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ORIGINAL ARTICLE

Plant trees for the planet: the potential of forests for climate change mitigation and the major drivers of national forest area

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Abstract

Forests are one of the most cost-effective ways to sequester carbon today. Here, I estimate the world's land share under forests required to prevent dangerous climate change. For this, I combine newest longitudinal data of FLUXNET on forests' net ecosystem exchange of carbon (NEE) from 78 forest sites ($N = 607$) with countries' mean temperature and forest area. This straightforward approach indicates that the world's forests sequester 8.3 $GtCO_2year^{-1}$. For the 2 °C climate target, the current forest land share has to be doubled to 60.0% to sequester an additional 7.8 $GtCO_2year^{-1}$, which demands less red meat consumption. This afforestation/reforestation (AR) challenge is achievable, as the estimated global biophysical potential of AR is 8.0 $GtCO_2year^{-1}$ safeguarding food supply for 10 billion people. Climate-responsible countries have the highest AR potential. For effective climate policies, knowledge on the major drivers of forest area is crucial. Enhancing information here, I analyze forest land share data of 98 countries from 1990 to 2015 applying causal inference ($N = 2494$). The results highlight that population growth, industrialization, and increasing temperature reduce forest land share, while more protected forest and economic growth generally increase it. In all, this study confirms the potential of AR for climate change mitigation with a straightforward approach based on the direct measurement of NEE. This might provide a more valid picture given the shortcomings of indirect carbon stock-based inventories. The analysis identifies future regional hotspots for the AR potential and informs the need for fast and forceful action to prevent dangerous climate change.

Keywords Forest area · Climate change mitigation · Carbon sequestration · Net ecosystem exchange · Fixed effects panel regression · FLUXNET · FAO

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1 Introduction

Forests provide many tangible and intangible ecosystem services integral for human well-being (e.g., Ellison et al. 2017; Federici et al. 2015). Beyond this, forests are considered one of the most suitable ways to sequester carbon today, as afforestation and reforestation (AR) are relatively cost-effective, and associated with least expected adverse effects on biogeochemical and biogeophysical systems (Fuss et al. 2018; Griscom et al. 2017; IPCC 2014; Smith et al. 2016; Sonntag et al. 2016).

Recent global estimates on the current net carbon sink of established forests (i.e., carbon sequestration) range from 2.2 (Federici et al. 2015) to 8.0 (Grassi et al. 2018; Oleson et al. 2013)[1] to 8.8 gigatons of carbon dioxide per year ($GtCO_2year^{-1}$; Pan et al. 2011). Evaluations of the maximum biophysical sequestration potential of AR vary from 1.1 to 12.1 $GtCO_2year^{-1}$ (Smith et al. 2016; Minx et al. 2018; Ciais et al. 2013). However, all these estimates are based on the calculation of changes in carbon stocks along Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC 2006) or the Houghton bookkeeping method (Houghton et al. 2012), providing an indirect and mostly incomplete measure of forests' net ecosystem exchange of carbon (NEE). This approach requires periodic information on the carbon content of biomass and involves fundamental assumptions on carbon stocks—especially when reliable data is missing. This is notably true for many developing nations (Grassi et al. 2018; IPCC 2006). Moreover, each of these country estimates is based on different data quality, definitions of forest area, and accounting methods. Though data quality is gradually improving, this suggests a sizable challenge to develop a valid and internationally comparable inventory of global forest carbon fluxes based on indirect stock-based techniques (Grassi et al. 2018).

This study has four objectives: First, I provide estimates of the annual carbon sequestration of established forests and the biophysical climate change mitigation potential of AR based on the direct micrometeorological measurement of NEE as provided by FLUXNET (NASA 2015) (Sect. 2). With this direct measurement of above canopy carbon flux, no information on carbon stocks is needed to infer NEE. Thus, NEE estimates based on FLUXNET data may provide a more valid picture of forests' carbon sink and their mitigation potential. Second, with this straightforward approach, I infer the forest land share required to meet the 2 °C climate target and three AR scenarios to acquire this goal (Sect. 3; see Appendix Methods and Materials for details). Third and subsequently, I identify the countries with the largest climate liabilities, and economic capabilities while having the greatest mitigation potential through AR (Sect. 4).

Fourth, for effective policies targeted at enhancing forests and climate change mitigation, knowledge on the key drivers of forest area is essential. However, information on causal relationships of forest gain and loss is sparse and unconsolidated (Aguilar and Song 2018; Morales-Hidalgo et al. 2015) with a focus on forest loss (Busch and Ferretti-Gallon 2017). Yet, this is only half of the story to be told. Thus, here I identify the major predictors of the forest land share of 98 countries from 1990 to 2015 gathered from the Food and Agriculture Organization of the United Nations (FAO 2018) applying causal inference (Sect. 5). The last section summarizes and discusses the main results and closes with some concluding remarks.

[1] Results from the simulations of the Dynamic Global Vegetation Model (DGVM) Community Land Model (CLM) version 4.5 (Oleson et al. 2013; Table SI 8 in Grassi et al. 2018);

2 Global and regional forest carbon sink

To quantify the NEE of countries' forests, I utilize the newest available micrometeorological FLUXNET data of 78 measurement towers in forests of 16 countries on five continents from 2000 to 2014 ($N = 607$; Table S1 in Supplementary Figures and Tables). Multiple linear ordinary least squares (OLS) regression identifies annual mean temperature as the main determinant of forests' NEE (u-shaped relationship) in this data (Table S2 and Fig. S1 in Supplementary Figures and Tables). Model predictions on countries' NEE of forests using countries' average temperature taken from the World Bank (2018) show that established forests sequester − 8.8 tCO_2ha^{-1} $year^{-1}$ on average in 2015 (median − 9.2; Appendix). This is rather close to prior assessments based on indirect measurements of NEE (Sohngen 2010). Portugal has the highest negative NEE with a net absorption of − 15.1 tCO_2ha^{-1} $year^{-1}$, whereas the highest positive NEE is observed for Canada with a net release of 16.3 tCO_2ha^{-1} $year^{-1}$ (Fig. 1a). The forests of almost all countries are net absorbers of carbon, except the boreal forests in Canada, the Russian Federation, and Mongolia that are net sources of carbon. This might be due to diebacks of these boreal forests resulting from insect outbreaks and wildfires due to higher mean temperatures and droughts induced by climate change (Canadell and Raupach 2008). As introspection of Fig. 1a reveals, NEE varies by climate forest domain following a u-shaped mean temperature–NEE relationship. The carbon sequestration of boreal forests is lowest with a mean NEE of − 1.1 tCO_2ha^{-1} $year^{-1}$, while it is highest for temperate forests with − 12.6 tCO_2ha^{-1} $year^{-1}$. Tropical forests' NEE lies in-between with an average of − 6.0 tCO_2ha^{-1} $year^{-1}$. This pattern is in line with former research (Brumme et al. 2005).

