

Article

Exploring the Links Between Forest Stewardship Council Certification and Biodiversity Outcomes at a Global Level

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Abstract: Forests contain just under 58% of all known species globally, with approximately 61% of these found in countries with Forest Stewardship Council (FSC)-certified forests. Few studies have directly analyzed the association between biodiversity and certification, often focusing on limited geographical or temporal scopes. There is a lack of understanding regarding the socio-political and ecological drivers of FSC certification's relationship with biodiversity conservation. We assess the associations between country-level characteristics and the relationship between FSC's forest management (FSC-FM) certification area and independently made biodiversity estimates from the International Union for Conservation of Nature (IUCN). Specifically, using generalized random forests (GRF) and data from 91 countries between 2008 and 2019, we examine the associated factors that govern FSC-FM certifications relationship with percentage threatened species. The results indicate that increasing FSC-FM-certified areas is linked to a reduction in the percentage of threatened species by 0.1 to 0.15. Moreover, FSC-FM certifications show a positive relationship with biodiversity in regions with high population densities and significant tree cover loss. Enhanced perception of corruption control and reduced extraction of non-forestry resources further strengthen this association. These findings provide the FSC with strategic insights to expand FM certification, contributing to biodiversity conservation through sustainable forest management.



Academic Editors: Guillermo J. Martinez-Pastur and Marco Marchetti

Received: 14 October 2024

Revised: 22 December 2024

Accepted: 8 January 2025

Published: 10 January 2025

Citation: Kadam, P.; Dwivedi, P. Exploring the Links Between Forest Stewardship Council Certification and Biodiversity Outcomes at a Global Level. *Land* **2025**, *14*, 130. <https://doi.org/10.3390/land14010130>

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Keywords: forest certification; Forest Stewardship Council; biodiversity; random forest; conservation

1. Introduction

Voluntary forest certification is a non-state and market-driven governance mechanism for conservation [1]. The Forest Stewardship Council (FSC)'s voluntary forest certification began in 1993 as a moderate response to the frequently contentious direct-action strategies of environmental NGOs, including disruptive environmental boycotts [2]. The FSC theory of change involves enhancing conservation benefits by encouraging forest management entities (FMEs) to adopt responsible forest management practices based on conformance to FSC's forest management (FM) standards, with assurance provided by third-party independent certification body (CB) audits [3].

The costs involved in assurance are ideally balanced by market benefits gained from selling high-demand certified products within this governance mechanism [4]. In spite of this, the motivations of FMEs to have their operations certified are different in different countries. They can include local market demands, environmental regulations, consumer pressure, and the specific forest management practices prevalent in that region [5]. Differing

national motivations, such as economic reliance on forestry, the state of sovereign rights over forest management activities (including hunting and ranching), and varying levels of commitment to recognizing indigenous rights have been identified as factors that shape the extent to which FSC's stringent environmental and social standards are supported, implemented, or contested [6]. This means that the efficacy of this market-based instrument depends on identifying and resolving institutional, social, and ecological externalities that may cause market failures by distancing decision-making from actual on-the-ground impacts [7].

Programme for the Endorsement of Forest Certification (PEFC) is another forest certification system, which, along with the FSC, offers opportunities and standards for the voluntary certification of forests. It was started in 1999, driven by the forestry industry to compete with FSC [6,8]. Being an umbrella certification (endorsing national level initiatives), it is larger than the FSC in terms of hectares of forest area certified [9]. The growth of FSC and PEFC which is supported by NGOs and the industry, respectively, adds to the complexity of motivations for forest certification when it comes to their impacts on ecosystem services like biodiversity conservation.

Globally, the FSC had certified 204.4 million hectares in 94 countries in 2020 [10], but this decreased to 160.4 million hectares in 89 countries in 2024 [11]. These areas are certified under a nationally unique set of verifiers while adhering to globally common principles and criteria. Figure 1 shows the distribution of the FSC-certified area as a percentage of the total forest area just in the year 2020 [10]. After almost 30 years, it has created a formal and informal dialogue surrounding sustainable forest management between various stakeholder groups, including FMEs, to drive positive impacts on the ground [12], but global relationships with biodiversity and other natural values remain to be assessed. This is especially relevant, as 57.9% of the total known species were found in forests in 2020, out of which 61.2% were found in countries that had FSC-certified forestlands, amounting to 35.5% of all species in the world (as reported by the International Union for Conservation of Nature (IUCN) [13]). Business-as-usual approaches will be detrimental to conservation efforts in light of projections showing a decrease in biodiversity [14].

