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Forest Area: Old and New Factors That Affect Its Dynamics

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Abstract: The analysis of the nexus between environmental degradation and economic progress has focused on polluting emissions. However, the forest area plays a significant role in achieving the Sustainable Development Goals (SDG) related to the environment. Forest area is directly related to air and water quality and the absorption of polluting residues. At the same time, in recent decades, economic progress processes have been internationalised and knowledge has improved in the context of persistent income inequality. The objective of this research is evidence that economic progress is destroying nature; for this, we use forest area as a measure of environmental quality. The nexus between the two variables is moderated by the globalisation KOF index, income inequality, and knowledge. Using non-linear methods, we find a threshold effect in globalisation, inequality, and economic progress. This result implies that before the threshold, the impact of the covariates differs from the impact after the threshold, generating findings different from those shown by the previous environmental literature. The results reveal that after a threshold, the impact of economic progress on forest area is negative. This fact reveals that the main obstacle to achieving environmental sustainability is in the least developed countries, where inequality and globalisation reinforce the degradation of the forest area. We find that knowledge is a mechanism to prevent deforestation, particularly in more developed countries. Those responsible for pro-environmental policy should promote global strategies to prevent economic progress from being based on the destruction of nature.

Keywords: forest area; economic progress; globalisation index; knowledge

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1. Introduction

In formulating the Sustainable Development Goals for 2030, environmental sustainability is necessary to achieve economic sustainability [1]. However, balancing economic and environmental issues is a considerable challenge for environmental policymakers, particularly in developing countries [2]. Unfortunately, what we know about the nexus between environmental quality and economic progress has focused mainly on analysing the factors that determine polluting gas emissions [3–6]. However, in the logic of the Environmental Kuznets Curve (EKC) [7], developed countries have at their disposal a greater variety of options and resources to promote environmental sustainability. On the other hand, in developing countries, the destruction of the forest area for agricultural, livestock, and mining activities is a frequent necessity to reach subsistence levels [8]. In addition, some factors pressure the demand for consumer products due to urban population growth, consumerism patterns, and the increase in the population's purchasing power [9]. This fact is associated with increases in the demand for natural resources that reduce the forest area necessary for various environmental processes [10]. The empirical evidence in this regard shows that the expansion of the agricultural frontier, livestock, and the use of wood as a raw material has caused the loss of forest land, causing the disappearance of half of the world's forests [11]. According to the Food and Agriculture Organization of the United Nations (FAO) and the United Nations Environment Program (UNEP), since 1990, 420 million hectares of forest have been lost due to the change in land uses even though the rate of deforestation has decreased in the last three decades. Nowadays, the deforestation rate is estimated to be 10 million hectares per year, up from 16 million hectares per year in the 1990s. The area of primary forests worldwide has decreased by more than 80 million hectares since 1990. More than 100 million hectares of forests are currently being affected by forest fires, pests, diseases, invasive species, droughts, and adverse weather phenomena conditions. Most of the loss of forests has occurred in developing or emerging countries due to the lack of policies to prevent deforestation and the encouragement of forest clearing by governments [12].

The loss of primary forests, humid tropical forests, and mature tropical forests have also experienced significant losses, reducing biodiversity and the capacity to absorb waste and polluting residues [12]. In addition, the reduction in forests implies an increase in carbon dioxide emissions and a loss of land cover. Forests are natural carbon sinks with a great capacity to absorb polluting gases from the atmosphere and mitigate climate change [13,14]. Forests absorb 7.6 billion net metric tons of carbon dioxide per year [15]. The net variation of the forest area presents significant differences that can be associated with the levels of income or economic and social progress of the regions. Several indicators suggest that the loss of forest area is more dramatic in developing countries. For example, Africa recorded the largest net loss of forest area in 2010–2020, with 3.94 million hectares per year. The second region with the highest deforestation in South America with 2.60 million hectares per year [12]. This fact results from the commercial felling of trees and the change of land use for agriculture, livestock, or legal or illegal mining. In contrast, Asia had the largest net increase in forest area in 2010–2020, followed by Oceania and Europe. Ecological restoration is the result of public policies of the states and of strategies of international organisations that seek to mitigate the loss of forests and conserve their areas [16].

Studies on the loss of forest area have focused on analysing the causes of environmental degradation using the loss of vegetation cover and the deforestation rate as a proxy [17–19]. Most research has focused on verifying the EKC hypothesis formalised and initially tested by Grossman and Krueger [20]. The EKC provides an informed explanation of the inverted-U-shaped relationship between economic progress and environmental pollution. The literature that relates forest area and economic progress has partially increased in recent years, which indicates that human activities have a negative impact on the forests [8,21–24].

The literature developed to date has systematically omitted the non-linear analysis between the two variables. Theoretically, the impact of economic progress before/after an equilibrium point (also known as a threshold) should be heterogeneous depending on the industrial structure. Therefore, the instrumental framework of threshold regressions is well suited with several advantages over other methods. Analysing the relationship between environmental pollution and economic activities using linear methods generates biased results and erroneous policy lessons. In addition, several countries are experiencing a clear trend towards economic and social openness, which is reflected in the number of cooperation and integration agreements and trade and capital flows. This fact raises the question of whether economic activities' effect is heterogeneous before and after a threshold of globalisation. In the same direction, in developing and emerging countries, how income is distributed can determine the population's behaviour with regard to caring for nature. We hypothesise that rural inhabitants of countries with greater inequality will be more likely to have a behaviour that is not very friendly to the environment. Several structural factors in the economies have shown cracks in the current development model. Persistent inequality is one of the most visible cracks in the capitalist development model.

Consequently, in this research, we answer whether the effect of regressors on forest area is homogeneous throughout the distribution. We propose the hypothesis that the unequal countries are those that most destroy the forest area.

The threshold regression strategy is reinforced using the quantile regressions of Chernozhukov et al. [25]. The existence of thresholds in the next variables: economic progress, globalisation index, income inequality, and knowledge support the adoption of this methodological strategy as a sensitivity analysis. In the previous literature, the nexus between vegetation cover and economic activities have been moderated by population size and energy consumption [26–32]. These investigations use linear methods in a relationship built on assumptions that explain the existence of a non-linear form between the variables. Researchers such as Salahodjaev [33] highlight that purely internal factors cannot explain deforestation, but it is necessary to include aspects that reflect the internationalisation of economic progress. Various researchers use a wide range of approaches and demonstrate a significant effect of globalisation on deforestation [34,35]. In understanding the factors that explain the dynamics of deforestation, it is necessary to include the role of knowledge as an endogenous factor that leads to better pro-environmental policies. Knowledge facilitates society's awareness of the importance of forest areas in the biological processes of adaptation and absorption of pollutants caused by human activity.

