# 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 $GtCO_2yr^{-1}$. For the 2 °C climate target the current forest land share has to be doubled to 60.0 % to sequester an additional 7.8 $GtCO_2yr^{-1}$, which demands less red meat consumption. This afforestation/reforestation (AR) challenge is achievable, as the estimated global biophysical potential of AR is 8.0 $GtCO_2yr^{-1}$ 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 analyse forest land share data of 98 countries from 1990 to 2015 applying causal inference (*N*=2,494). 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 ($GtCO_2yr^{-1}$; Pan et al. 2011). Evaluations of the maximum biophysical sequestration potential of AR vary from 1.1 to 12.1 $GtCO_2yr^{-1}$ (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).

[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);

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) (section 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 (section 3; see Appendix A 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 (section 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 (section 5). The last section summarizes and discusses the main results, and closes with some concluding remarks.

## 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 B.1 in Appendix B 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 B.2, and Figure B.1 in Appendix B). Model predictions on countries' NEE of forests using countries' average temperature taken from the World Bank (2018) show that established forests sequester -8.8 $tCO_2ha^{-1}yr^{-1}$ on average in 2015 (median: -9.2; Appendix A). 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 $tCO_2ha^{-1}yr^{-1}$, whereas the highest positive NEE is observed for Canada with a net release of 16.3 $tCO_2ha^{-1}yr^{-1}$ (Figure 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 Figure 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 $tCO_2ha^{-1}yr^{-1}$, while it is highest for temperate forests with -12.6 $tCO_2ha^{-1}yr^{-1}$. Tropical forests' NEE lies in-between with an average of -6.0 $tCO_2ha^{-1}yr^{-1}$. This pattern is in line with former research (Brumme et al. 2005).

Multiplying countries' average NEE per hectare by their forest area (FAO 2018, Figure 1b) suggests an overall forest carbon sink of -8.3 $GtCO_2yr^{-1}$ or -1.1 $tCO_2yr^{-1}$ per

capita (p.c., UNPD 2017) in 2015. Carbon sequestration is highest in the forests of the United States and Brazil (-3.2 $GtCO_2yr^{-1}$ each), followed by China (-2.0 $GtCO_2yr^{-1}$), Australia (-1.5 $GtCO_2yr^{-1}$) and the Democratic Republic of the Congo (-1.1 $GtCO_2yr^{-1}$). The rest of the world's countries has a net absorption of less than -1.0 $GtCO_2yr^{-1}$ each, and Canada, Mongolia, and the Russian Confederates have a substantial net release of 16.7 $GtCO_2yr^{-1}$ 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 $GtCO_2yr^{-1}$ for the Community Land Model (version 4.5; Oleson et al. 2013)[2] and Pan et al. (2011) estimate a sink of -8.8 $GtCO_2yr^{-1}$ based on changes in carbon stocks.

[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).