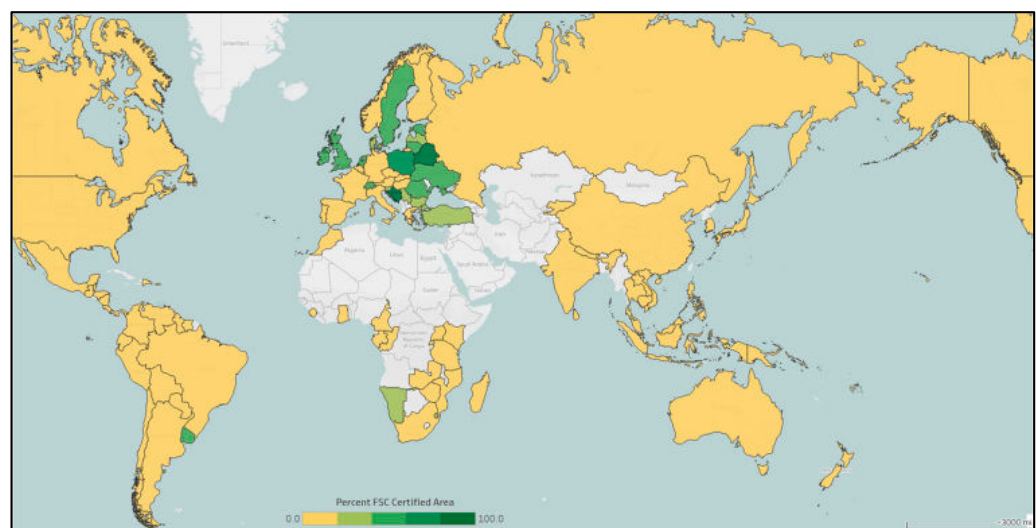


Figure 1. Global distribution of areas certified with Forest Stewardship Council's (FSC) forest management (FM) certification as a percentage of total forest area in a country in the year 2020 [10]. Countries with no color did not have any FSC-FM certification in 2020.

Direct analyses of possible associations between biodiversity and certified areas are limited. When conducted, they focus on smaller geographical or temporal scales. Some note

that the FSC system is not an adequate motivation for the forest landowners to maintain or enhance forest cover [15]. Blackman et al. also used the Differences-in-Differences robust methodology to determine that the FSC's forest management certification program has no impact on deforestation [16]. On the other hand, other studies found positive associations. Particularly, Miteva et al. found positive social and environmental impacts of the FSC certification using spatially explicit village-level data from Kalimantan, Indonesia [17]. Specifically, they found that FSC's FM certification reduced deforestation by five percent in that region. Damette and Delacote found a negative impact of certification on deforestation on a global level and that the extent of timber extraction increases deforestation [18]. They argued that certification may mediate (or rather soften) this relationship when the quality of governance, including corruption, is considered. An agreement exists that the forest certification mechanism is strengthened by parallel forest governance from governments or people [19]. The methodology of this study follows the importance of considering such mediating/confounding factors. For example, Maryudi shows that tenure security is a significant hurdle to forest certification, as conflicting governance frameworks "impinge on areas currently managed by forest concessions" [20]. According to Romero et al., to effectively assess the role of forest certification, it is crucial to have knowledge about the political economy of the forest sector, land use change, and the temporal dynamics of certification [21]. Other possible sources and mediating pathways of heterogeneity in the role of forest certification, in general, and FSC, in particular, could be socio-ecological factors, including tree cover loss [22], agricultural growth [23], and population density [24,25]. Similar factors affecting biodiversity could include politico-economic drivers such as the gross domestic product (GDP) [23,26], corruption [27,28], and natural resource rents [29,30].

The FSC-FM certification incorporates principles of sustainable forest management that inherently prioritize biodiversity through criteria such as maintaining high conservation value forests, protecting rare and threatened species, and minimizing ecological damage [8]. However, as these above studies have noted, the FSC mechanisms operate within broader socio-political and ecological frameworks that cover and affect anti-poaching initiatives, habitat restoration, and protected area management. The influence of external factors such as governance, enforcement, and regional conservation strategies likely plays a significant role in the relationship between FSC-FM certifications and biodiversity conservation.

The contextual variables noted above increase the difficulty in analyzing the FSC certification relationship with biodiversity as separate from that of activities towards compliance with governmental regulations or corporate social responsibility (CSR) activities, or other governance systems affecting biodiversity. Data availability, identifying corresponding scales of analyses, and other study design difficulties are argued to be some of the major factors that hinder undertaking impact assessments for forest certification [1]. Moreover, much of earlier research has been focused on processes instead of outcomes, and the researchers have used data received after third-party certification audits [31].

Our study aims to understand the relationship between the presence of FSC certification and biodiversity outcomes from a global perspective, given the heterogeneity in country-level complex politico-ecological and economic systems. The specific objective of this study is to assess the associations between country-level characteristics and the relationship between the FSC-FM certification area and independently made biodiversity outcome estimates from the IUCN. To achieve this, and considering the likely interdependence of variables, we compare the outputs of ordinary least square (OLS) models with those of generalized random forest (GRF) models, which are arguably better at specifying complex associations.

2. Materials and Methods

2.1. Data Assembly

The observations on FSC certification and the percentage of threatened species from IUCN were acquired from publicly available sources, i.e., FSC [10] and IUCN [13], respectively. FSC data on the presence or absence of forest management certification and the certified area were available from 1993 to 2021 for 94 countries. The IUCN's data on threatened species for the same countries were found to be complete only after 2008. Instead of raw hectares, the FSC-FM-certified areas were used as a percentage of the total forest area (source: Food and Agriculture Organization, FAO [32]) in a country in a given year. The percentage of threatened species was calculated from the numbers of species assessments (terrestrial forest-based: plants and animals), following IUCN [33], formulated as

$$\text{Percent Threatened Species} = ((\text{Critically Endangered} + \text{Endangered} + \text{Vulnerable}) / (\text{Total assessed} - \text{Extinct} - \text{Data Deficient})) \times 100, \quad (1)$$

IUCN has a “forest-based” option to select in the search filters under ‘habitats’ [13]. We do not use the ‘Red List Index’ in our analysis, as it is not separately available for forest-based species in the IUCN summary tables. Tree cover loss was calculated as a percentage of the total forest available in each country in a given year [34], while agricultural land was used as a percentage of the total land (source: FAO [33]). The data on economic and social dimensions relevant to this study were collected from the World Bank. Specifically, observations on the perception of the Control of Corruption index from the World Governance Indicators [35], the annual percent growth of GDP per capita [36], population density (the number of people per square km) [37], and natural resource rents (as a percentage of GDP) [38] were collected for each country for the required years. The natural-resource rent data included revenues from oil, natural gas, coal, and forestry; therefore, two different variables—non-forestry rent (containing oil, natural gas, and coal rents) and forestry rent—were used in the models to compare patterns within the total natural rents [39]. Observations for Taiwan, Eswatini, and Liechtenstein could not be used for statistical modeling, as data on several covariates, including GDP, tree cover loss, rents, and certification, were missing. Moreover, agricultural and rent observations for the year 2020 were not published yet, so the analyses were kept restricted to 2008–2019 across 91 countries.