The rest of this document is organised as follows. Section 2 presents the review of the previous literature. Section 3 describes the characteristics and data sources. Section 4 presents the econometric strategy. Section 5 reports the results and contrasts them with the previous literature. Finally, the last section presents the conclusions and policy implications derived from the research.

2. Literature Review

Based on a framework that Kuznets [7] originally developed to analyse inequality and economic growth, some modifications have been made mainly in the environmental sphere. According to Grossman and Krueger [20,36] and Stern [37], the relationship between the level of per capita income and the deterioration of the quality of the environment is represented by an inverted U-shaped curve. In this sense, most of the research has modelled the relationships between emissions and income [3,38–43], generating a great debate on the validity of the ECK for developing countries, whose main economic activity is based on the primary-extractives activities [44,45].

The world demand for goods and services is directly related to the demand for natural resources [10]. The deforestation rate is proposed as the variable of environmental degradation [8,17–19,46–52] and the change in vegetation cover as well as the forest area [10,21,32,53]. Likewise, the theoretical models that explain the expansion of agricultural lands can also be compatible with an EKC for deforestation [54]. The premise of this relationship is similar to the ECK of emissions, where initial levels of economic growth are associated with an increasing rate of forest loss, subsequently and, after reaching a certain level of development, there is an inflection point from the which the rate of deforestation begins to decline. Finally, in the long term, the level of forest declines turns negative for further economic development. This behaviour is also associated with the fact that forests begin to recover and increase their resilience [55].

Although the inclusion of forest variables related to ECK has been applied since the 1990s, the literature is still scarce. Shafik and Bandyopadhyay [17] conducted the first evaluation of annual and total forest loss, the first for 66 countries between 1962 and 1988, the last for 77 countries from 1961 to 1988. Through econometric panel techniques, they examined a linear, quadratic and cubic model. The signs of the independent variables were consistent with the EKC, but their coefficients were not statistically significant. Subsequently, Munasinghe [56] developed a static model showing that removing subsidies for timber exports could help relieve pressure on tropical forest reserves, laying the foundation for an EKC for deforestation.

Culas [57] estimates the EKC using deforestation for geographic regions of Latin America, Africa, and Asia between 1970–1994. Results based on panel data analysis from 43 countries provide evidence that the inverted U-shaped EKC is suitable for Latin America and Africa, while the U-shaped EKC applies to Asia. More recent studies have incorporated developed and developing countries into the analysis. Along the same lines, Joshi and Beck [21] analyse the relationship between forest area and GDP, demonstrating the existence of the inverse U-shaped curve only for African countries, while the results for OECD countries show an N-shaped trend. Latin American countries show a similar trajectory, while GDP per capita is not statistically significant for Asia. Curesma et al. [56], using satellite data on forest areas along national borders in 189 countries, found that per capita income is the strongest determinant of differences in the transboundary forest area. Furthermore, they show that the marginal effect of per capita income growth on forest area is strongest in the early stages of economic development and weakens in more advanced economies. These studies present some of the strongest evidence to date for the existence of at least half of the ECK of deforestation.

Andreé et al. [10] evaluate the relationship between environmental quality and income, for which they use data on tree cover loss, air pollution concentrations, and carbon emissions for 95 countries. The results find successive inverted U-shapes in tree cover loss, air pollution, and carbon intensities, followed by a J-shape in per capita carbon economic progress. Recent studies such as Benedek and Fertő [24] analyse the relationship between development and the increase in forest area in 72 countries between 1990 and 2015. Their findings support the existence of an N-shaped curve in the context of recovery forest, which implies that the quality and quantity of new forests in middle-income countries has increased the least. For their part, Ponce et al. [32] examine the causal link between renewable energy consumption, GDP, GDP2, the price of non-renewable energy, population growth, and forest area in the countries of high, middle, and low income. Their results justify the existence of a joint long-term relationship between the variables included for middle-income and low-income countries. Furthermore, they conclude that the speed of adjustment is slow when the forest area is not at its equilibrium level. However, the research does not show evidence of the equilibrium relationship in the short term.

For his part, Salahodjaev [33] mentions that deforestation rates cannot be explained only by internal factors, but variables such as globalisation have a significant impact on deforestation. For example, for Rudel [58], globalisation has spatially and temporally varied effects on forest areas in the tropics. In other words, globalisation destroys primary forests in some places and at the same time generates secondary growth and scrub in other places. In the case of forest area change in Southeast Asia and Africa, globalisation negatively influences biodiversity conservation and carbon sequestration. More recent studies such as Yameogo [35] examine the effect of globalisation and urbanisation on deforestation in Burkina Faso during 1980–2017. The study used the ARDL model and the Toda-Yamamoto causality approach. The empirical findings affirmed that globalisation, urbanisation, and agricultural lands have a positive and significant effect on deforestation in the long term. Furthermore, Granger's causality approach confirmed a two-way association between deforestation and urbanisation and globalisation and agricultural lands.

Regarding the impact of knowledge on deforestation, the literature is still limited. Most of the studies have focused on analysing the effect of education on deforestation rates. For example, Godoy et al. [59] concluded that for a community in the Honduran tropical forest, each additional year of education reduces the probability of cutting down the virgin forest by approximately 4% and reduces the area felled by 0.06 ha/family every one year. Thus, they show that the estimates of the social return rate of education for the indigenous populations of Latin America are high. Other studies such as Salahodjaev [33] show that inequality is negatively related to deforestation for 186 countries during 1990–2010. On average, going from a country with the lowest IQ score (61) to one with the highest score (107.1) is associated with a 1.15 percentage point reduction in the deforestation rate. These few findings allow us to conclude that investing in education leads to a mitigation of environmental degradation. In other words, efforts to combat the environmental problem could be concentrated on a country's human capital and social capital without greatly compromising economic growth rates, mainly for developing countries.