Multiplying countries' average NEE per hectare by their forest area (FAO 2018, Fig. 1b) suggests an overall forest carbon sink of − 8.3 $GtCO_2year^{-1}$ or − 1.1 tCO_2year^{-1} per capita (p.c., UNPD 2017) in 2015. Carbon sequestration is highest in the forests of the USA and Brazil (− 3.2 $GtCO_2year^{-1}$ each), followed by China (− 2.0 $GtCO_2year^{-1}$), Australia (− 1.5 $GtCO_2year^{-1}$), and the Democratic Republic of the Congo (− 1.1 $GtCO_2year^{-1}$). The rest of the world's countries has a net absorption of less than − 1.0 $GtCO_2year^{-1}$ each, and Canada, Mongolia, and the Russian Confederates have a substantial net release of 16.7 $GtCO_2year^{-1}$ in sum.

The global estimate of this rather simple approach using direct carbon flux measurements of NEE is fairly close to the estimates of two recent studies applying more complicated, indirect, carbon stock-based inventories of NEE (Grassi et al. 2018; Oleson et al. 2013; Pan et al. 2011). Grassi et al. (2018) report a global forest carbon sink of − 8.0 $GtCO_2year^{-1}$ for the community land model (version 4.5; Oleson et al. 2013)[2] and Pan et al. (2011) estimate a sink of − 8.8 $GtCO_2year^{-1}$ based on changes in carbon stocks.

3 Forest land share trends and AR scenarios

Before evaluating countries' climate change mitigation potential of AR (Fig. 1c), the current forest land share, suitable land for AR as well as competing land uses have to be quantified.

[2] This Dynamic Global Vegetation Model (DGVM) could be considered one of the most elaborate DGVMs as it comprises the most relevant ecological characteristics as compared to other commonly used DGVMs (Table SI 7 in Grassi et al. 2018).

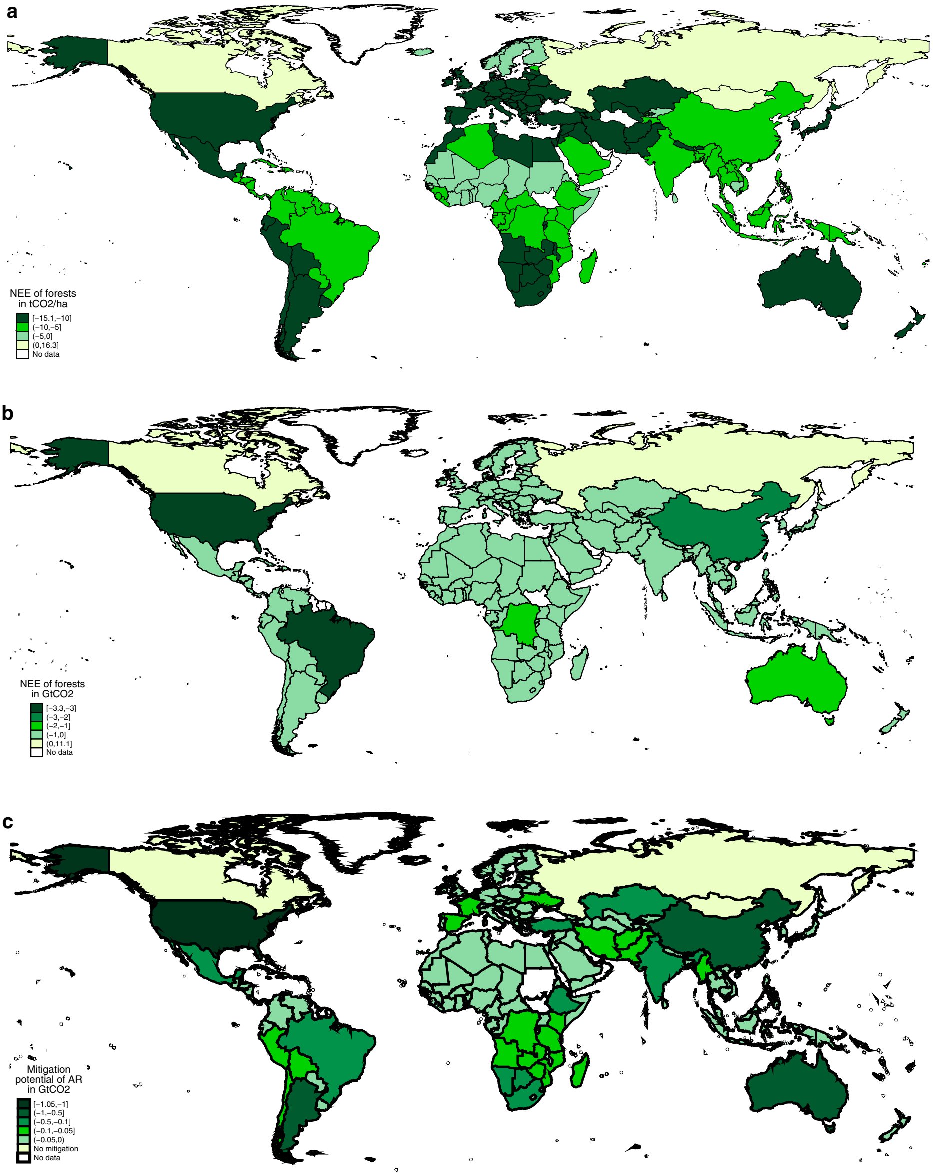

Fig. 1 Net ecosystem exchange (NEE) of CO_2 of countries' forests in 2015. **a**–**c** Data source for the calculation of NEE of CO_2 of countries' forests is FLUXNET (NASA 2015), World Bank (2018), and FAO (2018). Negative numbers indicate net absorption of carbon, positive numbers its net release. **a** Carbon sequestration in tCO_2ha^{-1} $year^{-1}$ of forest area (mean = − 8.8, median = − 9.2, min. (Portugal) = − 15.1, max. (Canada) = 16.3). **b** Countries' overall forest carbon sequestration in $GtCO_2year^{-1}$ (sum = − 8.3 $GtCO_2year^{-1}$). **c** Countries' overall NEE potential of afforestation/reforestation (AR) in $GtCO_2year^{-1}$ based on scenario 3 exceeding the 7.8 $GtCO_2year^{-1}$ required to meet the 2 °C respectively 3 tCO_2 per capita climate target (sum = −8.0 $GtCO_2year^{-1}$; see text and Appendix for details)

The average forest land share as provided by the FAO shrunk from 31.8% in 1990 to 30.8% in 2015 (Fig. 2), which corresponds to a forest loss of 1.3 Mkm^2—an area as large as Peru.