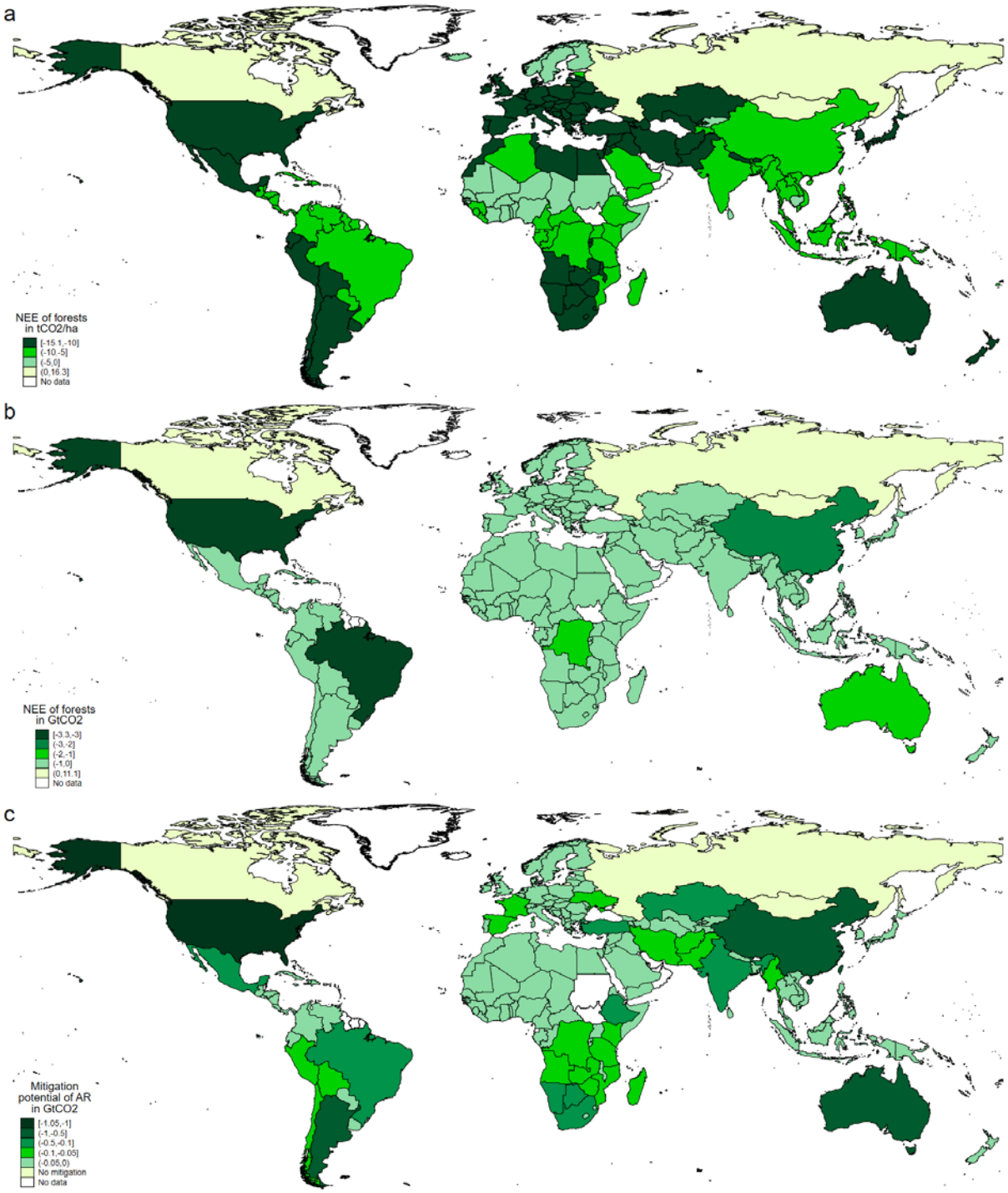


**Figure 1 | Net ecosystem exchange (NEE) of $CO_2$ of countries' forests in 2015. a-c,** Data source for the calculation of NEE of $CO_2$ of countries' forests is FLUXNET (NASA 2015), World Bank (2018) and FAO (2018). Negative numbers indicate net absorption of carbon, positive numbers its net release. **a,** Carbon sequestration in $tCO_2ha^{-1}yr^{-1}$ of forest area (mean = -8.8, median = -9.2, min. (Portugal) = -15.1, max. (Canada) = 16.3). **b,** Countries' overall forest carbon sequestration in $GtCO_2yr^{-1}$ (sum = -8.3 $GtCO_2yr^{-1}$). **c,** Countries' overall NEE potential of afforestation/reforestation (AR) in $GtCO_2yr^{-1}$ based on scenario 3 exceeding the 7.8 $GtCO_2yr^{-1}$ required to meet the 2 °C respectively 3 $tCO_2$ per capita climate target (sum = -8.0 $GtCO_2yr^{-1}$; see text and Appendix A for details).

