleration to be imported from outside the EU (Sikkema et al., 2011). Theoretically, the European Union countries would provide these biomass from forestry resources locally, it is most likely that imports may raise significantly (Alsaleh et al., 2017b). Sikkema et al. (2011) suggests that the European countries consumption for wood pellets will increase threefold by the end of 2020 in compare with the consumption in 2010, and this against the hypothesis of incrementing international consumption. Global trade of biomass from forestry resource is anticipated to expand by the end of 2020 to scales between 5 or 14 times in compare with the scale of 2010 (see Figure 2).

Expanding the consumption of forest residues for energy production' has obtained high value in energy market. The European countries strategy to generate more than 50% of its sustainable energy from biomass by the end of 2020, which is more than 10% of its total energy consumption (Alsaleh et al., 2017a). Although the majority is produced in forests within the EU region, import of wood pellets from overseas to Europe is considered significant supplier and will expand in the

future (Sikkim et al, 2011and Hewitt, 2011). The major exporting nations to Europe are North America and Russia. South America, especially Brazil and Southern Africa are highly important suppliers for forestry biomass to Europe (Hewitt, 2011). This raised of European consumption for biomass in 2020 dangers to lead for an additional escalation of deforestation and forest degradation worldwide.

Figure 2 Results of Domestic and International Bioenergy Markets in the EU Region from 2014-2020





Note: The black line referred to available data. The vertical line referred the threshold between historical data and forecasted data. Source: Alsaleh et al., (2017b).

The consumption of biomass for bioenergy output from the waste and residues of forestry resource, add up a further pressure on natural resource. In the case that no adequate cropland for bioenergy production is accessible, this may lead to food crop change (Al-Riffai et al., 2010). As biomass output for stable bioenergy production is highly considered, the most important impact of the timber biomass for bioenergy sustainability is on the condition of forests. Forests can be exposed to lose a great part of their timber and remain be considered as forest, although not as deforested, this can lead to a forestry destruction which is a main reason for global warming and biodiversity damage.

Good governance and the institutional quality can plays main role in ecological goodness (Esty and Porter, 2005; Djankov and Hoekman, 2002). Pushak et al. (2007) found that nations with higher regulatory quality, voice and accountability are more capable in perform ecological policies

and applications. For the aim of this study, good governance proxies will be applied fundamentally (Worldwide Governance Indicators) to investigate their effect on forest destruction in EU-28 Region (See Appendix B).

A crucial question is therefore; does bioenergy use under institutional framework across the developed and underdeveloped countries in EU-28 region impact forest degradation? And what is the role of institutional quality in reducing forest degradation? Due to the high consumption for bioenergy and the fast increasing of forest degradation scales, a further investigation for the causal correlation among forest degradation, institutional quality and bioenergy use variables is necessary for EU-28 region countries. The prime aim of this study is to shed light on the effect of bioenergy use within institutional framework on forestry degradation in developed and underdeveloped countries in EU-28 region during the period between 1990 through 2018.

This research contributes significantly to the body of research. It argue for incorporated governance indicators on sustainable expansion and growth in EU-28 region to evolve a further investigation of the linkages between the research's determinants. The research can support the governments of EU-28 region in fighting forest degradation and deforestation by understanding the role of bioenergy use under institutional framework plays in forest degradation. The need applying the research's interaction indicators was not applied before for EU-28 region. Over and above to bioenergy is a carbon natural energy source, the study considers bioenergy output within institutional framework to investigate if it achieves the sustainability characteristic prior framing regulations for additional implication of bioenergy into the energy security and accessibility.

Additional contribution of this study is using of the cross-sectional and longitudinal data regression method improved by Okui and Yanagi (2020). Differ from the empirical time series and cross-sectional size dataset applied in previous researches, for example the commonly applied panel data estimation model from Pesaran et al. (2001), the present research applies the recently improved empirical analysis, the Fixed Effect (FE) estimator, which is considered for the deceptive impacts of estimators on the dependent variable and covers the diversified complexity of the prevalent Pooled OLS, Random Effect (RE) and Least Square Dummy Variable Corrected (LSDVC) estimator's action and explanations. Finally, this research contributes to the previous researches on forest destruction by investigating the prevalent relationship among bioenergy, institution and forest destruction.

Literature Review:

Empirical Survey

Generally, in EU-28 region, the supply and demand of bioenergy output along with insufficient governance efficiency are main issues for sustainable strategy of the EU-28 zone's forest territory, as well as its timber territories. Anyhow, such a few scholars have concentrated on the forest destruction happened by forestry biomass energy extractions and they have not pay attention the impact of governance. Although only few researches that have been done have concentrated likely on one element of biomass energy, biofuel, coal, and only in specified forest lands in particular countries. Also, these studies focused on char-coal generation from wet and arid forestry resources (see Mwampamba, 2007; Chidumayo and Gumbo, 2013).

The "Fuelwood Gap Hypothesis", established in the 1970s, suggested that wood fuels were used without awareness foundation. The "Gap Hypothesis" pointed that in several nations demand was higher than the sustainable output from forestry areas. The hypothesis derived that deforestation and forest destruction were mainly due to fuelwood extraction. This, of course, enhanced a lot of attention between local and global firms in regard to the future of forests (Knight and Rosa, 2012) Many bioenergy input (Residual forest biomass, biomass coal and bio-wood fuel) extracting has been related to deforestation, although there are concerns as to the scale to which it exacerbates deforestation levels. In many areas, biomass input utilized for biofuel is deadwood harvested from the forestry and many recent researches; Hofstad et al. (2009), Knight and Rosa (2012), Berger et al. (2013), Abt et al. (2014), have suggested that fuelwood use is not mostly a driver of large level deforestation, although there are also studies where live cutting for fuelwood occurs as well.

Opposed to this discussion, Girard (2002) elaborated that coal is made from wood, which require harvesting forest. Also, coal creating required land cleaning and this causes deforestation. Equally, Ceccon and Miramontes (2008), Nijsen et al. (2011), Bailis et al. (2015) referred to that mostly all the countries counting on biomass and bio-wood from forestry resource facing a high scale of deforestation and forest degradation. Similarly, Sander and Zeller (2007) suggested that biomass energy from forestry resources is the main reason of desertification and forestry destruction in African countries. Similarly, the cost of biofuel is also recognized as a significant indicator controlling the deforestation level, as Samuelson (1981) suggested that an enhance in the cost of biofuel gives a indication to the suppliers that more biofuel is required and this lead to additional harvesting from forestry resource, which accordingly cause deforestation and environmental

destruction. All these researches claimed that timber harvesting or use to produce energy would lead to an opposite impact on deforestation, forest destruction or the ecological system.