Finally, the econometric results on the existence of an EKC for deforestation have not been conclusive and vary according to the level of development of each country. For example, according to Bhattarai and Hammig [8] and Barbier et al. [23], low-income countries have a relatively low deforestation rate as they do not have the technology to exploit their forests intensively. In the case of high-income countries, they deforest less because the environment is perceived as a valuable resource. Given this, the greatest loss of forests is associated with middle-income countries [24]. In this sense, if the EKC hypothesis were generally verified for all countries, it would imply that economic growth and environmental quality (understood as the persistence or increase in forest area) can coexist.

3. The Data and Statistical Sources

The statistical information used in this research comes from the World Bank [60], Standardized World Income Inequality Database (SWIID), Penn World Table 9.1 (PWT), and KOF Swiss Economic Institute. The dependent variable is forest area in all regressions, and the regressive variables are economic progress, inequality, knowledge, and globalisation KOF (see Table 1). The geographical coverage of the research includes 110 countries globally and a temporal coverage during 1990–2018. According to the World Bank Atlas method, the sample of countries for the study was classified into four groups [60]. Several previous empirical investigations have used carbon dioxide emissions and the ecological footprint as measures of environmental degradation. In this research, the variable that measures environmental quality is forest area for several reasons. First, forest area plays a central role in air quality, the water cycle, and soil quality and determines climate. Second, forest area is a relevant indicator in contexts where industrial development is low and polluting gas emissions do not represent a severe pollution problem. Third, natural forests' economically valuable ecosystem services depend on the level of plant cover available. Fourth, forest area dynamics can reflect the quality and effectiveness of the pro-environmental policies of national and local governments. In general, the land area with forests is an environmental indicator that allows evaluating the state of environmental degradation and contributes with a new way of measuring the environmental and economic sustainability of the countries. The covariates were chosen according to the objective of the research and the previous literature review.

Table 1. Description of variables and data sources.

Variable	Symbol	Definition	Measure	Data Source
Forest area	FA	The forest area includes the land under natural or planted stands of trees of at least 5 m in situ, whether productive or not.	Km	World Development Indicators (WDI).
Economic progress	EP	Economic progress is measured by real gross domestic product divided by the mid-year population.	US dollar per capita	World Development Indicators (WDI).
Inequality	GINI	The GINI coefficient measures the extent to which income distribution between individuals or households in an economy deviates from perfectly equitable distribution.	Index	Standardized World Income Inequality Database (SWIID).

Table 1. *Cont.*

Variable	Symbol	Definition	Measure	Data Source
Knowledge	K	Knowledge in an indicator based on years of schooling and returns to education.	Index	Penn World Table (PWT) 9.1.
Globalisation KOF (index)	GK	Globalisation KOF is an indicator that assesses globalisation's social, political, and economic aspects.	Index	KOF Swiss Economic Institute.

The research hypotheses are listed below:

Hypothesis 1 (H1). *We expect the relationship between product and forest area to be negative, indicating that economic progress increases reduce forest area.*

Hypothesis 2 (H2). *We expect the relationship between income inequality and forest area to be negative. In countries with higher inequality, people may have more incentives to deforest forests for survival.*

Hypothesis 3 (H3). *The relationship between knowledge and forest area is positive. Knowledge should provide sufficient evidence on the importance of forests for air, soil, and water quality, promoting forest conservation.*

Hypothesis 4 (H4). *We hope that the relationship between globalisation KOF and forest area is positive, indicating that if countries have greater economic, social, and political openness, institutional agreements and regulations should prevent deforestation of forests.*

Table 2 reports the descriptive statistics and the partial correlation matrix between the series. The variables form a perfectly balanced panel with 3190 observations over 29 years ($t = 1, 2, \ldots, 29$) and 110 countries ($i = 1, 2 \ldots, 110$). In theory, the problem of deforestation should be a problem closer to the reality of developing countries. However, comparison between levels of development provides lessons for pro-environmental policies that developing countries could adopt. The forest area is more stable within countries than between them, the standard deviation (SD) within countries is 0.96, and it is approximately 2.24. Economic progress shows less variability between countries than within them, the SD between countries is 0.25, which is less than the SD within countries (1.51). In inequality, the dispersion within countries corresponds to 1.67, and between countries is 9.04. Regarding the KOF globalisation index, the SD between countries is 14.35, while the SD within countries is 7.57. Finally, for the knowledge, there is no significant difference between cross-sectional and temporal variability.

Table 2. Descriptive statistics and correlation matrix of variables.

	Forest Area	Economic Progress	Inequality	Knowledge	Globalisation KOF	VIF
Mean	10.58	8.54	38.74	2.52	60.79	
Std. Dev Overall	2.23	1.53	9.16	0.68	16.17	
Std. Dev Between	2.24	1.51	9.04	0.66	14.35	
Std. Dev within	0.96	0.25	1.67	0.19	7.57	
Min.	4.14	5.10	17.50	1.03	22.36	
Max.	15.91	11.63	67.24	4.15	90.98	
N	3190	3190	3190	3190	3190	
N	110	110	110	110	110	
T	29	29	29	29	29	

Table 2. *Cont.*

	Forest Area	Economic Progress	Inequality	Knowledge	Globalisation KOF	VIF
Forest area	1.00					
Economic progress	0.03	1.00				3.77
Inequality	0.14 *	−0.49 *	1.00			1.50
Knowledge	−0.04	0.76	−0.56 *	1.00		4.27
Globalisation KOF	−0.02	0.84 *	−0.52 *	0.79 *	1.00	3.15

Note: * denotes the significance level at 1%.

The values of the VIF column (variance inflation factor) indicate that there are no collinearity problems between the independent series. This result ensures that the coefficients measure the isolated and individual impact of each regressor on the variable vegetation cover. The results of the partial correlation and collinearity test are similar for groups of countries.