## 3 Forest land share trends and AR scenarios

Before evaluating countries' climate change mitigation potential of AR (Figure 1c), the current forest land share, suitable land for AR as well as competing land uses have to be quantified. The average forest land share as provided by the FAO shrunk from 31.8 % in 1990 to 30.8 % in 2015 (Figure 2), which corresponds to a forest loss of 1.3 Mkm$^2$ – an area as large as Peru.

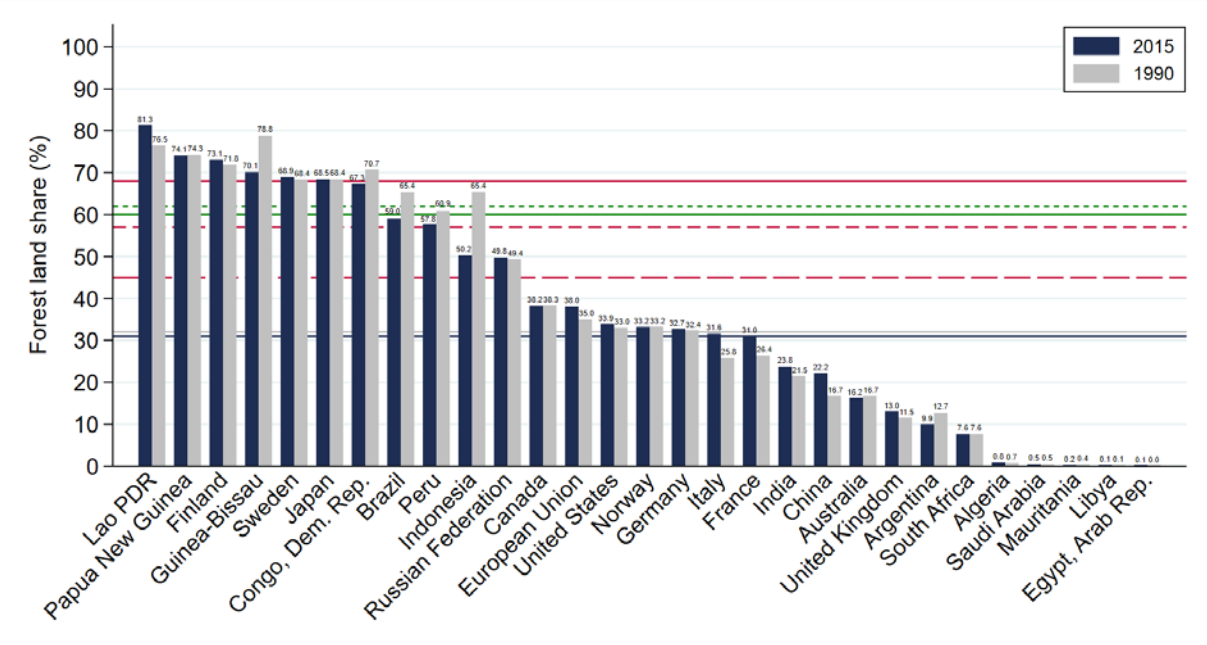


**Figure 2 | Forest land share in international comparison 1990 and 2015.** Depicted are the top and bottom five countries, top five countries with respect to overall forest area (FAO 2018) by climate domain in 2015, and members of the G7 and BRIICS if not already included. Dark blue solid line = mean 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 A for details.

As Figure 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 United States as top carbon absorbing nation, almost no change in forest cover was observed in this period.

Furthermore, Figure 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 fulfil 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 $tCO_2yr^{-1}$ p.c. after accounting for the overall forest carbon sequestration of 0.8 $tCO_2yr^{-1}$ 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 Figure 2) to additionally sequester 9.8 $GtCO_2yr^{-1}$ (Appendix A). 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 2,100 $m^2$ p.c. (Hallström et al. 2015) for feeding an expected 9.8 billion people per year (red dashed line in Figure 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 1,510 $m^2$ p.c. and reduce dietary-related emissions by 0.2 $tCO_2yr^{-}$

[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 Figure 2) equivalent to an additional 7.8 $GtCO_2yr^{-1}$ 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 $GtCO_2yr^{-1}$; green short-dashed line in Figure 2).