Earlier studies Allen and Barnes (1985), Bensel (2008), Maria et al. (2015), Agarwala et al. (2017) claimed that deforestation is accrued due to a many ecological causes such as heavy timber extracting for energy, population mounting, and direct/indirect land use change. Chase (1993) found that poorness is additional main cause for equatorial deforestation since the paupers crave to timber harvesting to meet their requirements for warming and food preparation. Mortimore and Fabiyi (2003) claimed that desertification and ecological destruction are most likely the consequence of government poor effort to identify lands ownership, which could discourage the raised obstacle if correctly identified and performed. Earlier studies Bhattarai and Hammig (2001), Maraseni and Cadman (2015), Ranjan (2018) argued that governance have an important positive influence on deforestation and claimed that efficient governance in a nation can help on mitigation deforestation, agricultural regulations may cause remarkable effect on the desertification scale. Sutton and Aghrout (1992) argued that farming governance in the 1980s as a main determinant in eliminating deforestation and forestry degradation in Algeria. On the opposite, Ali (2009) argued that governance have been inefficient in fighting against ecological destruction and, thus, the research claimed a regulation change to advancing enterprises. Moncada et al. (2017) explored the effects of an agricultural policy intervention and a bioenergy policy intervention in Germany in the period 1992–2014, applying modelling agent systems based on institutional analysis framework, complex adaptive systems theory, and neo institutional economics theory.

Various estimators were used in investigation the determinants of forest degradation among the world. In Sub-Saharan Africa, Sulaiman et al. (2017) argued a critical issue whether the use of biomass from timber harvesting for energy impact forest destruction applying dataset for 45 African nations for the 2005–2013 period. Additionally, the generalized method of moments (GMM) estimator was employed to regress the developed model. Globally, Kothke et al. (2013) used the causal theory and historical cross-sectional data analysis for more than 140 countries among the world to investigate the determinants of deforestation and forest degradation. Van and Azomahou (2007) conducted an empirical analysis using a panel data set of 59 underdeveloped countries over the 1972–1994 period to study the deforestation process and relying on both parametric and semiparametric models to examine nonlinearities and heterogeneity in the deforestation process. Wolfersberger et al. (2015) analyses forest transition and land–use change using a dynamic panel seemingly unrelated regression model along with a switching regression model for dataset of 57 underdeveloped countries observed over four time periods. Khuc et al. (2018) employs geographic information system tools, a structural regression model, and a regression tree method to quantify the extent as well as the approximate causes of deforestation and forest degradation in Vietnam during the 2000-2010 period. Ahmed et al., (2015) argued the investigation of the ecological kuznets curve assumption with deforestation for ecological destruction, and several independent indicators (economic development, energy demand, freedom of trade, and population density) applying Autoregressive Distributed Lag (ARDL) bounds estimator to cointegration and the VECM–Granger causality test for Pakistan from 1980-2013.

Having surveyed the above studies, one can find that the correlation between forestry biomass use and forestry destruction was founded. Nevertheless, this research varies in that it will concentrate

not only on the effect of bioenergy use, but furthermore on the effect of institutional quality, as well as the effect of intervention among bioenergy use and institutional quality in combating forestry destruction in EU28 Region, EU15 developed countries, EU13 underdeveloped countries during 1990 to 2018 using dynamic panel framework. As far as the authors know, this model was not covered in the surveyed literatures.

Methodology and Data

This research used collected data which were primarily yearly country information withdrawn for the 1990-2018 period. The collected data was built up to evaluate the presence of Environmental Kuznets Curve theory. The assessment and validation were relied on the estimators of General Least Square (GLD) approach. The data gathered for this research were extracted from the World Bank Data Open. The selected sample specification provided a balanced panel data of EU28 members.

The research used cross-sectional regression. Greene (2003), claimed panel data are mostly applied owning to the fact that panel data analysis have the feature of providing further elaboration as the panel data jointly built of cross-sectional data (that takes country difference) and time-series data (that takes speed of modulation). Firstly, the authors examined the presence of unit roots between the developed model indicators. The Levin, Lin & Chu (LLC), and Im, Pesaran, and Shin (IPS) examinations were applied to confirm the absence of unit root among the indicators. The LLC and IPS regressors apply an estimation of the 1st differences of the series counter to the series lagged

once, X_{t_1} and lagged difference terms. It can include a constant term a and α trend term Y_t as presented in Eq (1):

$$\Delta X_t = \alpha + \beta X_{t-1} + \sum_{i-1}^{m} \gamma_i \Delta X_{t-1} + \epsilon_t \quad (1)$$

where: Δ is a 1st difference operative, m is the most advantageous lagged length, γ_i is the time progression, β is parameter assess, α is the stationary parameter and ϵ_t is the constant random error. The examination for a unit root related to the assumption that $H_0 : \beta = 0$, $H_1 : \beta \neq 0$. The status is that at any rate the parameter is insignificant at statistical level, then the assumption that X_t implicate a unit root is declined.

The developed model would be regressed using the most suitable regressor the fixed effects (FE) or random effects (RE). Accordingly, the FE and the RE estimators were applied to test the validity of the findings. The developed model for this research was framed based on earlier study for Verbeek (2004) and can reframed as Eq (2):

$$Y_{it} = \alpha_i + X^{/}_{it}\beta + \epsilon_{it} \quad (2)$$

while β points to the fractional influence of $X^{/}_{it}$.. $X^{/}_{it}$ it is a k-dimensional vector of descriptive indicators, without involving a constant. The α_i tracks the influences of these indicators that are specific to the country and that are constant for the selected years. Generally, ε_{it} is supposed to be unconstrained and similarly allocated over the selected countries and years, with average 0 and discrepancy (Verbeek, 2004). The Hausman Fixed examination was applied to choose either to

employ FE estimator or RE estimator. The null-hypothesis of the Hausman Fixed examination argues that the RE estimator is more suitable for elaboration of the findings. If the null-hypothesis is disapproved, this implies that RE estimator is unsuitable and authors should apply FE estimator (Gujarat, 2004). The research developed the empirical model applied by Athanasoglou et al. (2006) to frame the empirical model in a linear setting as seen in Eq (3):

$$Y_{it} = C + + \sum_{k-1}^{k} \beta_k X_{it}^{k} + \epsilon_{it} \tag{3}$$

where Y_{it} is the environmental quality (forest degradation) of the members i in year t, with t = 1…..N; i = 1….T. C refers to constant term. X_{it} and k are descriptive indicators. ε_{it} points to the disturbances term. The developed formulation to evaluate the presence of environmental kuznets curve hypothesis and its variables is identified as Eq (4):

$$lnFD_{it} = \beta_0 + \beta_1\, lnBIO*IQ_{it} + \beta_2\, lnIQ_{it} + \beta_3\, lnPD_{it} + \beta_4\, lnTO_{it} + \beta_5\, lnGDP_{it} + \nu_{it} + \mu_{it} \tag{4}$$

where ν_{it} points to the unobserved individual particular impact. μ_{it} refers to the individualistic inaccuracy. The present research pursued Bloom et al. (2004), Afzal et al. (2010), Dao (2012) to develop the framed model. The indicators of the developed model in Eq (4) were logarithmized to permit the factors to be explicated as elasticities. The variables, abbreviation, data source, and the predicted sign of the indicators employed in the developed empirical model are presented in Table 1.