4. Econometric Strategy

The analysis of environmental deterioration is of great relevance due to the effects caused by human activity, which can contribute to the restoration or degradation of vegetation [61]. In this sense, the objective of the research is to evaluate the effect of economic growth on environmental deterioration using forest area as a measure. First, we estimate a linear relationship of panel data using Generalised Least Squares (GLS). The dependent variable corresponds to forest area, a function of economic growth as an independent variable. In Equation (1), the fundamental relationship is formalised as follows:

$$\mathrm{FA}_{it} = \beta_0 + \beta_1 \mathrm{EP}_{it} + \varepsilon_{it} \quad (1)$$

Likewise, other determinants of environmental deterioration have been included, such as inequality (GINI), knowledge (K), and globalisation KOF index (GK), which constitute the control variables of the model. The same variables are shown in Equation (2). In both equations, the subscript i represents the country, $i = 1, 2, \ldots,\ 110$ and t to the period analysed, where $t = 1990, 1991, \ldots, 2018$ and ε_{it} is the error term.

$$\mathrm{FA}_{it} = \beta_0 + \beta_1 \mathrm{EP}_{it} + \beta_2 \mathrm{GINI}_{it} + \beta_3 \mathrm{K}_{it} + \beta_4 \mathrm{GK}_{it} + \varepsilon_{it} \quad (2)$$

The impact of technical progress generates heterogeneous effects on pollution, the estimation of non-linear models has been considered. On the one hand, the threshold regression applied to panel data proposed by Chan [62] and modified by Hansen [63] is used. This methodology allows capturing the structural breakdown of the variables because each unit of analysis presents its own behaviour. On the other hand, this model is applied to the study of various economic, environmental, and financial phenomena, becoming a helpful tool for implementing economic policies [64]. This method shows that consistent estimators are obtained since the confidence intervals expand as the cross-sectional or temporal information increases [65]. In the next stage, the existence of statistically significant thresholds is verified. The null hypothesis is considered that $\beta_1 = \beta_2$, that is, there is no threshold. When this hypothesis is rejected and the alternative $H_1 : \beta_1 \neq \beta_2$ is accepted, it is concluded that there is a threshold effect. This condition is evaluated through the p-value of 1, 5, and 10% of significance. However, in this study, we consider the significance level of 95%, suggested by Hansen [66]. In order to obtain more robust and unbiased results, we used the bootstrap method with 300 repetitions. The threshold confidence intervals are established based on the likelihood ratio (LR) statistic denoted in Equation (3), where S_0 and S_1 symbolise the squared sum of residuals.

$$R = \frac{S_0(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad (3)$$

The lower limit of the threshold is given by the highest value presented by LR, while the upper limit equals the lowest value of the LR. The quantile that corresponds to the mean value of the threshold (γ) located at these extremes can be calculated under the function indicated in Equation (4). Therefore, if LR is greater than (γ), the null hypothesis is rejected, and therefore, it means that a threshold effect is established. Otherwise, it is convenient to use conventional linear models to identify the relationship of the variables.

$$c(\propto) = -2\ln(1 - \sqrt{1-\alpha}) \tag{4}$$

Once a threshold has been verified in any of the variables, the respective estimates are made. When the threshold effect is identified, it means that there is a before and after in the slope of the function. This fact means that there are countries that fall below the threshold and others above it. Equation (5) shows the formal model, where y_{it} represents the dependent variable, X_{it} the set of independent variables, q_{it} denotes the threshold variable and γ the threshold parameter that divides the coefficients β_1, β_2, β_n, which show the effect of the X_{it} on the vegetation cover. The function I (.) determines the validity of the expression given by the threshold. If it takes values other than zero, the effect is present before or equal to the threshold. Finally, ε_{it} is included, which is the error term.

$$y_{it} = \mu_i + \beta_1 X_{it} I(q_{it} \leq \gamma) + \beta_2 X_{it} I(q_{it} > \gamma) + \ldots \beta_n X_{it} + \varepsilon_{it} \tag{5}$$

Finally, we use the nonlinear quantile regression model developed by Koenker and Bassett [67]. The advantage of this model is that it allows identifying the impact of the independent variables on the vegetation cover throughout the distribution and not only at a specific point. The Chernozhukov et al. [25] estimator is used, which implements the bootstrap method through a series of algorithms that facilitates the estimation of panel data, which generates stability in the estimated coefficients as follows:

$$Q_i = Q_i | Y_{it} = \beta_0 + \beta_1 (X_1)_{it} + \beta_2 (X_2)_{it} + \ldots \beta_n (X_n)_{it} + \varepsilon_{it} \tag{6}$$

In Equation (6), the model's approach is detailed, where Q_i is the quantile of analysis, i is the quantile number, corresponding to the decile $(i = 1, 2 \ldots, 9)$. The parameters β_1, β_2, β_n are the coefficients obtained for the dependent variable under a conditioned quantile concerning X_1, X_2, X_n which are the independent variables, and ε_{it} is the stochastic disturbance.

5. Results and Discussion

The results in Table 3 indicate that the impact of the economic progress on forest areas is heterogeneous among groups of countries with different levels of development, and these results are consistent with Caravaggio [68]. In high-income countries, the impact of the product on plant cover is positive, supported by the sustainability of the development of these countries. However, in lower and lower-middle-income countries, the effect of the product on vegetation cover is negative, associated with the fact that economic activities in developing countries are destroying forest areas. Our results are not consistent with Culas [57] findings, Curesma et al. [69], Ajanakun and Collins [70], and Tsiantikoudis et al. [71]. Nevertheless, they validated the existence of at least half of the deforestation ECK in the various groups of countries. A possible explanation for this result is the heterogeneity in productive specialisation in the countries. For example, specialisation in services and manufacturing in high-income countries does not require the destruction of forest areas. On the contrary, in low-income countries, economic activities are strongly associated with agricultural, livestock, and forestry activities that demand a strong agricultural frontier expansion. These results offer an important lesson in environmental policy. Developing countries must apply more aggressive pro-environmental policies to mitigate the environmental degradation that human activity is causing. The inequality measured by the GINI coefficient is significant at the global level and for LIC and MLIC countries; that is, inequality directly relates to forest areas. On the other hand, the effect of knowledge is compatible with what was mentioned by Salahodjaev [33]. This study associates a lower deforestation rate with the existence of greater human capital. Globalisation is not significant for any group of countries.

Table 3. GLS regression results.

	Baseline Model					Model with Control Variables				
	GLOBAL	**HIC**	**MHIC**	**LIC**	**MLIC**	**GLOBAL**	**HIC**	**MHIC**	**LIC**	**MLIC**
Economic progress	0.01 **	0.04 ***	0.01	−0.02	−0.07 *	0.03 ***	0.02 ***	0.02	−0.0003	0.01
	(3.08)	(7.38)	(1.03)	(−1.49)	(−2.43)	(4.71)	(3.39)	(1.71)	(−0.05)	(0.20)
GINI						0.006 ***	−0.001	0.001	0.006 *	0.03 ***
						(9.79)	(−1.41)	(1.40)	(2.14)	(7.98)
Knowledge						−0.04 **	0.11 ***	−0.10 ***	−0.40 ***	−0.34 ***
						(−2.67)	(6.37)	(−4.14)	(−18.60)	(−8.00)
Globalisation KOF						−0.0001	0.0001	0.0001	−0.0002	0.001
						(−0.61)	(0.32)	(0.31)	(−0.78)	(1.28)
Const.	10.41 ***	9.80 ***	11.56 ***	10.43 ***	10.78 ***	10.19 ***	9.669 ***	11.74 ***	10.69 ***	9.815 ***
	(229.21)	(171.21)	(79.69)	(109.59)	(54.33)	(193.53)	(148.03)	(102.04)	(76.12)	(47.09)
Obs.	3190	1102	812	319	957	3190	1102	812	319	957

Note: *, **, and *** denote the level of significance at 5%, 10% and 1%.