The dataset includes observations from 91 countries over 12 years (2008–2019), resulting in a total of 1092 data points. To ensure the sample size is statistically sufficient, we conducted a post hoc statistical power analysis, considering the number of predictors in the regression and random forest models. The analysis confirmed that the dataset provides adequate statistical power (>0.80) to detect medium-to-large effect sizes at a significance level of 0.1. Moreover, the geographic, ecological, and governance diversity in the dataset aligns with established practices in cross-country analyses of biodiversity conservation and forest governance. This combination of temporal depth, geographic breadth, and statistical adequacy underpins the reliability and generalizability of our findings.

2.2. Statistical Methods—Ordinary Least Square (OLS)

We use the percentage of threatened species as the dependent variable and the percentage of FSC-certified area as the explanatory variable, while all other variables are considered control variables. We first ran simple heteroskedasticity and cluster-corrected OLS regressions, initially with only year as a fixed effect and then with both year and country as fixed effects to verify whether the estimates of the chosen independent variables show more cross-country or more within-country variation. Simple ordinary least square

regression (OLS) models were built, once with both year and country-fixed effects and again with only year effects, to assess the patterns in variable estimates and their significance. This was performed to verify whether the estimates of the chosen independent variables showed more cross-country or more within-country variation. Only heteroskedasticity and autocorrelation corrected robust standard errors were used in all the regression and other models. Under conditions of autocorrelation and heteroscedasticity, the usual OLS estimators remain unbiased, linear, and asymptotically normally distributed but lose the minimum variance property among all linear unbiased estimators [40]. Different combinations of these variables were used in modeling using the step-wise regression methodology. The full regression equation for the two-way fixed effects model was as follows:

$$\begin{aligned} \text{Percent Threatened Species}_{(i,j)} = & \text{dCountry}_{(i)} + \text{dYear}_{(j)} + \text{Percent tree cover loss}_{(i,j)} + \text{Percent agricultural} \\ & \text{land}_{(i,j)} + \text{GDP per capita percent growth}_{(i,j)} + \text{Population density}_{(i,j)} + \text{Corruption control perception}_{(i,j)} + \\ & \text{Non-forestry rent}_{(i,j)} + \text{Forestry rent}_{(i,j)} + \text{Percent FSC-certified area}_{(i,j)} + \text{dFSCcertification}_{(i,j)}, \end{aligned} \quad (2)$$

where i denotes the country, and j denotes the year.

2.3. Generalized Random Forest

The second part of the analysis involved training random forests, an ensemble learning methodology in which random subsets of observations are used to test which independent variables can partition the samples most effectively [41] using both full and country-level modeling, as suggested by Athey and Wager [42].

Amit and German introduced the core idea of the ‘random forest’, an ensemble learning methodology, in which a random subset of observational data is used to test which independent variables can partition the samples in the most effective way, creating a decision-tree of effects [41]. According to Breiman, estimates of effects are determined by averaging all the estimates in individual trees [43]. The ‘causal forest’ methodology of the generalized random forest (GRF) builds individual trees using greedy recursive partitioning and is randomized using bootstrap (or subsample) aggregation such as classical random forests. However, it is different in that, instead of the kernel weighting function, an adaptive weighting function is used to identify partitions and capture heterogeneity in the estimated average treatment effects using covariate-based conditional average treatment effects (CATEs) [44]. In the context of covariates, CATEs in GRF are informative, as they help uncover the varying treatment effects within different subgroups of the population defined by specific covariate values, enabling a comprehensive understanding of how the treatment variable (in our case: presence/absence of FSC-FM) interacts with covariates (control variables noted above) to influence the outcome variable (percent threatened species here).

The causal forest approach in GRF offers several advantages over OLS regression when estimating effects. Unlike OLS, which assumes linearity and strict parametric relationships between variables, the causal forest approach can capture non-linear and complex relationships without making strong assumptions about the underlying data distribution. Unlike OLS, the causal forest explicitly considers a treatment assignment as a split criterion, enabling the estimation of effects while accounting for confounders¹, which is very important in the case of potentially complex relationships involved in the scale and scope of this study. This is achieved by GRF’s ability to provide feature importance measures. This becomes particularly important when there are multiple confounders present, as GRF’s feature importance can help disentangle the effects of various predictors, including the confounders, and provide a comprehensive understanding of their relative importance in predicting the outcome, thereby addressing potential confounding and gaining deeper insights into the data. By leveraging the power of random forests, the causal forest approach

provides a flexible and robust framework for causal inference that surpasses the limitations of OLS in capturing complex and interdependent relationships in observational data.