Table 1. Overview of Dependent and Independent Indicators.

Indicator	Abbreviated	Data Source	Statistics/Sign	Unit
Forest Deforestation	FD	World Bank Datasets	No prediction	% Land Area
Institutional Quality	IQ	World Bank Datasets	Significant / -	% of governance confidence
Bio-energy Output	BIO	Eurostat	Significant / +	Terajoule (TJ)
Bioenergy*Institutional	BIO*IQ	Eurostat	Significant / -	Terajoule (TJ)
Gross Domestic Product	GDP	World Bank Datasets	Significant / +	GDP per capita growth %
Population Density	PD	World Bank Datasets	Significant / +	People Per sq.km
Trade Openness	TO	World Bank Datasets	Significant / +	% of GDP

where FD points to the forestry destruction, represented by modification in forestry as percentage of land area. BIO is bioenergy use, calculated in Terajouls (TJ) and anticipated to show a positive performance. QI refers to the goodness of institutions indicated by worldwide governance indicators with a predicted to present negative impact. BIO*QI indicates to the intervened bioenergy use and governance goodness indicator and its predicted to show negative effect. GDP is gross domestic product per capita growth by annual percentage and its predicted to influence positively. PD is the vector of dominating indicator, which points to population density indexed by people per square kilometre of land area with a predicted positive performance in the developed model. TO represents calculated trade openness calculated as export/GDP + import/GDP with predicted positive performance. ln is natural log. The selected EU28 members were segregated into two categories based on their development condition as follows; EU15 developed countries and EU13 underdeveloped countries (see Appendix C).

Results and Discussion

The evaluation of the selected sample starts with exploratory examination for the indicators. Table 2 shows the descriptive statistics, which claim that the indicators have ordinary allocation. The relationship validation outcomes are presented in Table 3. The validation show no high relationship between the independent determinants, which display nonappearance of multi-collinearity issue. Thus, the indicators can be evaluated within the same empirical model without experiencing multicollinearity (Prodan, 2013).

Table 2 Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
FD	723	1.419	0.330	-0.300	1.780
BIO	723	6.424	0.884	2.540	7.700
IQ	723	1.859	0.108	1.210	1.990
GDP	723	1.272	0.100	0.440	1.610
TO	723	1.958	0.213	1.530	2.610
PD	723	2.035	0.380	1.210	3.933

Table 3 Correlation Matrix.

Variables	TO	PD	IQ	GDP	BIO
TO	1.000				
PD	0.225	1.000			
IQ	0.112	0.842	1.000		

GDP	0.135	0.482	0.105	1.000	
BIO	0.585	0.406	0.123	0.437	1000

Unit root validation was applied and showed in Table 4. The findings from Levin, Lin and Chu (LLC) and Im, Pesaran and Shin (IPS) examinations claim that most of the indicators shall be considered as I (1), since most of them turned into stationary after applying 1st difference. As a result, panel approach for example fixed effect estimator and random effects estimator are acceptable. Having recognized the configuration of incorporated of the determinants, the research then investigated the presence of long-run relationship between the variables. The long-run validation was performed applying Pedroni residual cointegration examination. Table 5 shows the findings of the two validations. Pedroni (1999) recommended two different residual validations, specifically: within and between dimensions. The within dimension test contains 4 sub-examinations- panel-v, panel-rho, panel PP and panel ADF statistics. While the between dimension include 3 sub-examinations- group rho, group PP and group ADF statistics. The null-hypotheses of all the 7 statistical validations from both within and between dimensions show absence of cointegration. Disapproval of the null-hypothesis refers to presence of long-term correlation. It can be showed that from Table 5, 4 out of the 7 Pedroni examination are statistical significant, therefore, the null-hypothesis is disapproved. It suggests presence of long-term correlation between the indicators. This conclusion is according on the recommendation by Pedroni (1999), who endorse to derive about the presence of cointegration in Pedroni validation, panel ADF and group ADF statistics have to be fundamental. Likely, panel ADF and group ADF statistics are statistically significant (see Table 5).

Table 4 Panel Unit Root examination results for the EU28 members.

Variable	Difference		First Difference	
	LLC	IPS	LLC	IPS
FD	−14.925***	−16.871***	−15.874***	-16.177***
	(0.000)	(0.000)	(0.000)	(0.000)
BIO	−10.699***	−14.275***	−7.846***	−12.360***
	(0.000)	(0.000)	(0.000)	(0.000)
IQ	−10.834***	−13.747***	−8.267***	−12.192***
	(0.000)	(0.000)	(0.000)	(0.000)
GDP	−19.553***	−22.550***	−15.128***	−19.389***
	(0.000)	(0.000)	(0.000)	(0.000)
TO	−16.590***	−16.474***	−13.279***	−13.674***
	(0.000)	(0.000)	(0.000)	(0.000)
PD	-9.502***	-16.044***	-10.382***	-15.970***
	(0.000)	(0.000)	(0.000)	(0.000)

- Note: Values in parentheses are *p*-values. *p < .10, **p < .05, ***p < .01

- Levin, Lin & Chu test (LLC), and Im, Pesaran, and Shin W-stat test (IPS).

Table 5 Panel Co-Integration examination results for the EU28 members during

Dependent Variable: Forest Degradation		
Table Header	Without Trend	With Trend

Pedroni Residual Co-integration Test		
Alternative hypothesis: common AR coefficients. (within dimension):		
Panel v-Statistic	-0.649	−0.785
	(0.7241)	(0.783)
Panel rho-Statistic	2.378	3.003
	(0.991)	(0.998)
Panel PP-Statistic	−6.228***	−4.336***
	(0.000)	(0.000)
Panel ADF-Statistic	−4.126***	−3.428***
	(0.000)	(0.000)
Alternative hypothesis: common AR coefficients. (between dimension):		
Group rho-Statistic	5.074	1.000
Group PP-Statistic	−5.127***	(0.000)
Group ADF-Statistic	−3.986***	(0.001)