Table 4 reports the test results used to identify the existence of a significant threshold effect in the relationship between the variables. We check if there are one or two thresholds in the global panel and the panels according to the levels of economic progress. In addition, we report the threshold and the confidence interval of the threshold estimator. We used an interactive process of 300 repetitions for the estimates. We found a global threshold effect was demonstrated on the GINI coefficient, knowledge, and globalisation index. The results suggest that the knowledge and the globalisation index have a non-linear impact on forest area in the 110 countries considered. The existence of a non-linear effect has been extensively investigated in recent empirical investigations [65,72]. For the group of LIC countries, a double threshold effect on economic progress and the GINI coefficient was demonstrated. As mentioned in Hansen [66], the F value calculated is contrasted with the critical values at 1%, 5%, and 10%. We use a 5% significance level for hypothesis testing at the various thresholds. The threshold effect implies that the impact of the GINI coefficient, the knowledge, the globalisation index, and the forest area is heterogeneous below and above the threshold.

Table 4. Threshold effect test (bootstrap = 300,300).

Threshold Variable	Threshold Effect	F	*p*-Value	Critical Value of F		
				1%	**5%**	**10%**
		Global				
Economic progress	Single	90.41	0.21	188.18	145.35	116.46
	Double	44.14	0.53	185.96	143.68	105.37
GINI	Single	101.61	0.04	130.04	98.30	84.62
	Double	30.87	0.43	235.09	78.12	61.21
Economic progress	Single	103.90	0.05	158.24	104.91	90.05
	Double	52.54	0.22	160.19	91.59	73.07
Globalisation KOF	Single	102.65	0.05	128.50	104.35	79.04
	Double	50.50	0.18	60.94	75.69	95.64

Table 4. *Cont.*

Threshold Variable	Threshold Effect	F	p-Value	Critical Value of F		
				1%	5%	10%
Low-Income Countries						
Economic progress	Single	17.38	0.77	116.63	86.72	68.56
	Double	57.16	0.02	75.51	45.99	38.76
GINI	Single	25.52	0.82	207.24	145.31	115.39
	Double	86.58	0.03	104.57	79.01	65.66
Knowledge	Single	26.01	0.79	158.69	109.36	89.36
	Double	30.17	0.41	74.99	62.14	54.34
Globalisation KOF	Single	11.77	0.80	94.01	70.64	60.67
	Double	18.51	0.23	48.52	31.27	25.73

The threshold point values are shown in Table 5. At the global level, the significant thresholds for inequality, knowledge, and globalisation are 54.60, 2.92, and 72.38, respectively. On the other hand, in low-income countries (LIC), the double threshold for economic progress is at 5.48 and 5.39, while inequality is at 38.60 and 38.73. These findings suggest that these variables should be used for the respective threshold regressions and their incidence before and after the vegetation cover identified for these countries analysed.

Table 5. Threshold point values.

Threshold Variable	Model	Threshold Estimation Value	Interval	
			Lower	Upper
Global				
Economic progress	Th−1	10.37	10.35	10.39
	Th−21	10.37	10.35	10.39
	Th−22	6.04	5.99	6.08
GINI	Th−1	54.60	54.10	55.20
	Th-21	54.60	54.10	55.20
	Th-22	25.90	25.70	26.00
Knowledge	Th-1	2.92	2.89	2.92
	Th-21	2.92	2.89	2.92
	Th-22	1.52	1.47	1.53
Globalisation KOF	Th-1	71.38	70.43	71.51
	Th-21	72.38	70.91	71.51
	Th-22	63.54	63.17	63.69
Low-Income Countries				
Economic progress	Th-1	5.48	5.47	5.49
	Th-21	5.48	5.48	5.49
	Th-22	5.39	5.39	5.40
GINI	Th-1	38.60	38.20	38.62
	Th-21	38.60	38.40	38.62
	Th-22	38.73	38.71	38.80
Knowledge	Th-1	1.11	1.09	1.11
	Th-21	1.11	1.09	1.11
	Th-22	2.21	2.14	2.22
Globalisation KOF	Th-1	42.18	41.22	42.25
	Th-21	40.67	40.53	40.69
	Th-22	39.20	37.42	39.23

The threshold regression results are shown in Table 6, which are stable and robust. The parameters are consistent with theory and similar empirical evidence, ensuring the reliability of the findings. In model 1, where the threshold variable is the global GINI coefficient, it was found that below the threshold, the effect is less than after the threshold. Likewise, the effect of economic progress and knowledge is positive, and the effect of globalisation is negative. It agrees with what was analysed by Salahodjaev [33], who states that globalisation has an important weight in deforestation. In model 2, where the threshold is the knowledge, we also find that below the threshold, the effect is less than after the threshold. This result highlights the importance of human capital to reduce the use of forest area in the selected countries. In this model, the positive effect of economic progress and the GINI coefficient and the negative effect of the globalisation index is maintained.

Table 6. Threshold regression results.