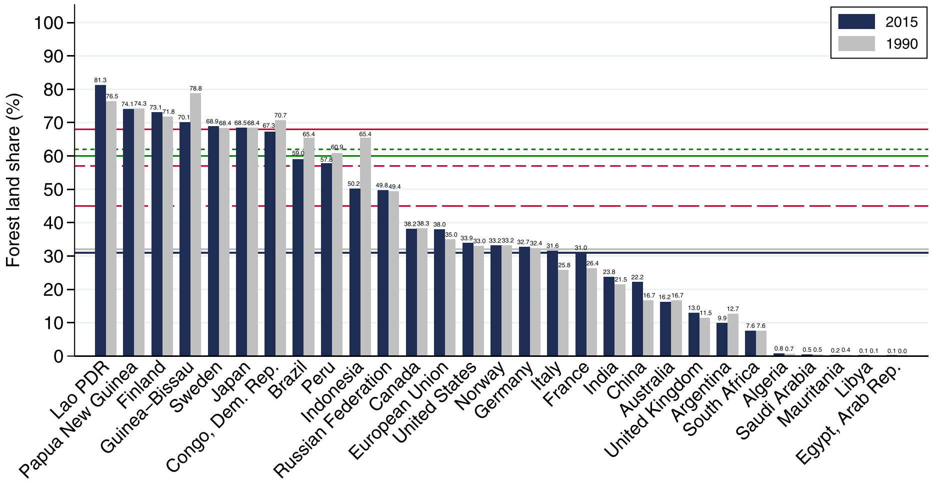

Fig. 2 Forest land share in international comparison 1990 and 2015. Depicted are the top and bottom five countries, top five countries with respect to overall forest area (FAO 2018) by climate domain in 2015 and members of the G7 and BRIICS if not already included. Dark blue solid line = mean 2015; grey solid line = mean 1990; scenario 1: red solid line = required forest share for the 2 °C climate target, red long-dashed line = achievable forest share; scenario 2: red dashed line = achievable forest share; scenario 3: green solid line = required forest share, green short-dashed line = achievable forest share. See text and Appendix for details

As Fig. 2 shows, European countries like France, Italy, Germany, and Norway resemble the mean of 2015. The forest land share varies strongly: Laos ranks highest with 81.3% and is followed by Papua New Guinea, Finland, Guinea-Bissau, and Sweden constituting the top five. The bottom five countries with almost no forests are Algeria, Saudi Arabia, Mauritania, Libya, and Egypt. Between 1990 and 2015, Indonesia incurred the greatest loss of almost a quarter and Brazil as top carbon-sequestering country lost 10.0% of its tropical forests. The greatest gain was accomplished by China with a one-third increase in forest area while ranking third in overall NEE. For the USA as top carbon-absorbing nation, almost no change in forest cover was observed in this period.

Furthermore, Fig. 2 presents the required as well as the achievable forest land share of three different AR scenarios to prevent dangerous climate change. The global annual gross carbon budget to fulfill the 2 °C climate target with a probability of at least 66% is an estimated 30 $GtCO_2$ (IPCC 2014; Friedlingstein et al. 2014; Meinshausen et al. 2009). Assuming an average annual world population of 9.8 billion people until 2100 (UNPD 2017), this goal translates into ~3 t of gross CO_2 emissions per capita (p.c.) and year.

First, scenario 1 is the baseline scenario. It assumes constant production and consumption patterns, constant other carbon sinks, and a further required emissions reduction of 1.0 tCO_2year^{-1} p.c. after accounting for the overall forest carbon sequestration of 0.8 tCO_2year^{-1} p.c.. Hence, in scenario 1, the required forest land share to meet the 2 °C respectively the 3 tCO_2 p.c. climate target is 67.8% (red solid line in Fig. 2) to additionally sequester 9.8 $GtCO_2year^{-1}$ (Appendix). The red long-dashed line is the forest land share that can be achieved via 100% AR of all shrub-covered areas and herbaceous vegetation as retrieved from the FAO (2018) (44.8% forest land share). This is more than one third of the required AR. Second, in scenario 2, a forest land share of up to 57.5% can be achieved by additionally afforesting and reforesting 44% of permanent grassland and cropland (FAO 2018), assuming current diets and an average land demand of 2100 m² p.c. (Hallström et al. 2015) for feeding an expected 9.8 billion people per year (red dashed line in Fig. 2). This represents more than two thirds of this tremendous AR challenge. Finally, in scenario 3, healthier diets with reduced red and ruminant meat consumption decrease agricultural land demand further by 28.0% to 1510 m^2 p.c. and reduce dietary-related emissions by 0.2 tCO_2year^{-1} p.c. (Hallström et al. 2015). This yields a required forest land share of 60.0% to meet the 2 °C climate target (green solid line in Fig. 2) equivalent to an additional 7.8 $GtCO_2year^{-1}$ to be sequestered by forests. Thus, in this healthy diet scenario, further AR of grassland and cropland results in an attainable 62.0% of forest land share (8.0 $GtCO_2year^{-1}$; green short-dashed line in Fig. 2).

Consequently, the 2 °C climate target can be met by almost doubling the current forest area while safeguarding food security with a healthy diet. This outstanding challenge means 37.9 Mkm^2 more of forest area or an estimated 2.6 trillion additional trees. Approximately, this corresponds to the number of trees lost since the start of human civilization (Crowther et al. 2015). This challenge translates into approximately 260 trees p.c. or one tree p.c. per week for a realization time of 5 years.