- Note: Values in parentheses are *p*-values. *p < .10, **p < .05, ***p < .01

Model 1 presented the impact of bioenergy use under intuitional framework on the forest degradation scale in the EU28 members (both EU-15 and EU-13 countries) starting from 1990 to 2018 (Table 6). Firstly, the authors used the variance inflation factor (VIF < 5) examination to show that there is absence of multicollinearity issue in Model 1 (VIF = 1.37). Thus, the authors applied Breusch & Pagan Lagrangian Multiplier (BPLM) examination for Model 1, and the finding points to that the BPLM examination is significant at the 1 percent statistical scale and that the p-value of the BPLM examination (= 0.000) is lower than 1 percent. This refers to the findings that

the RE estimator is more suitable than the Pooled OLS estimator because of the individual criteria influences in the used data. Following that, we implemented a Hausman Fixed examination to select whether FE or RE estimators, and the results showed that the p-value is significant at the 1 percent statistical scale because the p-value is lower than the significant scale (1 percent), driving the authors to decline the null-hypothesis. This implies that RE estimator is inappropriate and to conclude that the FE estimator criteria to be recognized and adopted by LSDVC examination processes a biased evaluation of the coefficients. The influence of bioenergy use indicator on forestry destruction was not estimated in the 3 models. The removal of the bioenergy consumption was took place to prevent the issue of collinearity due to employing more than one associated bioenergy use variables in one model. Thus, the authors applied a single good governance variable and the intervention factor among good governance and bioenergy use were integrated.

In Table 6, Panel FE estimator was then implemented and Model 1 presents its findings along with the findings of RE, pooled OLS and LSDVC estimators. This research concentrates on the finding of FE estimator. While the outcomes of RE, pooled OLS and LSDVC estimators contribute as validations tests. The FE estimator finding shows that the interaction bioenergy use variable is negatively and significantly pertaining to forest degradation at 5 percent scale. This suggest that a raise in bioenergy use within institution framework can reduces forest degradation in the EU-28 region. Exactly, 1 percent rise in bioenergy use will have 0.015% reduction in forest degradation. This outcome is align with Sulaiman et al. (2017). This points to that efficient governance and institutions may help in mitigating forest destruction due to bioenergy use.

As expected, the FE model finding reveals that population density had a significant and positive impact on the forest degradation at 1 percent statistical level. Specifically, 1 percent increase in

population density will increase the forestry degradation by 0.30 percent. This is in line with the prior prediction of earlier research Jorgenson & Clark (2013) which points that population density lead to increase in environmental degradation. This can be derived from the actuality that a raise in population increases depletion of the natural resource accessible, driving to high rates of ecological contamination.

Model 1 result shows that trade openness had a statistically significant and positive impact on the forest degradation at 5% level. Precisely, 1% raise in trade openness will lead to 0.11% raise in the forestry degradation in EU28 countries. This is confirm with the anticipation of earlier research Adu and Denkyirah (2017) which indicates that trade openness lead to increase in natural resource degradation. Once the borders of countries unlocks for free import and export, the potential of experiencing natural resource depletion is larger than in countries that does have taxation trade system for import and export.

Table 6 Summary of the panel regression Model 1 for the EU-28 members.

Model 1. Panel Data Analysis Evaluation for EU-28 Members 1990–2018				
Table Header	Pooled OLS	Random Effect	Fixed Effect	LSDVC
Constant	1.927*** (0.000)	1.077*** (0.000)	0.538*** (0.000)	-
BIO*IQ	-0.183*** (0.000)	-0.029*** (0.000)	-0.015*** (0.027)	-0.011* (0.073)

IQ	-0.407***	-0.091***	-0.031	-0.011
	(0.000)	(0.008)	(0.329)	(0.710)
GDP	0.093	0.179***	0.007	0.004
	(0.156)	(0.000)	(0.527)	(0.675)
TO	0.063	0.002	0.111***	0.074***
	(0.105)	(0.862)	(0.000)	(0.000)
PD	-0.460***	1.077	0.301***	0.223***
	(0.000)	(0.170)	(0.000)	(0.000)
R-Squared	0.722	0.176	0.582	-
F-Statistic	373.26***	128.91***	35.75***	-
	(0.000)	(0.000)	(0.000)	
Breusch-Pagan LM Test	8331.84 (0.000)			
Hausman Test		161.94 (0.000)		

- Note: Values in parentheses are *p*-values. *p < .10, **p < .05, ***p < .01

Model 2 showed the influence of bioenergy use under intuitional framework on the forest degradation level in the EU15 countries for the 1990-2018 period (see Table 7). Firstly, the authors implemented the VIF examination to give a justification for the absence of multicollinearity issue in Model 2 (VIF = 1.45). Then, the authors applied BPLM examination for Model 2, and the authors discovered that the BPLM examination is significant at the 1 percent statistical scale. This points to the finding that the RE estimator is further suitable than the Pooled OLS estimator

because of the individual criteria impacts in the implemented data (see Table 7). Next, he authors implemented a Hausman Fixed examination and the results driving the authors to decline the null hypothesis. This index directs the authors to derive that RE estimator is inappropriate and to discover that the FE estimator peculiarities to be suggested and adopted by LSDVC examination gives a biased evaluation of the coefficients.

In Table 7, Panel FE estimator was then applied and Model 2 presents its outcome along with the outcomes of RE, pooled OLS and LSDVC estimators. This research concentrates on the finding of FE estimator. While the outcomes of estimators RE, pooled OLS and LSDVC participate as validation tests. The estimator FE finding implies that the interaction bioenergy use variable is negatively and significantly pertaining to forest degradation at 10 percent scale. This suggest that a raise in bioenergy use in coordination with related government institutions can reduces forest degradation in the EU-15 members. Exactly, 1 percent mount in bioenergy use will give 0.014% reduction in forest degradation. This result is align with Sulaiman et al. (2017). This implies that efficient energy policies can boost the bioenergy use and decrease forest degradation in EU-15 countries.

As expected, the FE model finding reveals that institutional quality had a statistically significant and negative effect on the forest degradation at 1% level. Specifically, 1% increase in institutional quality will decrease the forestry degradation by 0.219%. This is in line with the previous research Sulaiman et al. (2017) which indicates that institutional quality lead to decrease in forest degradation. This implies that the development of the institutional performance and align with high standard implementation should assist to decrease forest destruction.

Model 2 result shows that trade openness had a statistically significant and positive impact on the forest degradation at 5% level. Precisely, 1% raise in trade openness will have 0.05% raise in the forestry degradation in EU15 countries. This is align with the a-priori expectation of earlier study Adu and Denkyirah (2017) which refers trade openness mounts resource degradation by mounting economic development effectiveness for example producing as alternative of importing energy efficacious technology.

In Table 7, the findings of Model 2 indicates that GDP had a significant and positive influence on the forest degradation at 5% statistical level. Accurately, 1% incline in GDP will show 0.40% increase the forestry degradation in EU15 countries. This is aligned with the finding of earlier research Apergis et al. (2010) which shows that because of the reality that a nation's economic growth only increase as a consequences of the generation of products which drive to enhanced natural resource drain and contamination.