GLOBAL						LIC			
Model 1: Threshold: GINI		**Model 2: Threshold: Knowledge**		**Model 3: Threshold: Globalisation KOF**		**Model 1: Threshold: Economic Progress**		**Model 2: Threshold: GINI**	
Single Threshold Model	**Coefficient**	**Single Threshold Model**	**Coefficient**	**Single Threshold Model**	**Coefficient**	**Double Threshold Model**	**Coefficient**	**Double Threshold Model**	**Coefficient**
GINI < 54.60	0.01 ***	HC < 2.92	0.04 *	IG < 71.38	−0.004 ***	EP < 5.48	0.003	GINI < 38.60	0.005
	(9.79)		(2.30)		(−8.72)		(0.11)		(1.23)
GINI > 54.60	0.009 ***	HC > 2.92	−0.01	IG > 71.38	−0.003 ***	5.48 < EP < 5.39	−0.04	38.60 < GINI <38.73	0.02 ***
	(9.11)		(−0.74)		(−7.31)		(−1.34)		(4.36)
						EP ≤ 5.39	0.001	GINI ≥38.73	0.008 *
							(0.05)		(2.28)
Economic progress	0.07 ***		0.07 ***		0.06 ***				0.07 **
	(5.98)		(6.12)		(5.46)				(2.92)
GINI			0.006 ***		0.007 ***		0.01 ***		
			(5.77)		(6.32)		(3.71)		
Globalisation KOF	−0.002 ***		−0.002 ***				−0.005 ***		−0.007 ***
	(−4.84)		(−5.10)				(−4.31)		(−5.84)
Knowledge	0.03				0.0003		−0.20 ***		−0.21 ***
	(1.70)				(0.02)		(−4.57)		(−4.98)
Const.	9.70 ***		9.90 ***		10.01 ***		10.14 ***		10.07 ***
	(113.09)		(114.36)		(114.54)		(50.83)		(54.88)
Obs.	3190		3190		3190		319		319
Adjusted R^2	0.04		0.04		0.04		0.57		0.61
N_groups	110		110		110		11		11
R^2 (within)	0.07		0.08		0.08		0.59		0.63
R^2 (between)	0.02		0.02		0.01		0.09		0.44
R^2 (overall)	0.02		0.01		0.01		0.03		0.18

Note: *, **, and *** denote the level of significance at 5%, 10% and 1%.

Finally, in model 3, the findings indicate that the impact of globalisation on forest area is negative around the threshold, but the intensity changes (−0.004 to −0.003). The effect of the rest of the variables is similar to the rest of the models. For the group of LIC countries in model 1, where the threshold variable is EP, it was found that the elasticity below the threshold has a maximum at –0.04 and decreases slightly. The effect of knowledge and globalisation is negative, and the effect of the GINI coefficient is positive on forest areas. The model fit ranges from 0.04 to 0.67. The existence of thresholds of a non-linear effect improves the compression of the dependent variables on forest areas in the countries analysed. Figure 1 shows the thresholds in the countries globally and LIC. Although the cross-sectional units included in the research have several similarities, they present some differences between them. The main differences are determined by the GINI coefficient, knowledge, and globalisation index.

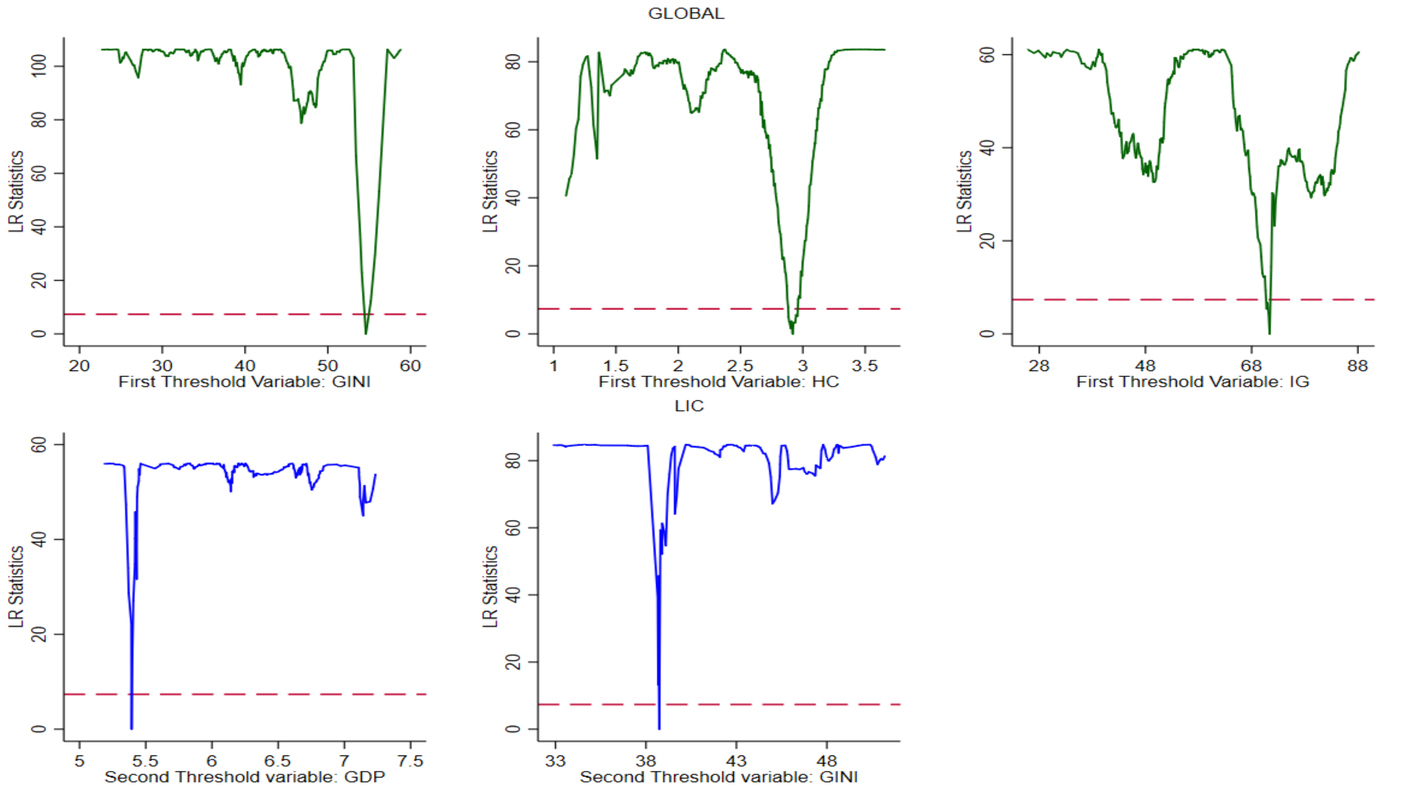

Figure 1. LR statistic of economic progress and GINI for global and low-income countries.