Consequently, the 2 °C climate target can be met by almost doubling the current forest area whilst 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 realisation time of five 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 %). 260 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 (Figure 1b), and the world's second largest carbon emitter (Janssens-Maenhout et al. 2017), the United States of America rank highest in the climate change mitigation potential of countries through AR (NEE = -1.0 $GtCO_2yr^{-1}$; Figure 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 $GtCO_2yr^{-1}$). This offers a great opportunity for the United States, 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 Figure 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 (Figure 3a-c,e-j,n). These countries are Japan, Spain, France, Australia, the United States, Argentina, Italy, Germany, Brazil, and the United Kingdom. Hence, these states could take over their responsibility for 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 United Kingdom, 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 (Figure 3k-m,o,p). Indonesia and Peru reflect this, since these countries lost forests between 1990 and 2015 (Figure 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 (Figure 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 (Figure 3d, q-s). This could be a worthwhile enhancement of the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) framework.

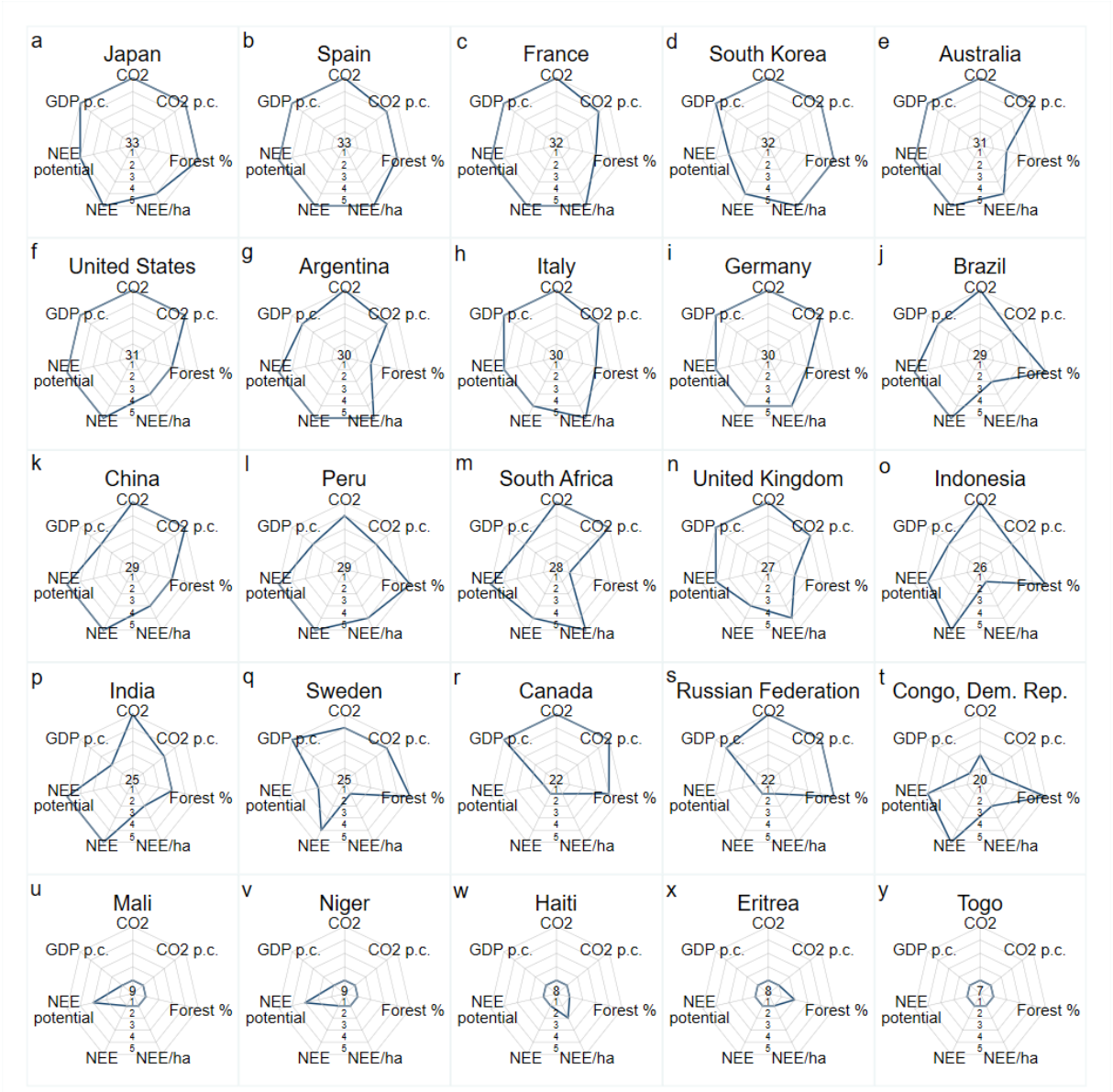


**Figure 3 | Country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015. a-y,** Radar plots of countries' relative performance with regard to climate responsibility ($CO_2$, and $CO_2$ per capita (p.c.) emissions (Janssens-Maenhout et 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 centre 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 B.4 in Appendix B.

## 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 analysing 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 analysing 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 A). The 98 countries analysed (Table B.7) 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 Figure 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]