As predicted, the FE model finding reveals that population density had a significant and positive influence on the forest degradation at 1% statistical level. Exactly, 1% increase in population density will increase the forestry degradation by 0.77%. This is coherent with the earlier study Jorgenson & Clark (2013) which refers that higher population density lead to rise in environmental degradation. This can be derived from the fact that a raise in population intensity lead to increase stress on the available resource for final consumption, leading to high risk of environmental degradation.

Table 7 Summary of the panel regression Model 2 for the EU15 developed members

Model 2. Panel Data Analysis Evaluation for the EU15 members 1990–2018				
Table	Pooled OLS	Random Effect	Fixed Effect	LSDVC

Header				
Constant	1.673*** (0.000)	1.118*** (0.000)	0.158 (0.325)	-
BIO*IQ	-0.286*** (0.000)	-0.009*** (0.266)	-0.014* (0.057)	-0.225*** (0.000)
IQ	-0.922*** (0.000)	-0.260*** (0.000)	-0.219*** (0.000)	-0.028 (0.158)
GDP	0.080 (0.459)	0.013 (0.513)	0.040** (0.015)	0.005 (0.739)
TO	0.153*** (0.001)	0.102*** (0.000)	0.054** (0.013)	0.003 (0.632)
PD	0.302*** (0.000)	0.243*** (0.000)	0.778*** (0.000)	0.014*** (0.000)
R-Squared	0.728	0.432	0.431	-
F-Statistic	211.10*** (0.000)	173.80*** (0.000)	79.68*** (0.000)	-
Breusch-Pagan LM Test	3300.93 (0.000)			
Hausman Test		519.75 (0.000)		

- Note: Values in parentheses are *p*-values. *p < .10, **p < .05, ***p < .01

Model 3 showed the influence of bioenergy use within intuitional framework on the forest degradation level in the EU19 countries starting from 1990 to 2018 (Table 8). Firstly, the authors implemented the VIF examination to show that there is absence of multicollinearity issue in Model 3 (VIF = 2.13). Following that, the authors applied BPLM examination for Model 3, and this drives to the finding that the RE estimator is further suitable in comparison with the Pooled OLS estimator because of the individual criteria influences in the used dataset (see Table 8). Next, the authors implemented a Hausman Fixed examination and the findings leaded the authors to derive that RE model is unsuitable and to conclude that the FE model peculiarities to be considered (see Table 8). Panel FE estimator was then implemented and Model 3 presents its finding along with the findings of estimators RE, pooled OLS and LSDVC. This research concentrates on the finding of FE estimator. While the outcomes of estimators RE, pooled OLS and LSDVC participate as validation tests.

In Table 8, the estimator FE finding argues that the interaction bioenergy use variable is negatively and significantly pertaining to forest degradation at 1 percent statistical scale. This suggest that a raise in bioenergy use under institution framework can reduces forest degradation in the EU13 members. Specifically, 1 percent mount in bioenergy use will have 0.022% reduction in forest degradation. This result is in line with former study Sulaiman et al. (2017). This suggest that institutional quality may help in decreasing forestry destruction in cooperation with bioenergy use. This implies that in EU13 countries, the supply and demand of bioenergy industry associated with efficient governance can both boosts the confidence for having effective sustainable strategy of the EU13's forestry resource and timber sites. Also, this can implies the role of effective institutions in regards of giving an efficient substitutional and economical bioenergy output for bioelectricity, bio-heat, bio-cool and biofuel sectors will go along way in leading EU residents

apart from the use of wood fuel energy. This will consequently decrease stress on forestry resources. Institutional quality in this situation can additionally seek subsidizing substitutional biofuel that is friendly environment and having it available to the rural territories.

Model 3 result shows that trade openness had a statistically significant and positive impact on the forest degradation at 1% level. Precisely, 1% raise in trade openness will give 0.07% raise in the forestry degradation in EU13 countries. This is aligned with the earlier anticipation of previous research Adu and Denkyirah (2017) that trade openness adds more ecological degradation for underdeveloped members in compare with developed countries due to the weakness of environmental taxation system.

Table 8 Summary of the panel regression Model 3 for the EU13Underdeveloped members

Model 3. Panel Data Analysis Evaluation for the EU13 members 1990–2018				
Table Header	Pooled OLS	Random Effect	Fixed Effect	LSDVC
Constant	1.872*** (0.000)	1.764*** (0.000)	1.099*** (0.000)	-
BIO*IQ	-0.131*** (0.000)	-0.035*** (0.003)	-0.022* (0.060)	-0.011 (0.358)
IQ	-0.360*** (0.000)	-0.054 (0.269)	-0.001 (0.978)	-0.008 (0.860)
GDP	0.089 (0.180)	0.004 (0.768)	0.007 (0.637)	0.005 (0.725)

TO	0.188*** (0.006)	0.032 (0.238)	0.070*** (0.008)	0.062** (0.025)
PD	0.687*** (0.000)	0.262*** (0.000)	0.023 (0.782)	0.006 (0.940)
R-Squared	0.849	0.854	0.676	-
F-Statistic	357.53*** (0.000)	24.90*** (0.000)	6.06*** (0.000)	-
Breusch-Pagan LM Test	3266.34 (0.000)			
Hausman Test		53.43 (0.000)		

- Note: Values in parentheses are *p*-values. *p < .10, **p < .05, ***p < .01

The assessment of FE model was evaluated by estimators Pooled OLS, RE and LSDVC. It should be noticed that the coefficients given from estimator RE own the similar sign and significant scale with these resulted in FE estimator. This presents that findings from FE estimator are validated and therefore, can be suitable for conclusion. The coefficients from Pooled OLS equivalently present the similar sign with these from FE estimator, except a small variance in significant scale. Although, the assessment of FE estimator can be considered to be validated and absence of endogeneity and serial relationship issues. To evaluate the influence of bioenergy use on forest degradation in EU28 members according to their development status, the members were segregated into two categories; developed members (EU15) and underdeveloped members

(EU13), see Appendix C. Table 7 exhibits the regressed finding for the influence of bioenergy use within framework of institutional goodness on forestry destruction in the EU15 countries. Whereas Table 8 shows the finding of the evaluated influence of bioenergy use within institutional goodness framework on forestry destruction in EU13 countries. The findings from both Table 7 and Table 8 suggest that bioenergy use under institutional goodness framework has significant negative impact on forest degradation. The findings more denote that the significant negative influence of bioenergy use on forest degradation is greater in EU15 members than in the EU13 members. Specifically, the weight of the influence are – 0.014 and – 0.022 for EU15 and EU13 members, respectively. This implies that a remarkable mitigation in forestry destruction can be implemented in EU15 members applying bioenergy use and intuitional quality than in EU13 members.