Table 7 shows the description of numerical changes between countries in different threshold ranges between 1990 and 2018. The categories of countries with low and high economic growth, low and high inequality, low and high knowledge, and low and high globalisation are highlighted. Low-income countries decreased from 96 to 87 below the threshold. On the other hand, they increased from 14 to 23 countries with high incomes after the threshold. Countries below the threshold remained stable for the GINI coefficient, only going from 106 in 1990 to 105 in 2018. Above the threshold, they increased from 4 to 5. For the knowledge, countries below the threshold went from 91 to 60 in the study period and above the threshold from 19 to 50. Finally, the change below the threshold was from 98 to 62 and above; it went from 12 to 48 countries.

Table 7. Description of number changes among countries in different threshold ranges.

Threshed Regime	1990	1995	2000	2005	2010	2015	2018
Low economic progress (GDP $\leq$ 10.376)	96	95	90	89	89	88	87
High economic progress (GDP > 10.376)	14	15	20	21	21	22	23
Low inequality (GINI $\leq$ 54.600)	106	106	106	104	104	104	105
High inequality (GINI > 54.600)	4	4	4	6	6	6	5
Low knowledge (HC $\leq$ 2.918)	91	87	81	72	67	63	60
High knowledge (HC > 2.918)	19	23	29	38	43	47	50
Low globalisation (IG $\leq$ 71.38)	98	90	82	73	67	64	62
High globalisation (IG > 71.38)	12	20	28	37	43	46	48

The regression results of the quantile model of Chernozhukov et al. [25] are shown in Table 8. For all quantiles, the EP is statistically significant at 5% and 1% at the global level. Its impact on forest area changes from negative in the first three quantiles to positive in the following. By groups, EP is still significant for most quantiles, but the sign varies differently. It is significant and positive for all quantiles in MHIC, and in HIC and LIC, it changes signs depending on the quantile. The GINI coefficient is significant and positive from quantile two, which shows that the greater the inequality, the more significant the deterioration of the forest area. For groups of countries, the significance changes, as does the sign. For the MIC group, the variable is significant and positive for all deciles, and for LIC countries, it is significant but negative for all quantiles. In the 110 countries studied, knowledge has greater significance for the lowest quantiles and little or no significance for the highest. For the HIC countries, knowledge is significant for all quantiles. In the other groups, the behaviour is similar on a global level. Finally, the globalisation index is significant in all quantiles but changes to a negative sign from the fifth quantile. However, at developmental levels, the results are different and changing between quantiles. In other words, for some groups, the effect is concentrated at the extremes of the distribution.

Table 8. Quantile model regression results using Chernozhukov et al. [25].

	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
GLOBAL									
EP	−0.53 ***	−0.28 ***	−0.14 *	0.08 *	0.25 ***	0.40 ***	0.55 ***	0.38 ***	0.54 *
	(−4.32)	(−4.61)	(−2.47)	(2.11)	(7.85)	(10.58)	(16.03)	(5.97)	(2.26)
GINI	−0.006	0.06 **	0.07 ***	0.05 ***	0.06 ***	0.06 ***	0.08 ***	0.07 ***	0.07 ***
	(−0.21)	(3.13)	(12.06)	(5.94)	(24.26)	(7.52)	(9.95)	(12.18)	(5.25)
HC	0.27 **	0.53 **	0.38	0.10	0.25 **	0.13	0.19 *	0.29	1.11 *
	(3.23)	(3.29)	(1.90)	(0.60)	(2.59)	(1.11)	(2.41)	(1.59)	(2.33)
IG	0.03 **	0.03 ***	0.02 *	0.002	−0.009 ***	−0.009	−0.03 ***	−0.023 ***	−0.06 *
	(3.00)	(4.91)	(2.08)	(0.40)	(−4.01)	(−1.70)	(−6.01)	(−3.59)	(−2.23)
Const.	9.93 ***	5.39 ***	5.73 ***	7.30 ***	6.22 ***	5.51 ***	5.22 ***	6.94 ***	6.35 ***
	(5.98)	(4.32)	(10.07)	(12.88)	(28.01)	(11.96)	(11.82)	(10.00)	(4.10)
Obs.	3190	3190	3190	3190	3190	3190	3190	3190	3190
HIC									
EP	−0.92 ***	−0.85 ***	−0.40 **	0.05	0.38 ***	0.49 ***	0.57 ***	0.74 ***	0.90 ***
	(−17.53)	(−7.76)	(−2.82)	(0.41)	(5.87)	(19.48)	(25.80)	(6.64)	(19.43)
GINI	−0.18 ***	−0.16 ***	0.008	0.07 **	0.09 ***	0.09 ***	0.07 ***	0.05 **	0.06 ***
	(−13.53)	(−8.77)	(0.20)	(3.15)	(8.29)	(10.78)	(15.94)	(2.77)	(11.35)
HC	1.39 ***	1.55 ***	1.69 ***	1.89 ***	1.62 **	1.70 ***	1.31 ***	1.92 ***	2.44 ***
	(4.63)	(6.76)	(5.72)	(4.90)	(3.10)	(4.26)	(9.72)	(7.13)	(29.22)
IG	0.04 ***	0.04 **	0.0005	−0.04 **	−0.03 **	−0.03 **	−0.03 ***	−0.03 *	−0.05 ***
	(4.79)	(2.83)	(0.03)	(−2.87)	(−2.89)	(−3.20)	(−6.03)	(−2.54)	(−9.54)
Const.	14.68 ***	13.46 ***	7.59 ***	4.23 *	1.58	0.424	1.29	−0.47	−1.72 ***
	(8.65)	(10.64)	(4.72)	(2.57)	(1.01)	(0.39)	(1.71)	(−0.31)	(−5.08)
Obs.	1102	1102	1102	1102	1102	1102	1102	1102	1102
MHIC									
EP	1.48 ***	1.76 ***	2.31 ***	1.81 ***	1.468 ***	1.49 ***	1.18 ***	0.87 ***	0.38
	(8.73)	(14.24)	(8.52)	(7.14)	(3.58)	(4.26)	(5.42)	(3.92)	(0.78)
GINI	0.09 ***	0.07 ***	0.05 ***	0.03 ***	0.04 ***	0.07 **	0.08 ***	0.09 **	−0.03
	(6.68)	(11.91)	(5.66)	(8.64)	(4.97)	(3.24)	(4.09)	(3.10)	(−0.92)
HC	1.87 **	0.59	−0.59	−0.7 ***	−0.66 **	−0.21	0.09	0.43	2.89 **
	(3.01)	(1.76)	(−1.41)	(−4.81)	(−3.02)	(−0.40)	(0.21)	(1.09)	(3.05)
IG	−0.07 ***	−0.05 ***	−0.02	−0.006	0.002	−0.002	−0.02	−0.02	−0.09 **
	(−9.58)	(−7.18)	(−1.56)	(−0.84)	(0.25)	(−0.20)	(−1.60)	(−1.35)	(−3.02)
Const.	−8.29 ***	−6.93 ***	−8.873 ***	−3.91	−1.521	−3.47	−0.45	1.27	10.87 *
	(−5.60)	(−7.07)	(−3.97)	(−1.87)	(−0.43)	(−0.77)	(−0.15)	(0.37)	(2.39)
Obs.	812	812	812	812	812	812	812	812	812
LIC									
EP	1.16 ***	1.05 *	0.45	0.12	−0.16	1.49 *	1.25 ***	1.11 ***	1.29 ***
	(6.72)	(2.54)	(0.61)	(0.16)	(−0.19)	(2.00)	(3.82)	(4.13)	(4.06)
GINI	−0.08 **	−0.12 **	−0.23 ***	−0.25 ***	−0.26 **	−0.15 *	−0.15 ***	−0.15 ***	−0.18 ***
	(−2.79)	(−2.65)	(−6.50)	(−5.58)	(−2.79)	(−2.21)	(−5.37)	(−5.14)	(−7.43)
HC	2.43 ***	3.15 ***	3.71 ***	4.12 ***	3.70 *	0.81	0.63	0.18	−0.69 **
	(6.42)	(6.21)	(4.96)	(4.15)	(2.48)	(0.89)	(1.51)	(0.33)	(−2.67)