Realizing the need for large-scale AR, there are promising worldwide projects like "Plant for the Planet," which aims at planting one trillion trees. Since 2007, this project has planted 13.6 billion trees (Plant for the Planet 2019)—0.5% of the climate target. In 2017, the World Wildlife Fund, the Wildlife Conservation Society, and BirdLife International launched the "Trillion Trees" program aiming at restoring one trillion trees by 2050 (Trillion Trees 2019). Furthermore, the "Bonn Challenge" strives for the restoration of 3.5 Mkm^2 of forests by 2030 (~ 9.2% of AR required for the 2 °C target). To date, pledges exceed 1.7 Mkm^2 (International Union for Conservation of Nature 2019). To achieve the targets of all three voluntary initiatives together would account for the vast majority of the required AR (86%). Two hundred sixty trees per capita seems a relatively low number. However, the need for fast and forceful AR is high leaving this venture an ambitious challenge.

4 Liabilities, AR potentials, and capabilities

Given that call, who is in charge of action? Being the country with the highest negative NEE of established forests (Fig. 1b), and the world's second largest carbon emitter (Janssens-Maenhout et al. 2017), the USA ranks highest in the climate change mitigation potential of countries through AR (NEE = − 1.0 $GtCO_2year^{-1}$; Fig. 1c). Figure 1c also demonstrates that the world's largest carbon emitter and third largest carbon absorber in forests, China, has the second highest AR potential (− 0.8 $GtCO_2year^{-1}$). This offers a great opportunity for the USA, and China, accounting for almost half of the global carbon emissions and having to bear one of the highest domestic social costs of carbon emissions (Ricke et al. 2018), to take their responsibility for climate change mitigation seriously. Together with Australia, Argentina, and Brazil, they form the top five countries with respect to mitigation potential through AR, accounting for almost half of its total.

The radar plots in Fig. 3 provide a more comprehensive picture of the countries' climate change liabilities, forests' mitigation contributions, AR potentials, and economic capabilities for action in worldwide comparison. One group of countries at the top of the ranking of the sum score of these characteristics is formed by those ranking highest in mitigation potential of AR, while being among the largest emitters of CO_2 (p.c.) and the wealthiest nations (Fig. 3a–c, e–j, n). These countries are Japan, Spain, France, Australia, the USA, Argentina, Italy, Germany, Brazil, and the UK. Hence, these states could take over their responsibility for

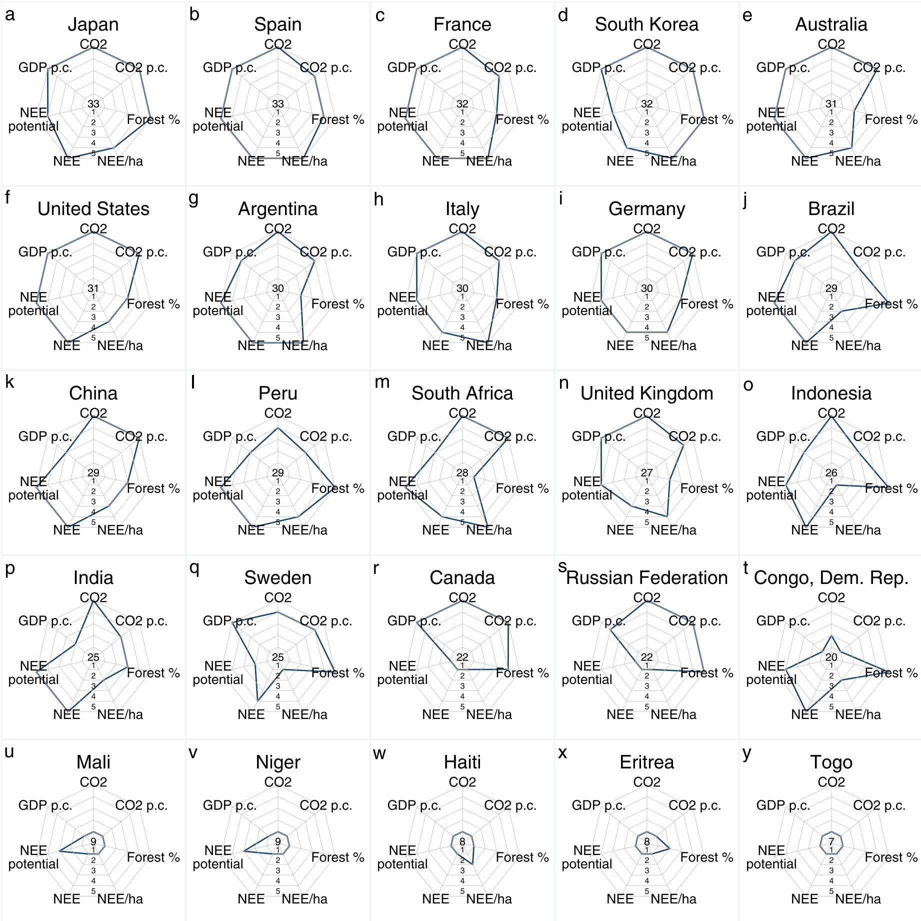

Fig. 3 Country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015. **a**–**y** Radar plots of countries' relative performance with regard to climate responsibility (CO_2, and CO_2 per capita (p.c.) emissions (Janssens-Maenhout et al. 2017)), forests' mitigation contribution (forest land share (%; FAO 2018), net ecosystem exchange (NEE) per ha, and national NEE), forests' mitigation potential (NEE potential)), and economic capabilities (gross domestic product (GDP) p.c. (IMF 2018)). The numbers 1 to 5 on the spokes of the radars indicate the quintile the country ranks (1 = lowest, 5 = highest). The numbers in the center of each radar represent the sum of quintiles of each country. Presented are the top and bottom five countries with respect to this sum, the top five countries of overall forest area by climatic forest domain and members of the G7 and BRIICS. The full country ranking of the sum score and all included variables can be obtained from Table S4 in Supplementary Figures and Tables

climate change mitigation relatively easily via large-scale domestic AR activities. Figure 2 indicates that the forest land share of three of these countries, France, Italy, and the UK, grew between 1990 and 2015, while Brazil and Argentina experienced forest loss.

Another group of nations is both liable of global warming and has high AR potential, but to some extent lacks economic strength to implement large-scale measures. Countries like China, Peru, South Africa, Indonesia, and India fall into this group (Fig. 3k–m, o, p). Indonesia and Peru reflect this, since these countries lost forests between 1990 and 2015 (Fig. 2). By contrast, China and India gained forest in this period probably due to large-scale AR programs. These nations and poor countries with little climate responsibility but large AR potential like the

Democratic Republic of the Congo (Fig. 3t) need multilateral financial assistance, foremost from wealthy, climate-responsible states, to unfold their AR potential. This applies to countries, which additionally have relatively low or no AR mitigation potential like South Korea, Sweden, Canada, and the Russian Federation (Fig. 3d, q–s). This could be a worthwhile enhancement of the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) framework.