Conclusion and Policy Implications

The study was conducted to answer the following research question: What is the effect of bioenergy use within institutional framework on forest degradation in EU28 countries in the period 1990–2018? To answer that question, an empirical model was developed. The model was used to explore the impact of interaction bioenergy use and institutional goodness on forestry destruction in EU28 countries during 1990 - 2018. FE model was employed to achieve this objective. While the findings of estimators RE, pooled OLS and LSDVC participate as validation tests. The results indicated that bioenergy use within institutional framework and institution quality indicators significantly mitigates forestry destruction at EU28, EU15, and EU13 scales. Oppositely, the trade openness, GDP and population density indicators were significant in decreasing destruction of forestry in EU28, EU15, and EU13 scales. Moreover, the intervention term among bioenergy use

and institutional quality appeared negative and significant coefficients in regards to forestry destruction at EU28, EU15 and EU13 scales. Thus, the effect of bioenergy use on mitigate the forest degradation is greater in EU15 members than in the EU13 members. Adopting new technologies with higher government effectiveness actions in EU13 (underdeveloped) countries will be a handy instrument to achieve higher bioenergy production and mitigate more forest degradation.

The policy implications of this research were explained as the following. Firstly, since bioenergy use was analytically confirmed to show a negative influence on forestry destruction, decision makers in EU28 countries can emphasize their obligations to supplying sufficient and economical bioenergy output in order to decrease the consumption of biomass wood for energy production. Secondly, the institutional quality indicator in EU15 developed members, as revealed in Model 2 by the research, may highly decrease forestry destruction. Thus, further effort needs to be allocated for boosting institutional quality in EU13 underdeveloped members to prevent more degradation of forestry lands. Thirdly, as elaborated by the research, the interaction of bioenergy use with efficient institutions should be a magnificent tool for mitigating forestry destruction in the EU28 members. Thus, specific sustainability criteria are being adopted beside the modern regulations that lead to a mounted implementations of bioenergy end-uses (including heating/cooling and electricity) due to the promotion of renewable energy in EU28 countries. Last, policy makers in EU13 countries need to create awareness of the economic principle that “cleaner earns, polluter pays” suggests that carbon storage should be subsidised and emissions from forest bioenergy should be fully accounted for and controlled through appropriate means.

Author's contribution section

All three authors contributed to writing, estimation, analysis, and revision of the paper.

Declaration of competing for interest

I wish to declare that there is no conflict of interest.

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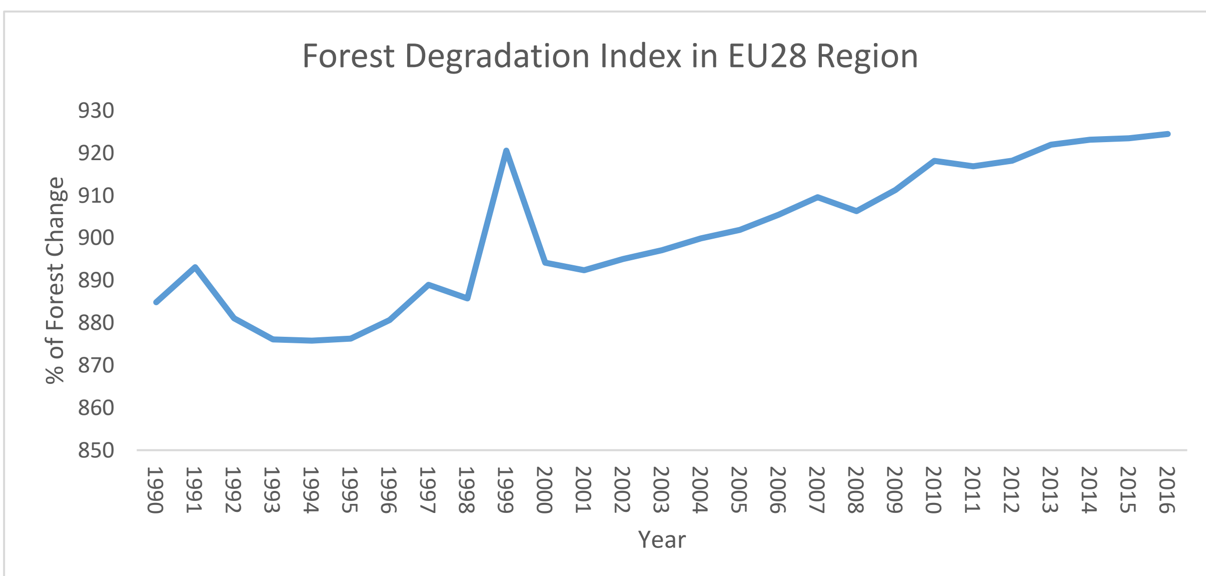
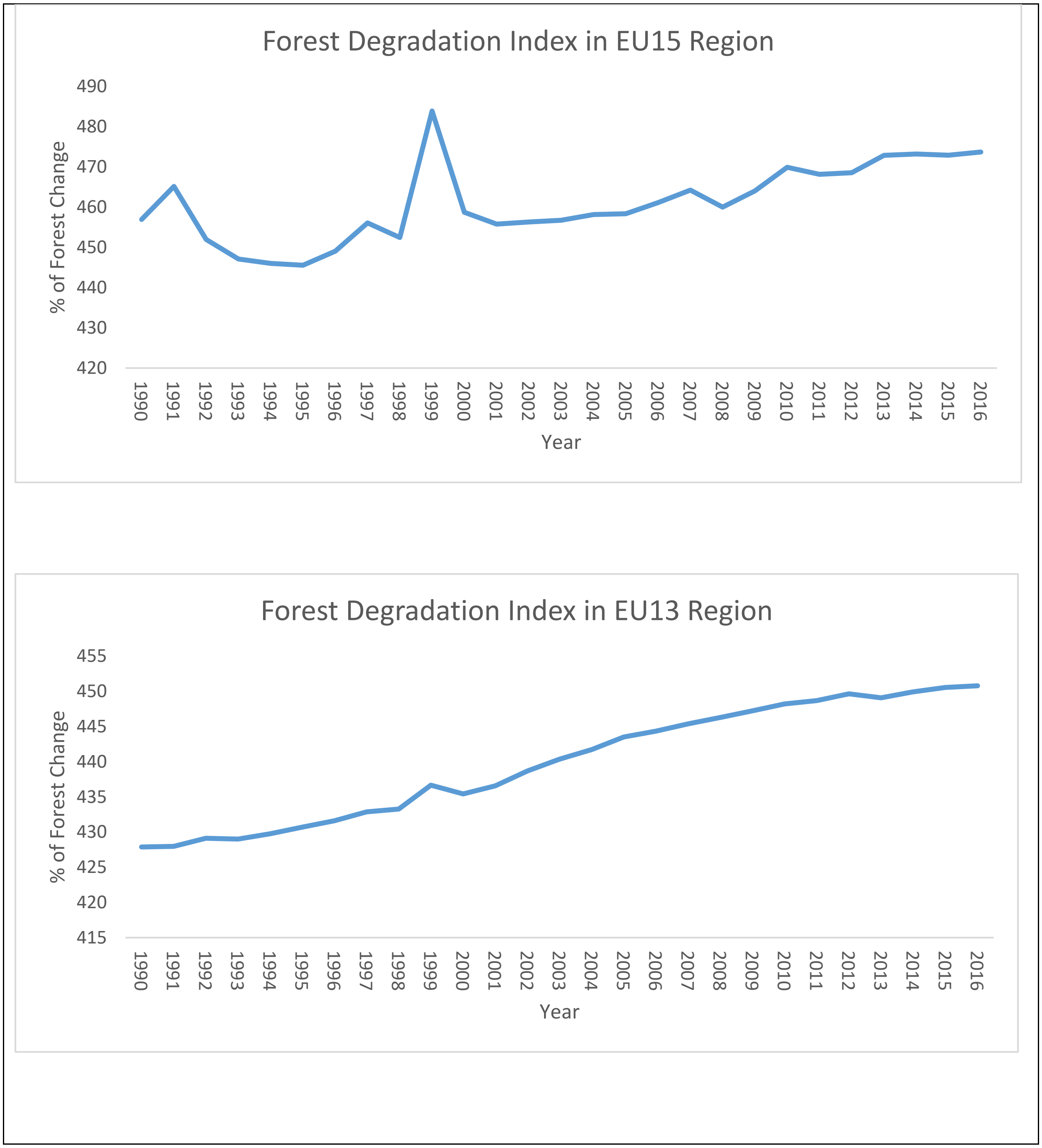
Appendices