We used the stepwise regression models from Equation (2) to train our data, using the *grf* package in R (version 2024.12.0+467) (a detailed algorithm is provided by Athey and Wager [42]). We trained a ‘pilot’ raw random forest with all covariates first, and a second causal forest on only those covariates, which showed a higher number of splits in the pilot forest trees. As suggested by Athey et al. [44], we trained both forests to reduce the out-of-bag error (of subsamples not used to train main forests) using (i) 2000, 4000, 6000, 8000, 10,000, and 12,000 trees, (ii) using the ‘mtry’ parameter (how many covariates are used to construct splits) as $\min(\sqrt{p} + 20, p)$, where p is the number of variables, and (iii) honesty fractions (fraction of samples used in selecting tree split) from 0.5 to 0.8. We recorded the importance of each covariate in the first raw forest, as denoted by the percent share of the number of splits, and then trained a second forest on only those features that saw a reasonable number of splits in the first step. Plotting the distributions of CATEs to explore directions of heterogeneity in the FSC-FM association with biodiversity, we also tested whether the difference between high and low estimates, conditioned on each covariate, was statistically significant. Finally, we trained a third forest using country-level data averaged out over all the years under analysis to assess whether an analysis focusing on country-level associations can capture heterogeneity signals better than the full forest. We tested heterogeneity in the data captured by the three forests using the ‘best linear predictor’ methodology developed by Chernozhukov et al. [45], which fits CATE as a linear association of the out-of-bag causal forest estimates [42]. It provides information on whether the predictions are correct (if the coefficient of ‘mean.forest.prediction’ is 1 and significant), and whether the forest could capture the underlying heterogeneity signals in the data (if the coefficient of ‘differential.forest.predictions’ is 1 and statistically significant).

To empirically demonstrate that GRF performs better than OLS, we compared the results using mean squared error (MSE) and R^2 . MSE quantifies the average squared difference between predicted values and actual values. Lower MSE values indicate better model performance. By comparing the MSE of the GRF and OLS models, we assess which model provides more accurate predictions. R^2 , also known as the coefficient of determination, measures the proportion of variance in the dependent variable that is explained by the independent variables. Higher R^2 values indicate a better fit of the model to the data. We calculated R^2 for both GRF and different combinations of the OLS models and compared their values to determine which model better captures the relationships in the data.

3. Results

3.1. Data Distributions

Table 1 gives the distribution of each variable considered in the analysis, including their measurement units, mean values, and standard deviation (SD). A complete list of the 91 countries under analysis is given in Appendix A.

To explore regional distributions, we calculated the average percentages of threatened species and FSC-certified areas (as % of forest area) for all the regions that the 91 countries fall in. Figure 2 illustrates the variations in the average percentages of threatened species and FSC-certified areas from 2008 to 2019 for the selected regions using a stacked bar chart. Figure 2 clearly shows the divergences between the two variables. Europe has a high FSC-certified area, but the percentage of threatened species is higher in the tropical regions. The likely reason why the percentage of threatened species is low could be because the presence of FSC is greater in the developed world, where the percentage of threatened species is relatively low.

Table 1. The distribution of each variable considered in the analysis of associations between globally threatened species and the Forest Stewardship Council’s (FSC) forest management certifications. GDP = gross domestic product.

Name of Variable	Mean Value	Standard Deviation
Percent threatened species (%)	16.54	14.56
FSC-certified area (% of forest area)	11.59	20.06
GDP per capita growth (%)	1.99	3.51
Non-forestry rents (% of GDP)	2.78	5.49
Forestry Rents (% of GDP)	1.42	2.78
Control of Corruption (Index)	0.15	1.04
Population Density	106.09	115.76
Percent Agricultural Land (% of total land)	39.29	19.19
Tree Cover Loss (% of forest area)	0.71	0.87

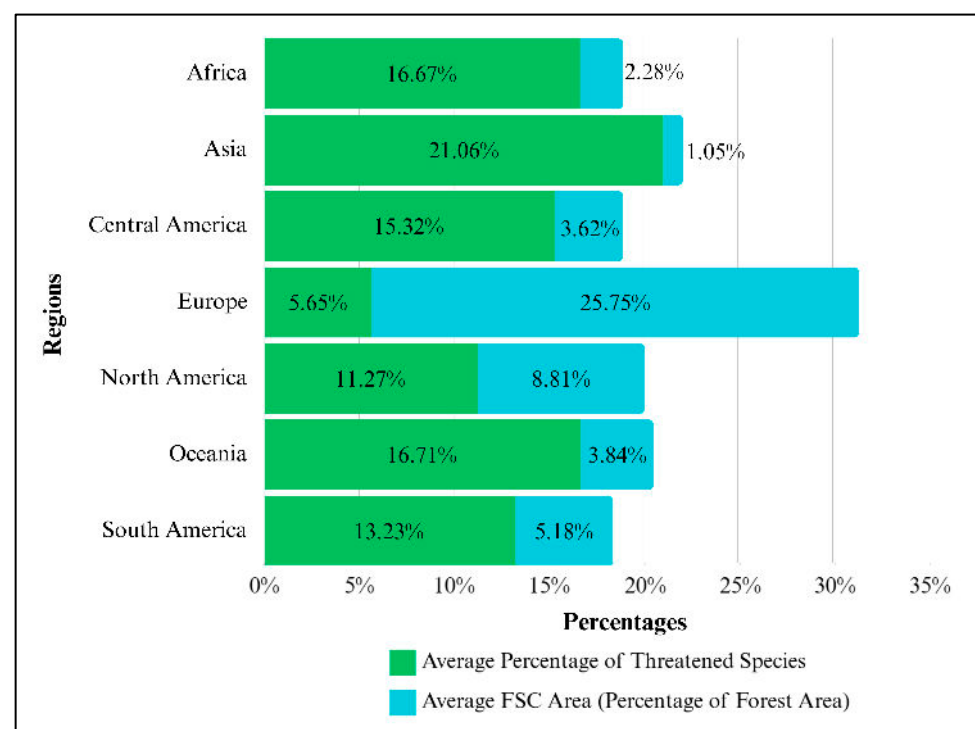


Figure 2. Average percentage of threatened species and Forest Stewardship Council (FSC) forest management (FM) certified area (as % of forest area) from 2008 to 2019 across different global regions, covering 91 countries with existing FSC FM certifications.