5 Predictors of national forest land share

Nonetheless, the plea for international cooperation and referring to climate change responsibility is not enough. For effective policies targeted at the enhancement of forests, profound knowledge on the key drivers of national forest area is crucial. Previous research has focused on determinants of forest loss with different regional and temporal cover and a focus on satellite-derived data in recent years (Busch and Ferretti-Gallon 2017; Leblois et al. 2017). However, these studies are agnostic about AR and forest regrowth, as some authors critically remark themselves (DeFries et al. 2010). Focusing on forest loss only shines light on half of the story to be told. Hence, causal information on the predictors of national forest land share analyzing panel data of many countries by means of causal inference is still sparse and unconsolidated (Aguilar and Song 2018; Morales-Hidalgo et al. 2015).

Aguilar and Song (2018) and Morales-Hidalgo et al. (2015) are the only two studies regressing changes in national forest area as provided by the FAO on changes in countries' socioeconomic characteristics utilizing fixed effects (FE) panel regression models. Morales-Hidalgo et al. (2015) is the first study regressing national forest area between 1990 and 2015 gathered from the FAO on a few socio-economic and political indicators applying causal inference. The results of their country and year FE panel regression models (Table 6 in Morales-Hidalgo et al. 2015) suggest that population growth reduces forest area, whereas GDP p.c. and protected areas increase it. Nonetheless, the results of Morales-Hidalgo et al. (2015) could be biased by omitting other substantial drivers of forest land share. Aguilar and Song (2018) is the only study analyzing the ratio between national forest area and land area (i.e., forest land share) ensuring comparability of changes in forest cover between countries irrespective of their total land area. In their FE models, Aguilar and Song (2018) include agricultural land area, 10-year lagged GDP growth rate, GNI p.c., population growth rate, population density, share of rural population, rate of secondary school enrolment, its 15-year lagged values, and the squares of all these characteristics as independent variables. The results of their beta-logistic generalized linear mixed models with ratio response indicate that all of the considered covariates are substantially related to forest land share (Table 3 in Aguilar and Song 2018). However, FE models including both levels and lags of the same characteristics produce biased results, if the causal effects emerge immediately (Vaisey and Miles 2017), as it is the case in Aguilar and Song (2018). Furthermore, the results of Aguilar and Song (2018) could be biased by omitting important confounding variables.

To improve, consolidate, and expand previous studies, here, I regress the forest land share of 98 countries from 1990 to 2015 as provided by the FAO on socio-economic, political, and ecological characteristics applying country and year FE regression models (Brüderl and Ludwig 2015; Appendix). The 98 countries analyzed (Table S7) have high or sufficient quality of forest area data (tiers 3 and 2; FAO 2016) and comprise around 89% of global forest area in 2015 (Keenan et al. 2015). All other countries, which have unreliable data solely based on expert estimates (tier 1), are excluded from the analysis.

First, one of the best-documented drivers of deforestation is agricultural expansion (Jorgenson 2006). As model 1 of Fig. 4 shows, a 1% within-country increase in agricultural land share on average leads to a 0.2% within-country decrease in the forest land share. Population growth explains this effect, as it disappears when population size is included in the regression (model 2). Population growth of 1% yields deforestation of 0.27%. This suggests that agricultural expansion allows population growth, which in turn exerts pressure on forests, because of land demands for housing, mobility, and other resources.[3]

Second, it has often been hypothesized that urbanization slows deforestation and promotes AR, because the per-capita land demand of cities is assumed to be lower as compared to rural areas (Jorgenson 2006). However, the models 2–6 of Fig. 4 reveal that increasing rates of the population living in urban areas are not substantially related to countries' forest area.

Third, the direction of the impact of growing wealth on forest cover is widely discussed in the literature (e.g.. Jorgenson 2006). There has been widespread consent that deforestation activities prevail at low and middle levels of gross domestic product (GDP) p.c. and AR activities outweigh deforestation at higher levels of GDP p.c. following a trajectory referred to as the environmental Kuznets curve (EKC; Aguilar and Song 2018). However, the empirical evidence for a forest EKC is mixed and the two most recent and elaborate studies found evidence for a clear positive relationship between GDP and forest cover invalidating the forest EKC hypothesis (Aguilar and Song 2018; Morales-Hidalgo et al. 2015). Models 3–6 of Fig. 4 highlight this as well: Economic growth of 1% increases forest land share by 0.1% irrespective of economic structure and wealth levels.[4] Hence, this supports the notion that wealth at least to some extent leads to more awareness for the ecosystem services of forests and the need to protect them.

In addition to that and extending prior studies, economic structural change could affect forest transition net of GDP growth. An increasing GDP share of the industry sector might introduce pressure on forestlands because of relatively high land requirements of industrial production sites and higher returns for industrial production than for forest products. As models 3–6 of Fig. 4 indicate, there is some evidence in favor of this argument, because a 1% increase in the GDP share of the industry sector yields a 0.1% decrease in forest land share. In turn, expansion of the service sector could release pressure from forests, as services are presumed to have less land demand. However, in the data, there is no support for this notion, since a 1% increase in the GDP share of the service sector is also related to a 0.1% decline in forest cover. Yet, this effect is not statistically significant at the $p = 0.05$ level.

Furthermore, the model is enhanced by including an indicator of foreign trade in forest products. It has been a common concern that forest product trade could be one of the reasons for deforestation especially in poor countries with tropical forests and few alternatives of employment to timber logging or farming. By contrast, one can argue that foreign trade of forest products could be an incentive for forest conservation, when the net return of forestry investments and sustainable forest management is greater than the net return for forest clearing for agricultural production (Burgess 1993). However, models 4–6 of Fig. 4 demonstrate that increases in exports of forest products relative to their imports do not substantially alter countries' forest area.

[3] Moreover, in the FE regression of population ($N = 2504$, $n = 98$), the elasticity of agricultural land is 0.49 ($p < 0.001$). Together with the results of the models 1 and 2 of Fig. 4, this suggests that population growth mediates the relationship between agricultural expansion and forest loss.

[4] The partial residual plot for GDP of a penalized splines FE regression (Ruppert et al. 2003) adequately modelling non-linearities confirms this, too (Figure S2 in Supplementary Figures and Tables).