Appendix A

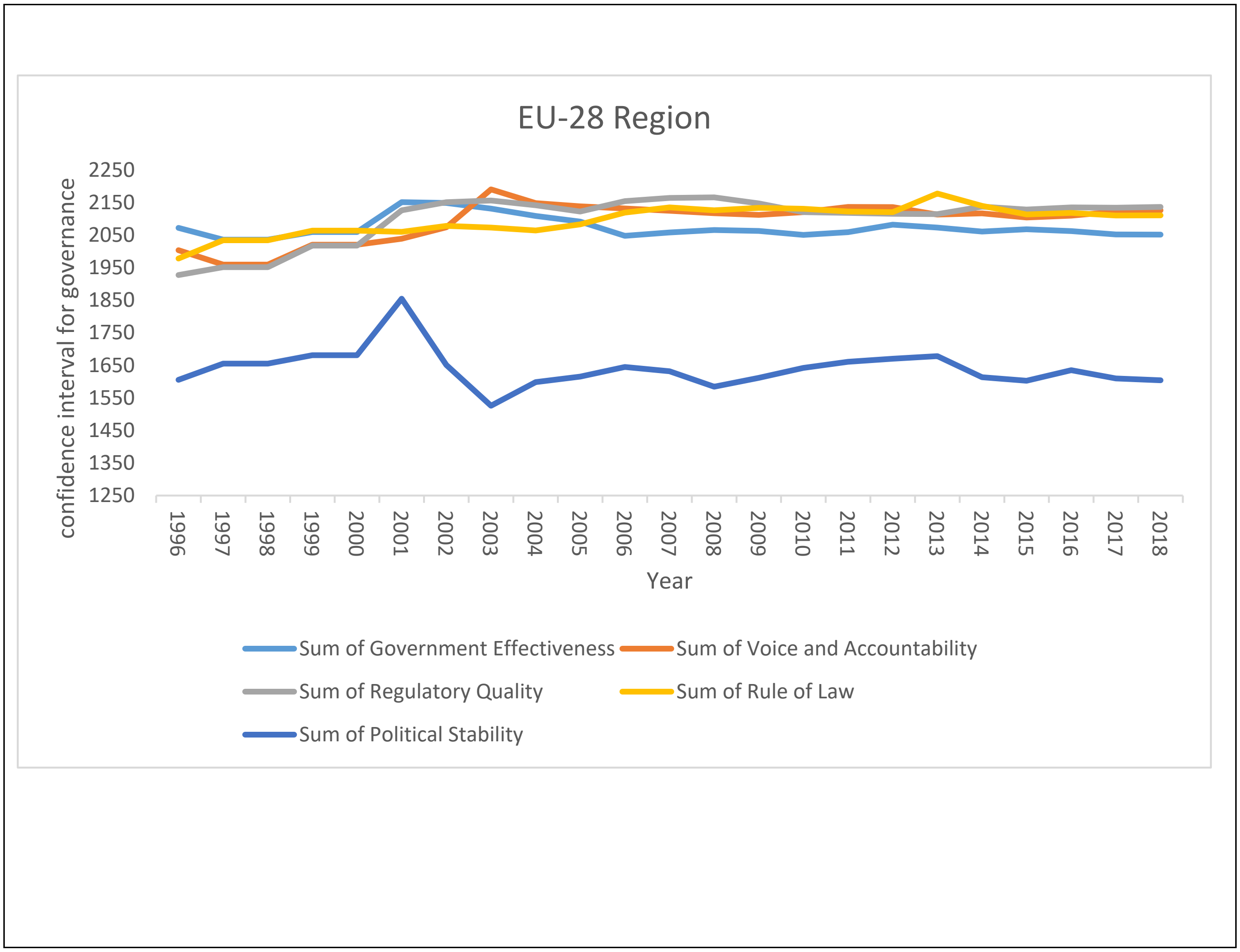
Comparisons of Forest Degradation Indicator in Underdeveloped (EU13) and Developed (EU15) Countries in EU-28 Region during the 1990-2016 period.