3.2. OLS Regression of FSC-FM Certification Presence on Biodiversity

According to regression modeling, in the best model based on MSE and R^2 , many covariates became statistically significant when country-level fixed effects were not included in the model (Table 2). When year-fixed effects were included, increasing GDP per capita, population density, and percent tree cover loss were positively associated with the percent of threatened species. Moreover, the percentage of FSC-certified areas and the perception of control of corruption were negatively associated. However, the same covariates were not significant after including country-level fixed effects. The interaction between resource rents and control of corruption was only significant for non-forestry rents and had a positive estimate. The two-way fixed effects model estimates in Table 2 indicate the importance of non-forestry rent, which was statistically significant in the two-way fixed effects model despite the inclusion of country fixed effects; it was positively associated with the percent threatened species.

Table 2. Findings of ordinary least square regression model. Dependent variable: percentage of threatened species. Estimates and heteroskedasticity and cluster-corrected robust standard errors (in the brackets) are noted for each independent variable.

Independent Variables	Two-Way Fixed Effects	Only Year Fixed Effects
FSC certification presence (0,1)	−1.68 (2.12)	−0.52 (1.58)
FSC-certified area (% of Forest)	0.05 (0.03)	−0.11 (0.02) ****
GDP per capita percent growth	0.13 (0.09)	0.27 (0.11) **
Non-forestry rents (% of GDP)	0.36 (0.12) **	0.12 (0.03) **
Forestry rents (% of GDP)	−0.07 (0.01)	−0.16 (0.12)
Control of corruption	−0.21 (3.21)	−0.49 (0.23) ****
Interaction of Corruption Control and Non-forestry Rents	0.36 (0.15)	0.38 (0.11) ***
Interaction of Corruption Control and Forestry Rents	−0.01 (0.34)	0.03 (0.21)
Population Density	0.02 (0.05)	0.007 (0.004) *
Percent Agricultural Land	0.10 (0.25)	−0.001 (0.02)
Tree Cover Loss (% of Forest Area)	0.75 (0.73)	2.13 (0.78) ***
R-squared	0.3542	0.1927
Mean squared error	76.29	89.15
Number of observations	1087	1087

p values = *: 0.1, **: 0.05, ***: 0.01, ****: 0.001.

3.3. Generalized Random Forest: Variable Importance, Calibration, and Best Model Results

Both in the full forest with selected variables and the country-level forests, non-forestry rent was the most split variable, indicating its importance in the recursive partitioning algorithm. It amounted to around 53% of the total splits in the country-level forest. The percentage of tree cover was consistently the second most important variable in this model (29.4%), and the percentage of FSC-certified area was also important (9.6%). Other important variables in the country-level forest were the interaction between resource rent and control of corruption (8.1%) and population density (7.4%).

Table 3 contains the results of the ‘best linear predictor’ methodology of Chernozhukov et al. [46] to assess whether the trained forest was well-calibrated. The predictor indicates that the conditional average treatment effects, i.e., CATEs could be fitted as a linear association of the out-of-bag causal forest estimates using our model (the coefficient of mean.forest.prediction was 1 and statistically significant) and that the country-level forest could identify heterogeneous linkage signals in the data (the coefficient of differential.forest.predictions was also very close to 1 and significant for both country-level forests) (Table 3).

Table 3. Forest calibrations for best model combinations of Equation (2)².

	Selected Variables’ Forest	Country-Level Forest
Mean.forest.prediction	0.65 (1.21)	1.004 (0.08) ****
Differential.forest.prediction	−5.4 (1.96)	1.13 (0.12) ****

p values = ****: 0.001.

Figure 3 shows the distribution of high to low CATEs, along independently taken covariates that were statistically significant ($p < 0.05$). Association of FSC certification presence with biodiversity conservation may be higher (meaning less percentage of threatened species) in countries with a higher loss of tree cover, higher population density, lower extraction of non-forestry resources, higher perception of control of corruption, and higher percent FSC-certified area. The association between FSC certification presence and biodiversity, along with the interaction term of natural resource rent and corruption control may exhibit a U shaped relationship; FSC presence may be negatively associated with

biodiversity in countries with ill-governed high extraction and slightly less negatively for those with extremely well-governed high extraction countries with an inflection at zero.