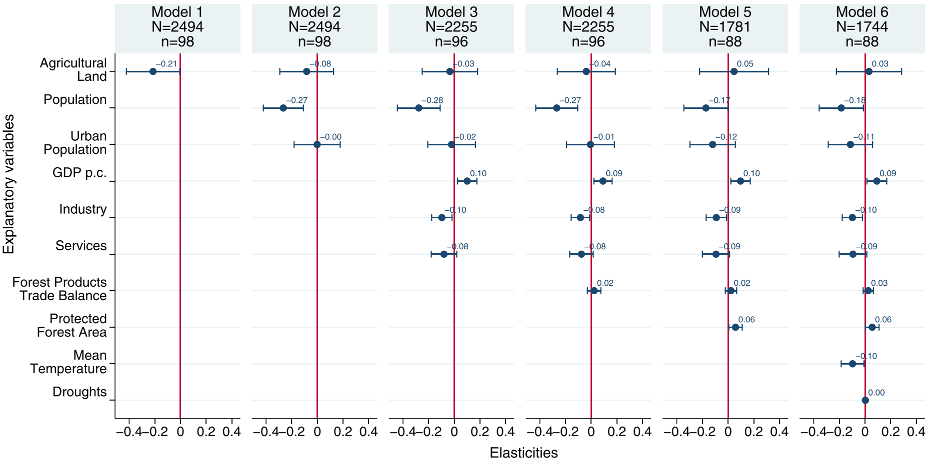

Fig. 4 Predictors of national forest land share. Coefficient plots of unstandardized regression coefficients (dark blue filled circles) of country and year fixed effects regressions of national forest land share on various successively included predictors (models 1–6) including 95% confidence intervals (dark blue bars; see Table S5 in Supplementary Figures and Tables for details). All six models contain dummy variables for each year to control for overall time-trends. All variables are included by taking their natural logarithm allowing the estimation of elasticities. "*n*" refers to the number of countries, and "*N*" to the number of observations (number of countries (*n*) times the number of years). Table S6 in Supplementary Figures and Tables describes all variables and Table S7 lists all countries included in the models

Moreover, policies for forest protection may contribute to stop deforestation and forest degradation and foster AR activities with the aim of enhancing the global forest carbon sink, conserving biodiversity, and safeguarding other ecosystem services of forests. These goals are part of manifold international initiatives and agreements on forest protection. Designating and managing protected areas has been a primary strategy to achieve these goals (Morales-Hidalgo et al. 2015). Hence, protected forest area serves as an indicator for a country's willingness to sustain the ecosystem services of forests and to commit to AR activities. As models 5 and 6 of Fig. 4 reveal, a 1% increase in protected forest area is associated with forest growth of 0.06%. This effect is statistically significant, but rather small. This is in line with the results of Morales-Hidalgo et al. (2015).

Finally, climate change itself might harm forest ecosystems leading to forest degradation and forest loss. Long-term case studies of tree mortality indicate that higher mean temperature and droughts increase tree mortality and the frequency of wildfires (Canadell and Raupach 2008; Young et al. 2017; Martin 2015). However, it is still unclear whether this also applies to forest loss on a global scale. As model 6 of Fig. 4 shows, a 1% increase in countries' mean air temperature reduces their forest area on average by 0.1%, while severe drought events do not affect forest cover immediately and ceteris paribus. This suggests that global warming contributes to forest loss, even though the effect is rather small.

6 Discussion and conclusion

Altogether, this study suggests that dangerous climate change could be prevented solely by AR, as forests' biophysical climate change mitigation potential safeguarding food security with healthy diets (scenario 3) exceeds the required additional carbon uptake for the 2 °C target. For this, the study estimates countries' carbon sequestration of forests based on the direct micrometeorological measurement of NEE, average temperature, and forest area. This straightforward, direct carbon flux-based method provides estimates that are comparable to the most recent studies applying more complicated, indirect carbon stock-based inventories of NEE. The direct approach followed here might provide a more valid picture given the outlined shortcomings of indirect carbon stock-based inventories. However, the direct approach rests on the assumption that countries' average temperature is a valuable approximation of the mean climatic conditions of their forests. Moreover, uncertainties stem from data gaps on the NEE of tropical forest biomes, as Fig. S1 in Supplementary Figures and Tables demonstrates. Further uncertainties may arise from varying tree density, age, species, species richness, and the health of forests (Hawes 2018). Hence, further validation of these initial findings is needed. This includes the establishment of additional and more precise FLUXNET measurement towers especially in tropical forests to close data gaps and to increase accuracy and spatial resolution of model predictions.

Furthermore, the analysis identifies future regional hotspots for the AR potential. The USA, China, Australia, Argentina, and Brazil are the top five countries with respect to mitigation potential through AR, accounting for almost half of its total. However, to unfold the AR potential effectively, it is vital to establish a global mandatory carbon certificate market incorporating the forest carbon sink of countries and private forest owners. This generates financial incentives to restore and sustain forest biomes (Sohngen 2010). Enriching voluntary initiatives like REDD+ with countries' AR potentials, climate liabilities, and economic capabilities might be a valuable starting point for that.

Evenly important, the analysis of the major drivers of countries' forest land share highlights that curbing agricultural expansion and population growth may be a focus for AR policies. Moreover, forests' vulnerability to global warming points to the necessity to plant the right trees in the right places. Therefore, sustainable regional forest management needs to identify the tree species most resilient to temperature increases, and enhance the biodiversity of forests (Huang et al. 2018; Liang et al. 2017). Together with growing wealth, the expansion of protected forest areas is a suitable way to amplify the forest carbon sink, conserve biodiversity, and safeguard other vital ecosystem services provided by forests.