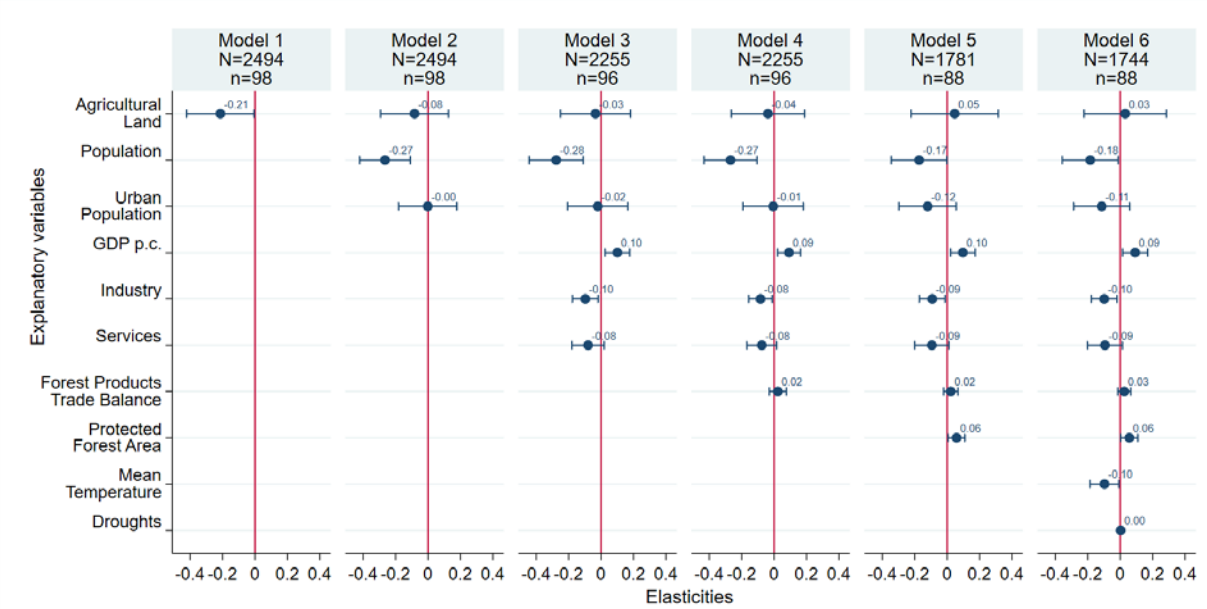


**Figure 4 | Predictors of national forest land share.** Coefficient plots of unstandardized regression coefficients (dark blue filled circles) of country and year fixed effects regressions of national forest land share on various successively included predictors (models 1-6) including 95 % confidence intervals (dark blue bars; see Table B.5 in Appendix B 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 B.6 in Appendix B describes all variables and Table B.7 lists all countries included in the models.

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 Figure 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

[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 Figure 4, this suggests that population growth mediates the relationship between agricultural expansion and forest loss.

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 Figure 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 Figure 4 indicate, there is some evidence in favour 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 products 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,

[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 B.2 in Appendix B).

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 Figure 4 demonstrate that increases in exports of forest products relative to their imports do not substantially alter countries' forest area.

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 Figure 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 Moral-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 Figure 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 Figure B.1 in Appendix B 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 United States, 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 transition 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 whilst 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.

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# Appendices

## A. 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 2000-2014 provided by FLUXNET (NASA 2015). See Table B.1 in Appendix B for an overview of the analysed 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 minutes interval. Table B.3 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 B.2) indicate that only average temperature substantially relates to NEE. As Figure B.1 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 B.2 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 B.2 according to the following formula:

$$y_i = \frac{1}{T}\sum_{t=1}^{T}(\beta_0 + \beta_1 a_{it} + \beta_2 a_{it}^2 + \beta_3 b_i + \gamma_t) \quad \text{(Eq. A.1).}$$