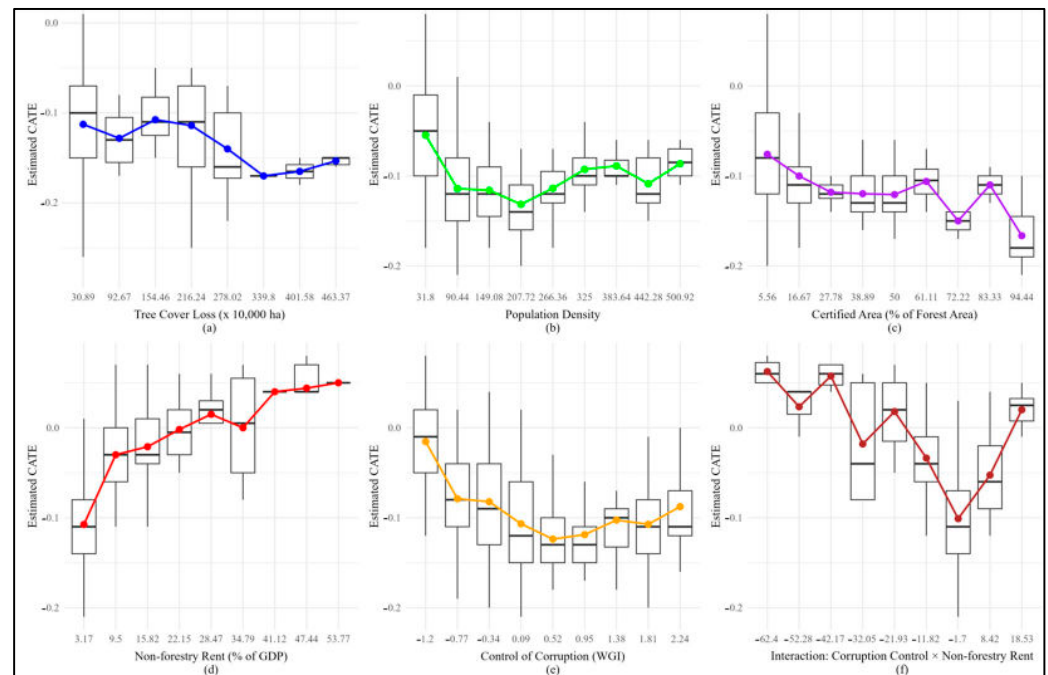


Figure 3. Statistically significant distributions of conditional average treatment effects (CATEs) of Forest Stewardship Council's forest management (FSC-FM) presence on percentage threatened species, along with six covariates (a–f), based on the best country-level generalized random forest (GRF) model for data across 91 countries between 2008 and 2019. GDP: gross domestic product; WGI: Worldwide Governance Indicator.

Table 4 contains the results of country-level forests showing the estimates and robust standard errors for modification in the association between FSC certification presence and biodiversity. Figure 3 shows the distribution of CATEs when covariates are considered independently, while Table 4 shows a modification in the association when other covariates are controlled for. The association between FSC certification and biodiversity is positive in contexts with higher percentage of FSC area and higher tree cover loss but negative when natural resource rent and its interaction with a perception of corruption control increases. The mean squared error of the GRF models was lower, and R^2 was higher than both OLS models.

Table 4. Results of modifications in the association between FSC certification and biodiversity (2008 to 2019) as identified by the country-level forest. Dependent variable: Percent threatened species. Treatment variable: FSC certification (presence/absence)³.

Independent Variables	Effect Modification
FSC-certified area (% of forest area)	−0.15 (0.04) ****
GDP per capita percent growth	0.82 (0.21)
Non-forestry rents (% of GDP)	0.96 (0.29) ****
Forestry rents (% of GDP)	−0.03 (0.36)
Control of corruption	−0.51 (1.02)
Interaction between Corruption Control and Non-forestry Rents	0.64 (0.42) **
Interaction between Corruption Control and Forestry Rents	−0.25 (0.36)
Population density	−0.007 (0.006)
Percentage of agricultural land	0.03 (0.04)
Tree cover loss (% of forest area)	−4.82 (1.56) ***

Table 4. *Cont.*

Independent Variables	Effect Modification
R-squared	0.5768
Mean squared error	36.75
Number of observations	91

p values = **: 0.05, ***: 0.01, ****: 0.001.

4. Discussion

Using a novel machine-learning algorithm based on generalized random forests, this study analyzed the linkages between FSC-FM certifications and biodiversity loss from a global perspective and successfully identified country-level factors that moderate the estimated association. By comparing the results from the OLS regressions with fixed effects and the findings from the random forest analyses, we can identify and validate the linkages and associations between the variables. The OLS regressions establish the statistical significance and directionality of the relationships. At the same time, the random forest analyses provide insights into the relative importance and conditional effects of the variables in the relationship between FSC-FM and biodiversity.

Our findings contribute to the existing literature by demonstrating the nuanced biodiversity relationship with FSC certifications across diverse governance contexts. While prior studies have emphasized the variability in certification implementation based on different country-level factors [21], our analysis using GRF provides novel insights into how country-specific factors are associated with these outcomes.

4.1. OLS Regression Results

Year-fixed effects control factors that affect biodiversity consistently across all countries in a given year. They control for time-specific factors that may influence the outcome variable but are constant within each country. In the OLS model with year-fixed effects, we find that a decrease in the GDP per capita, population density, and the percentage of tree cover loss, along with an increase in the percentage of certified area, and the perception of control of corruption may be associated with higher biodiversity. Lower GDP per capita suggests that economic development that focuses on sustainable practices and reduces ecological footprints can contribute to higher biodiversity. This highlights the need to balance economic growth with conservation efforts to minimize the negative relationships between ecosystems and species. Lower population density indicates that areas with lower human population pressure are associated with higher biodiversity, underscoring the importance of managing human activities and preserving natural habitats. A reduction in the percentage of tree cover loss signifies the preservation and restoration of forests, which are critical for supporting diverse ecosystems and species. Promoting sustainable forest management practices and mitigating deforestation are imperative for maintaining biodiversity. Additionally, a higher percentage of FSC-FM-certified areas indicates that responsible and sustainable forest management practices support biodiversity. This emphasizes the value of certification schemes in promoting conservation measures and ensuring the long-term health of forest ecosystems. Furthermore, the positive association between the perception of control of corruption and biodiversity highlights the importance of good governance and anti-corruption measures in protecting ecosystems. Effective governance can deter illegal activities that harm biodiversity and support sustainable resource management.