Nevertheless, biophysical, social, and economic challenges alongside large-scale AR might jeopardize its potential benefits (e.g., Canadell and Raupach 2008; Smith et al. 2016; Fuss et al. 2018) and contest the feasibility of the three presented AR scenarios. In general, all three presented AR scenarios a priori exclude land cover types that are, by themselves, biophysically unsuitable for near-term and cost-efficient AR (i.e., artificial surfaces, permanent snow and glaciers, terrestrial barren land, and sparsely natural vegetated areas). In addition, all scenarios safeguard food supply for 10 billion people. However, the feasibility of all three scenarios more or less depends on the socio-economic pressure exerted on the land designated to be afforested/reforested. Griscom et al. (2017) report that almost half of the existing AR potential could be cost-effectively realized below US\$100 tCO_2^{-1} (the estimated social cost of 1 tCO_2 emitted within the 2 °C climate target). More than 10% of the AR potential are achievable at low cost (< US\$10 tCO_2^{-1}). At least part of scenario 1, the AR of shrub-covered and herbaceous vegetation might be reachable at low cost. However, costs are expected to be higher for the AR of agricultural land (permanent grassland and cropland; scenarios 2 and 3). Agricultural expansion and increases in population density increase the opportunity costs of not clearing forests and the costs of AR, and decrease forest cover (as shown in this study). Near-term costs might be even higher, when a large-scale diet transitions away from red and ruminant meat is demanded to free up additional land for AR (scenario 3). Yet, meat-reduced diets are regarded as "win-win diets" fostering both public health and the environment in the long run (Willett et al. 2019). Moreover, and as this study demonstrates, the growing wealth of nations decreases the relative costs of AR and conveys forest protection and AR. Nonetheless, well-tailored AR policies have to account for possible trade-offs between climate change mitigation through AR and benefits for the local population. Here, agroforestry and policies targeted at the promotion of timber as building material while substituting carbon-intensive concrete and steel could be especially beneficial and may substantially promote climate change mitigation (Oliver et al. 2014; Tollefson 2017).

All told, permanent carbon storage is a prerequisite to outpace the burning of fossil carbon and reduce the CO_2 concentration in the atmosphere. Hence, it is vital to combine sustainably managed, large-scale AR activities with technologies for permanent carbon storage like bioenergy with carbon capture and storage (BECCS) at the end of the trees' life cycle for effective climate change mitigation (Fuss et al. 2018; Smith et al. 2016). What is more, abating emissions and applying other negative emissions technologies are valuable in order to hedge the impact of potential side effects of one mitigation option like AR (Minx et al. 2018; Sohngen 2010; Fuss 2010) to keep up with the need for fast and forceful action to prevent dangerous climate change.

Data availability All data used in this article is publicly available at the referenced webpages.

Compliance with ethical standards

Competing interests The author declares that he has no competing interests.

Appendix

Methods and materials

Global and regional forest carbon sink

To assess the net ecosystem exchange of carbon (NEE) of countries' forests, I use the newest available direct measurements of NEE of 78 micrometeorological measurement towers located in forests of 16 countries from 2000 to 2014 provided by FLUXNET (NASA 2015). See Table S1 in Supplementary Figures and Tables for an overview of the analyzed tower sites. FLUXNET sites collect data on the exchanges of CO_2 between forests and the atmosphere, precipitation, and air temperature at least in a 30-min interval. Table S3 provides a summary of the descriptive statistics. The tower sites use eddy covariance methods to measure forests' NEE. The unique dataset utilized here, "FLUXNET2015", provides standardized values for these characteristics and underwent several quality control tests and gap-filling (Pastorello et al. 2017).

To infer the NEE of countries' forests from these 78 FLUXNET sites, I apply a straightforward approach consisting of three steps: Firstly, I regress their annual NEE on several site characteristics (average temperature, average temperature squared, precipitation, latitude, and elevation) controlling for overall time-trends by including dummy variables of the years observed. While primarily interested in the variation between the forest sites, the inclusion of the 607 site-years available for this model minimize the influence of a specific observation period stemming from annual variation in climatic and other conditions. Therefore, all standard errors are clustered by tower site to ensure robustness with respect to heteroscedasticity and autocorrelation. The results of this linear ordinary least squares (OLS) regression model (Table S2) indicate that only average temperature substantially relates to NEE. As Fig. S1 shows, the temperature-NEE relationship of forests follows a u-shaped pattern. Forests with an annual mean temperature of − 5 to 0 °C are net emitters of carbon, whereas the carbon sequestration of forests is highest in climatic domains with an average of about 15 °C. Even higher temperatures are associated with lower sequestration. Note that uncertainty between 15 and 26 °C is relatively high, because of a rather limited number of tower sites in this climatic forest domain. The reported regression results of Table S2 were tested for robustness: First, the model was rerun excluding one measurement tower each time from the regression. Second, all parameters were tested for linearity including a penalized splines fixed-effects (FE) regression model (Ruppert et al. 2003). Furthermore, the robustness of standard errors was investigated via non-parametric bootstrapping. None of these checks had any substantial influence on the estimates. In addition, the robustness of all estimates with respect to model specification was assessed using the procedure suggested by Young and Holsteen (2017). The potential influence of omitted variables was examined using the method suggested by Frank (2000). Also, these checks detected no fundamental deviations from the reported results. The analyses were conducted using the statistical software package STATA 15.1.

Secondly, I predict the mean annual sequestration between the years 2000 and 2014 (t) of country i's forests in tons CO_2 per hectare (y_i) from model 1 of Table S2 according to the following formula:

$$y_i = \frac{1}{T}\sum_{t=1}^{T}\left(\beta_0 + \beta_1 a_{it} + \beta_2 a_{it}^2 + \beta_3 b_i + \gamma_t\right) \tag{1}$$

β_0 represents the model intercept. a_{it} stands for the average air temperature of country i in year t, β_1 for the regression coefficient of the sites' average temperature, and β_2 for the coefficient of its square. b_i denotes country i's centroid's latitude, and β_3 the regression coefficient for the forest sites' latitude. γ_t represents the regression coefficient for year t. With β_0=5.60, $\beta_1 = -2.20$, $\beta_2 = 0.07$, $\beta_3 = -0.06$ from model 1 of Table S2 follows:

$$y_i = \frac{1}{T}\sum_{t=1}^{T}\left(5.60–2.20a_{it} + 0.07a_{it}^2–0.06b_i + \beta_t\right) \tag{2}$$

Data for a_{it} is taken from the Climate Change Knowledge Portal of the World Bank (2018); Table S6), and from the Country Geography Database of Portland State University (2018) for b_i. Computation of Eq. 2 yields a global average of − 8.8 tCO_2ha^{-1} $year^{-1}$ (median = − 9.2, sd. = 4.8, min = − 15.1, max = 16.3) sequestered by forests in 2015. With roughly 2.7 trillion trees (Crowther et al. 2015) in the 40.0 Mkm^2 (FAO 2018) of forests worldwide, this translates into a mean of − 8.8 $kgCO_2year^{-1}$ per tree (tropical forests (latitude 0° to < 25° North (N) or South (S)) − 8.4, temperate forests (25° to < 50° N or S) − 17.3, boreal forests (≥ 50° N): − 1.9) as weighted by the share of trees by forest type (tropical 0.48, temperate 0.24, boreal 0.27; Crowther et al. 2015).