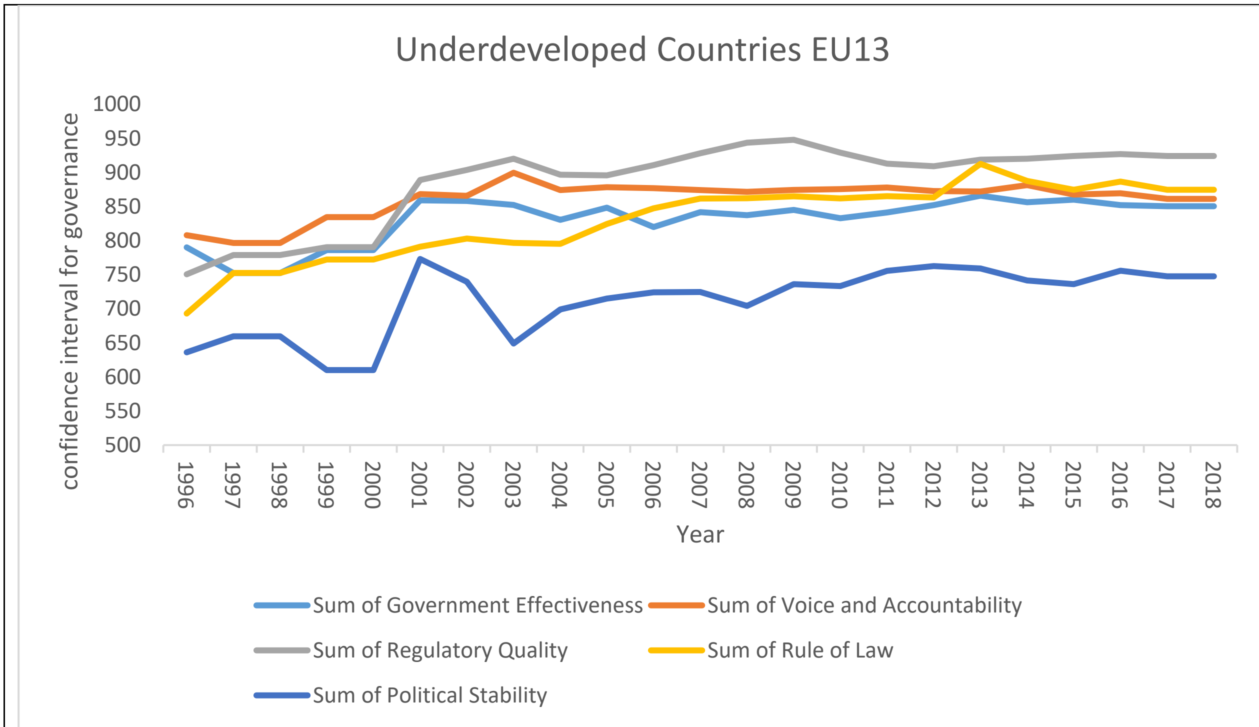


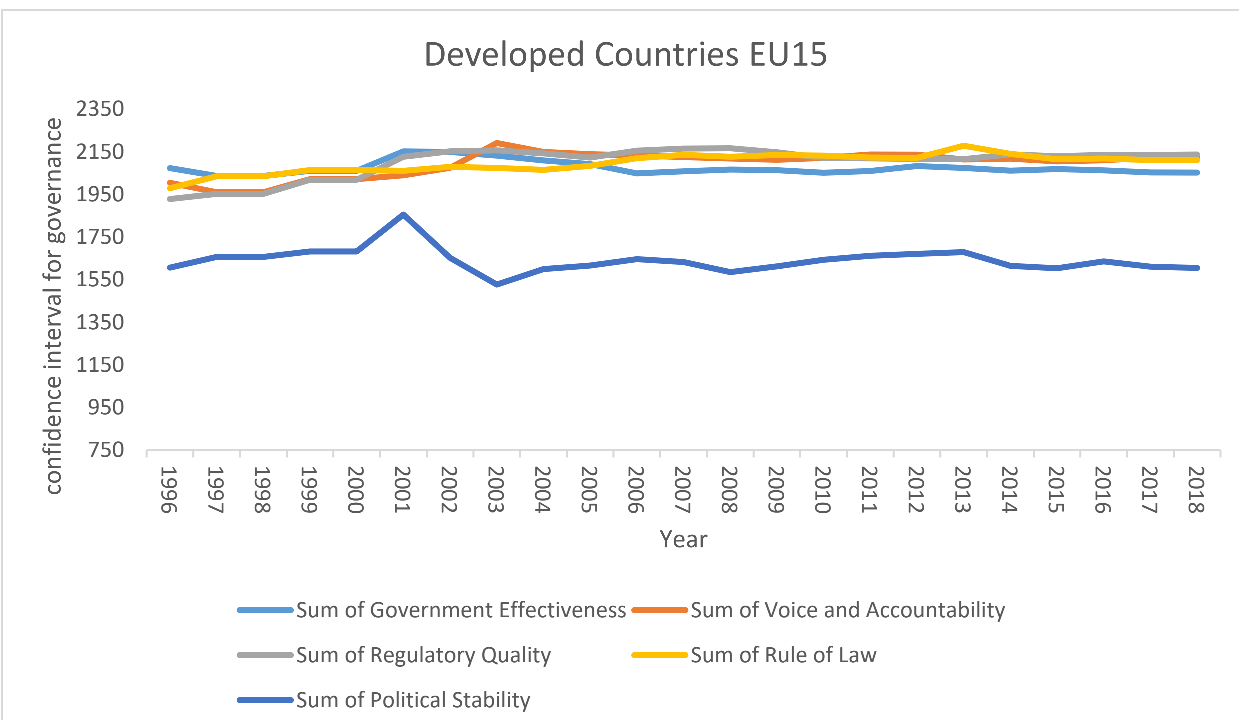

Forest Degradation Index in EU15 Region
490
480
470
460
450
440
430
420
% of Forest Change
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year
Forest Degradation Index in EU13 Region
455
450
445
440
435
430
425
420
415
% of Forest Change
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

Appendix B

Comparisons of World Governance Indicator (WGI) in Underdeveloped and Developed Countries in EU-28 Region during the 1996-2018 period.




Underdeveloped Countries EU13
confidence interval for governance
1000
950
900
850
800
750
700
650
600
550
500
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
Year
Sum of Government Effectiveness
Sum of Voice and Accountability
Sum of Regulatory Quality
Sum of Rule of Law
Sum of Political Stability


Developed Countries EU15
confidence interval for governance
2350
2150
1950
1750
1550
1350
1150
950
750
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
Year
Sum of Government Effectiveness
Sum of Voice and Accountability
Sum of Regulatory Quality
Sum of Rule of Law
Sum of Political Stability

Appendix C

List of the EU-28 Region Member Countries

European Union (EU28) Region			
Developed Countries (EU15)		Underdeveloped Countries (EU13)	
Member Countries	Year	Member Countries	Year
Austria	1995	Bulgaria	2007
Belgium	1958	Croatia	2013
Denmark	1973	Cyprus	2004
Finland	1995	Czech	2004
France	1958	Estonia	2004
Germany	1958	Hungary	2004
Greece	1981	Latvia	2004
Ireland	1973	Lithuania	2004
Italy	1958	Malta	2004
Luxemburg	1958	Poland	2004
Netherlands	1958	Romania	2007
Portugal	1986	Slovakia	2004
Spain	1986	Slovenia	2004
Sweden	1995		
United Kingdom	1973		

Source: European Union Official Website (www.Europa.eu)