As this is a global study, it is important to consider these associations, as they can provide insights into the within-country dynamics of biodiversity conservation. There is likely a wide range of differences between countries in our study, which results in the

non-significance of these variables when country effects are included to assess cross-country dynamics. Future studies can categorize the countries into different groups and test the importance of country-level factors, such as geographical characteristics, governance, or cultural and political norms, using a two-way fixed effects model.

It is relevant to note that the non-forestry rent globally was the only statistically significant variable in the two-way fixed effects model. It was also the most crucial variable at the national level, both in its direct association with biodiversity and as a moderating factor in the association between forest certification and biodiversity loss. Moreover, this association does not seem to exist for just forest rents, as none of the estimates were found to be significant. This indicates that forest extractions per se might not be important to the association of FSC-FM with biodiversity, but other natural resources may play a significant role. Total and forestry natural resource rents have been known to have different moderating influences due to their respective contexts and roles in globalization [1]. This means that the international supply chains and trade networks for natural resource rent for oil and gas are higher in volume compared to forest products, indicating possible stronger linkages with biodiversity. This might be one of the reasons why, in our models, forest rent was not significant, but natural resource rent was. Future research must include relevant variables from dimensions of globalization and international trade—such as trade flows, cross-country regulations, foreign direct investments, etc.—to make the modeling more robust, as biodiversity outcomes are known to be exported from high-income to low-income countries [46]. Furthermore, including the forest-related dimension of economic inequality—including income disparities, poverty levels, land ownership and control, the human development index, etc.—along with corruption is also important, as they are known to increase threatened species [47], likely through an increase in rent-seeking activities. The linkage found in our study aligns with the findings of Okada and Samreth [30], who found that forest rents are not broadly associated with corruption, unlike total natural resource rents, which include oil, natural gas, coal, and forestry.

4.2. Implications of Generalized Random Forest Modeling

In our study, the application of GRF analysis allowed us to explore the confounding nature of variables and uncover crucial insights regarding the relationship between the presence of FSC-FM certification and biodiversity conservation. GRF analysis offers several advantages over traditional OLS regression, as it enables the identification of non-linear relationships, interactions, and heterogeneity in the data, providing a more comprehensive understanding of the underlying dynamics. By leveraging GRF, we can disentangle the intricate relationships among variables and gain valuable insights that may have been obscured by confounding effects. Our analysis focused on the treatment variable of FSC-FM presence/absence and considered both the full forest with selected variables and the country-level forests. This allowed us to account for potential confounding factors and capture the complexity of the relationships involved. By examining the variable importance measures obtained from GRF, we identified key factors that play a significant role in the association between FSC certification and biodiversity outcomes.

Among the significant variables identified, non-forestry rent emerged as the most influential, indicating its importance in the recursive partitioning algorithm. It accounted for approximately 53% of the total splits in the country-level forest, underscoring its confounding nature and potential to distort the relationship between FSC certification and biodiversity conservation. Additionally, the percentage of tree cover consistently ranked as the second most important variable (29.4%), highlighting its confounding effect on the association of interest. The percentage of FSC-FM-certified area also emerged as an important factor (9.6%), indicating its potential to confound the relationship between FSC

certification and biodiversity outcomes. Furthermore, the interaction of resource rent with control of corruption (8.1%) and population density (7.4%) contributed to the confounding nature of the variables under investigation.

By explicitly considering the confounding effects of these variables, we gain a clearer understanding of the association between FSC-FM presence and biodiversity conservation. Figure 3 displays the distribution of conditional average treatment effects (CATEs), along independently taken covariates that were statistically significant ($p < 0.05$). This analysis reveals that confounding variables can potentially influence the direction and magnitude of the relationship between FSC certification and biodiversity outcomes. It suggests that the actual association of FSC certification with biodiversity may be masked or distorted without adequately accounting for these confounding factors. Table 4 complements the analysis by presenting the estimates and robust standard errors for modifications in the association between FSC certification presence and biodiversity. The results demonstrate that the association of FSC certification with biodiversity is positive in the context of a higher percentage of FSC-FM-certified areas and higher tree cover loss. However, the association becomes negative when non-forestry rent and its interaction with the perception of corruption control increase, indicating the potential negative impact of poorly managed resource extraction and corruption on biodiversity outcomes.

These results support the arguments that (a) FSC-FM certification likely has a positive association with biodiversity where it is most needed, possibly in developing countries, where population densities and tree cover loss are high (see Winkler et al. [48] and Bjelle et al. [46]), and (b) enabling conditions, such as a higher perception of corruption control and lower extraction of non-forestry resources, are needed for that positive association with FSC-FM.

The calibration results presented in Table 3 indicate that the country-level forests could sufficiently capture the heterogeneity in the association of FSC certification with the percent threatened species, but the full forest could not. As the fully trained model is not as well calibrated as the country-level forest, it suggests that the model's performance may vary across different subgroups or levels of the data. This could indicate that the model is better calibrated or more accurate at a broader global level (consistent across all countries) but may exhibit inconsistencies or poorer performance when applied to more granular levels of the data (viz., between-country associations).

4.3. Limitations

This study has important limitations that should be considered when interpreting the findings. Firstly, FSC certifies only a small portion of global forests, which is primarily motivated by a price premium for timber characterized by SFM. Though this process could benefit biodiversity conservation, biodiversity conservation is mainly implemented and supported by anti-poaching, habitat management, designation of protected areas, and species rescue, which are part of the FSC-FM standard implementation. Nevertheless, the association discussed in this study might be determined by other factors, which need further study.