Thirdly, simply multiplying countries' average NEE per hectare by their forest area gathered from the FAO (2018) gives countries' forest carbon sink. Summing up yields an estimate for the global forest carbon sequestration of − 8.3 $GtCO_2year^{-1}$ or − 1.1 tCO_2year^{-1} per capita (p.c.; UNPD 2017).

Afforestation/reforestation (AR) scenarios

To prevent dangerous climate change, the required and achievable forest land share of three different AR scenarios is developed. The basis for these scenarios is the 2 °C target and the associated remaining carbon budget until 2100. With the Paris Climate Agreement, the world community has agreed upon the limitation of global warming to well below 2 °C relative to preindustrial levels (UNFCCC 2015). A maximum of 2 °C of warming until 2100 may provide a relatively safe operating space for humanity and prevent dangerous climate change alongside a lock-in of a "Hothouse Earth" pathway with potentially hazardous consequences for ecosystems and human socio-economic systems (IPCC 2014; Steffen et al. 2018; Fischer et al. 2018; Rockström et al. 2009). Yet, humanity allegedly has already committed to 1.3 °C of warming (Mauritsen and Pincus 2017). Hence, limiting global warming to 1.5 °C and presumably providing an even safer operating space (IPCC 2018) seems out of reach (Raftery et al. 2017). Global CO_2 emissions of fossil fuel use and industrial processes have risen to 35.8 $GtCO_2$ or 4.8 tCO_2 per capita (p.c.) in 2016 (Janssens-Maenhout et al. 2017). This surpasses the global annual gross carbon budget (an estimated 30 $GtCO_2$) to fulfill the 2 °C target with a probability of at least 66% (IPCC 2014; Friedlingstein et al. 2014; Meinshausen et al. 2009). Assuming an average annual world population of 9.8 billion people until 2100 (UNPD 2017), this goal translates into ~ 3 t of gross CO_2 emissions p.c. and year.

Scenario 1 is the baseline assuming business-as-usual production and consumption patterns, constant other carbon sinks, further required emission reductions of 1.0 tCO_2year^{-1} p.c. after accounting for the overall forest carbon sequestration of 0.8 tCO_2year^{-1} p.c. with an expected average population of 9.8 billion people per year until 2100. Hence, the required additional absorption by forests for the 2 °C respectively the 3 t p.c. target is 9.8 $GtCO_2year^{-1}$. Assuming similar carbon sequestration of established forests and afforested/reforested land, simple solution of the rule of three and addition to the existing forest area (40.0 Mkm^2) delivers a required forest area of 88.0 Mkm^2. With a global land area of 129.7 Mkm^2 (FAO 2018), this corresponds to a forest land share of 67.8% necessary to reach the 2 °C target with AR activities alone. This implicitly assumes similar tree density, species, species richness, and forest health of afforested/reforested land and established forests. To quantify the land area suitable for AR, land unsuitable for near-term and cost-efficient AR was excluded. These land cover types are artificial surfaces (including urban and associated areas), permanent snow and glaciers, terrestrial barren land, and sparsely natural vegetated areas as quantified by the FAO (2018). One hundred percent AR of all shrub-covered areas and herbaceous vegetation (18.1 Mkm^2) result in an achievable 44.8% of forest land share in this scenario.

S*cenario 2* further assumes current diets and an associated demand of agricultural land of 2100 m^2 p.c. (Hallström et al. 2015). As there are 3770 m^2 p.c. of agricultural land currently available, 44% of permanent grassland and cropland (FAO 2018) can be additionally afforested/reforested (16.4 Mkm^2) for feeding an expected 9.8 billion people per year. Hence, a forest land share of 57.5% can be realized in scenario 2 (77.6 Mkm^2). This accounts for more than two thirds of the AR climate target outlined in scenario 1.

To achieve the AR target fully, further reduction in the demand for agricultural land is required. In *scenario 3* healthier diets with reduced red and ruminant meat consumption further decrease agricultural land demand by 28.0% to 1510 m^2 p.c. while dietary-related emissions decrease by 0.2 tCO_2yr^{-1} p.c. (Table 1 in Hallström et al. 2015). Hence, this reduction in carbon emissions implies a global reduction of the required carbon uptake by forests of 2.0 $GtCO_2year^{-1}$ to 7.8 $GtCO_2year^{-1}$. This resembles a required forest land share of 60.0% or 77.9 Mkm^2 of forest area. Via a further 28.0% AR of permanent grassland and cropland, a forest land share of 62.0% or 80.4 Mkm^2 of forest area can be achieved to additionally sequester 8.0 $GtCO_2year^{-1}$.

Predictors of national forest land share

Compared to cross-sectional regression models, the FE panel model has the advantage of exploiting the longitudinal structure of the data as it only includes within-country variation. Hence, the FE model is not biased by cross-sectional unobserved heterogeneity (Brüderl and Ludwig 2015; Wooldridge 2010). If the strict exogeneity assumption ($r\ (\boldsymbol{x}_{it}, \varepsilon_{it}) = 0$) holds, FE models adequately estimate unbiased causal effects (Vaisey and Miles 2017). The model can be written as

$$y_{it} - \overline{y}_i = \left(\boldsymbol{x}_{it} - \overline{\boldsymbol{x}}_i\right)\boldsymbol{\beta} + \boldsymbol{Z}_t\gamma + \varepsilon_{it} - \overline{\varepsilon}_i \tag{3}$$

Here, y_{it} denotes the forest land share of country i in year t. $\overline{y}_i$ represents country i's mean of the whole observation period. $\boldsymbol{x}_{it}$ stands for the vector of all exogenous variables for country i at time t, and $\overline{\boldsymbol{x}}_i$ for the average of the time observed. The model further comprises a vector of dummy variables ($\boldsymbol{Z}$) for every year to control period effects for all countries (time FE). A country's time-varying stochastic error term is represented by ε_{it}. All metric variables are included by taking their natural logarithm, which allows the estimation of elasticities. All standard errors are clustered by country and year and are therefore robust with respect to heteroscedasticity and autocorrelation. The reported regression results of Fig. 4 were tested for robustness analogous to the results of the analysis for the FLUXNET data as already explained above. Furthermore, all six models were recalculated using the total forest land area as dependent variable instead of forest land share. None of these checks detected any substantial deviations from the results reported in Fig. 4.

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