Table 8. *Cont.*

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
IG	−0.05 ***	−0.06 **	−0.07 **	−0.07 **	−0.04	−0.02	−0.02	−0.0005	0.04 **
	(−3.90)	(−2.83)	(−2.79)	(−2.75)	(−1.29)	(−0.81)	(−0.78)	(−0.01)	(2.60)
Const.	2.77 ***	4.76	13.94 **	16.39 **	18.29 **	7.63	9.77 ***	10.83 ***	11.55 ***
	(3.34)	(1.47)	(2.78)	(3.12)	(2.68)	(1.60)	(5.01)	(7.60)	(9.49)
Obs.	319	319	319	319	319	319	319	319	319
MLIC									
EP	−0.58	−0.31	−1.48 ***	−1.31 ***	−0.69 *	−0.53	−0.29	−0.01	−0.19
	(−1.28)	(−0.60)	(−22.26)	(−5.30)	(−1.97)	(−1.72)	(−0.87)	(−0.07)	(−0.68)
GINI	−0.15 *	0.014	0.05 ***	0.06 *	0.05 **	0.0004	−0.007	0.06 ***	0.08 ***
	(−2.14)	(0.61)	(7.51)	(2.46)	(2.70)	(0.02)	(−0.19)	(9.01)	(9.11)
HC	−0.36 ***	−0.29 *	−0.59 ***	−0.75 **	−0.82 ***	0.09	0.24	0.06	0.17
	(−4.08)	(−2.15)	(−5.24)	(−2.63)	(−4.77)	(0.27)	(0.48)	(0.30)	(0.59)
IG	−0.01	0.016	0.06***	0.06***	0.04**	0.01	−0.005	−0.001	0.003
	(−0.84)	(0.88)	(11.35)	(4.26)	(3.23)	(0.61)	(−0.36)	(−0.43)	(0.66)
Const.	18.98 ***	9.98 ***	15.74 ***	15.10 ***	13.32 ***	14.23 ***	13.55 ***	9.82 ***	10.20 ***
	(5.17)	(4.24)	(51.55)	(9.70)	(8.51)	(8.07)	(7.52)	(9.65)	(6.97)
Obs.	957	957	957	957	957	957	957	957	957

Note: *, **, and *** denote the level of significance at 5%, 10% and 1%.

6. Conclusions and Policy Implications

In order to test the old and new factors that determine the forest area, this research analysed the relationship between forest area, economic progress, globalisation KOF, and knowledge. This article offers empirical evidence in various groups of countries classified according to their income and tests the relationship between the variables in the period 1990–2018. For this, non-linear econometric techniques such as threshold regressions proposed by Hansen [63] and the quantile regression estimator of Chernozhukov et al. [25] were used to capture the heterogeneous effect of the explanatory variables on the vegetation cover. Contrary to expected results, there is insufficient evidence that economic progress affects forest areas in the countries analysed. Therefore, the econometric results on the existence of an EKC for deforestation have not been conclusive and vary according to the development level of each country. For this reason, future research could include an analysis of EP squared to know if there is any influence concerning the vegetation cover. One of the limitations of this research is that the data does not have an adequate update that allows incorporating the effect of recent aspects that have influenced environmental quality, such as COVID-19. Nevertheless, improved data availability will allow proposing better pro-environmental policies that mitigate climate change. Likewise, future lines of research should differentiate the quality of forest cover and the ecosystem services that they can offer to society. Legislation to protect natural protected areas can play a central role in nature conservation.

The results differ from previous works [8,23,24], where high-income countries have lower deforestation rates because when economic progress increases, pollution decreases every time. Likewise, middle-income countries tend to have the highest deforestation.

Countries must reduce their dependence on forest areas for economic progress since all productive activity generates environmental deterioration. The regulation can be applied in integration agreements through greater research and development of products aimed at recycling and circular economy. The inclusion of the GINI coefficient, the knowledge, and globalisation made it possible to capture the countries' economic patterns and social inequalities as determinants of the variation in forest areas. We find that the variables: Inequality, knowledge, and the globalisation KOF present a significant threshold effect. The results obtained from the non-linear regressions imply that the impact of the regressors below the threshold differs from the effects of the threshold. This result shows that countries with greater inequality have a greater dependence on the use of forest areas. Knowledge (if well invested) could reduce the burden on deforestation. The relationship between the knowledge and forest area is expected to be negative, fulfilled by the GLS regression. However, the quantile analysis is not negative for all quintiles and depends on the group of countries. Knowledge should offer sufficient evidence on the importance of forests for air, soil, and water quality, promoting forest conservation as hypothesised. Finally, globalisation has an essential role in deforestation in most countries, following Yameogo's [35] study. These results provide evidence in favour of the fact that knowledge should be a policy instrument to promote forest use control measures. Furthermore, given globalisation, policies should focus on preventing negative effects. Knowledge and globalisation KOF index could become sources of innovation that reduce input costs for new products that are more efficient.

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