Secondly, the analysis is constrained by this study's timeframe, which only covers observations between 2008 and 2019. This limited period may not fully capture long-term trends and dynamics in the relationship between FSC-FM certification and biodiversity conservation. Additionally, this study does not consider the potential influence of the global slowdown in land-use changes following the economic crisis of 2007–2009 [48]. Incorporating this temporal context would provide a more comprehensive understanding of the association between certification and biodiversity outcomes.

Moreover, while this study offers valuable insights at the global level, it may mask regional variations and disparities between areas where certification is needed, and where it has been implemented. The analysis acknowledges the lack of significant progress towards FSC-FM certification in tropical regions (Figures 1 and 2), which are particularly important for biodiversity conservation. Therefore, the generalizability of the findings to these high-diversity regions may be limited. Furthermore, this study's use of identified species under threat and their changes as proxies for biodiversity outcomes may introduce biases. The process of identifying threatened species may vary across different regions, potentially leading to inconsistencies and inaccuracies in the measurement of biodiversity. This could impact the reliability and applicability of the biodiversity measures used in the analysis.

In terms of methodologies, it is important to acknowledge the limitations of both OLS regression and GRF. OLS regression assumes linearity and independence of variables, which may not fully capture the complex, non-normal, and non-linear relationships inherent in ecological systems. On the other hand, even though the mean squared error of GRF was lower and R^2 higher, and offers flexibility and the ability to capture non-linear associations, it is subject to potential biases and uncertainties related to the algorithm and assumptions made during model training. These can be potential sampling bias, failing to generalize well to unseen data through overfitting, and violating the assumption that treatment assignment is random or quasi-random. These limitations emphasize the need for caution when interpreting the results. Our results do not indicate causality but potential associations, and we suggest that alternative modeling approaches or complementary analytical methods could provide additional insights into the nuanced relationship between FSC-FM certification and biodiversity conservation.

5. Conclusions

This study highlights the critical association between FSC-FM certification and biodiversity conservation, providing empirical evidence of its impact across diverse geographic regions and governance contexts. By employing the GRF methodology, which is able to navigate complex and interdependent variables, our analysis reveals that while FSC-FM certification has a measurable positive effect on biodiversity, as indicated by lower percentages of threatened species, this association is nuanced and varies significantly by region and different factors. It is clearly necessary to incorporate socioeconomic and ecological knowledge for efficiently developing strategies for biodiversity management in the context of FSC certifications [49].

Key findings include the association between tree cover loss, non-forestry resource rents, and governance indicators, such as population densities and corruption control on the effectiveness of FSC-FM certification in promoting biodiversity. Our study highlights the indirect association of FSC-FM certification with biodiversity conservation through its alignment with the principles of sustainable forest management, despite the relatively small proportion of forests currently certified globally. These findings contribute to the growing literature on sustainable forest management and provide actionable insights for policymakers, certification bodies, and conservation organizations.

Despite this study's limitations, our results still provide valuable insights a) for FSC to strategically plan expansion into regions with better-enabling conditions for sustainable and responsible forest management and b) for governments to consider relevant policies that affect enabling factors for FSC FM certifications to be successful at promoting biodiversity conservation, striking a balance between economic growth and the preservation of ecosystems.

Author Contributions: Conceptualization: P.K. and P.D.; data curation: P.K.; formal analysis: P.K.; investigation: P.K.; methodology: P.K.; project administration: P.K. and P.D.; resources: P.K. and P.D.; software: P.K.; supervision: P.D.; validation: P.K. and P.D.; visualization: P.K.; roles/writing original draft: P.K.; and writing—review and editing: P.K. and P.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All the data used in this study are publicly available, and their sources have been cited and referenced throughout the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. List of countries used in the analysis in this study.

Names of Countries Included in the Analysis					
Argentina	The Republic of Congo	Guatemala	Madagascar	Poland	Thailand
Australia	Costa Rica	Guyana	Malaysia	Portugal	Turkey
Austria	Croatia	Honduras	Mexico	Romania	Uganda
Belarus	Czech Republic	Hungary	Morocco	Russia	Ukraine
Belgium	Denmark	India	Mozambique	Rwanda	United Kingdom
Belize	Dominican Republic	Indonesia	Namibia	Serbia	United States
Bolivia	Ecuador	Ireland	Nepal	Sierra Leone	Uruguay
Bosnia And	Estonia	Italy	Netherlands	Slovakia	Venezuela
Herzegovina	Fiji	Japan	New Zealand	Slovenia	Vietnam
Brazil	Finland	Kenya	Nicaragua	Solomon Islands	Zambia
Bulgaria	France	Republic Of Korea	Norway	South Africa	Zimbabwe
Cambodia	Gabon	Kyrgyzstan	Panama	Spain	
Cameroon	Germany	Laos	Papua New	Sri Lanka	
Canada	Ghana	Latvia	Guinea	Suriname	
Chile	Greece	Lithuania	Paraguay	Sweden	
China		Luxembourg	Peru	Switzerland	
Colombia			Philippines	United Republic of Tanzania	

Notes

- ¹ Confounders refer to variables that are associated with both the treatment variable and the outcome variable, posing a risk of bias by potentially influencing the relationship between the treatment and the outcome.
- ² Estimates, along with heteroskedasticity and cluster-corrected robust standard errors (in the brackets) are noted for each model prediction.
- ³ Estimates and heteroskedasticity and cluster-corrected robust standard errors (in the brackets) are noted for each independent variable.

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