$\beta_0$ represents the model intercept. $a_{it}$ stands for the average air temperature of country *i* in year *t*, $\beta_1$ for the regression coefficient of the sites' average temperature, and $\beta_2$ for the coefficient of its square. $b_i$ denotes country *i*'s centroid's latitude, and $\beta_3$ the regression coefficient for the forest sites' latitude. $\gamma_t$ represents the regression coefficient for year *t*. With $\beta_0$=5.60, $\beta_1$=-2.20, $\beta_2$=0.07, $\beta_3$=-0.06 from model 1 of Table B.2 follows:

$$y_i = \frac{1}{T}\sum_{t=1}^{T}(5.60 - 2.20 a_{it} + 0.07 a_{it}^2 - 0.06 b_i + \beta_t) \quad \text{(Eq. A.2).}$$

Data for $a_{it}$ is taken from the Climate Change Knowledge Portal of the World Bank (2018; Table B.6), and from the Country Geography Database of Portland State University (2018) for $b_i$. Computation of Eq. A.2 yields a global average of -8.8 $tCO_2ha^{-1}yr^{-1}$ (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 $kgCO_2yr^{-1}$ 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 $GtCO_2yr^{-1}$ or -1.1 $tCO_2yr^{-1}$ 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 are 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 fulfil 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 $tCO_2yr^{-1}$ p.c. after accounting for the overall forest carbon sequestration of 0.8 $tCO_2yr^{-1}$ 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 $GtCO_2yr^{-1}$. 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). 100 % 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 2,100 m$^2$ p.c. (Hallström et al. 2015). As there are 3,770 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 1,510 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 $GtCO_2yr^{-1}$ to 7.8 $GtCO_2yr^{-1}$. 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 $GtCO_2yr^{-1}$.

### 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

$$y_{it} - \bar{y}_i = (\boldsymbol{x}_{it} - \bar{\boldsymbol{x}}_i)\boldsymbol{\beta} + \boldsymbol{Z}_t\boldsymbol{\gamma} + \varepsilon_{it} - \bar{\varepsilon}_i \qquad \text{(Eq. A.3).}$$

Here, $y_{it}$ denotes the forest land share of country *i* in year *t*. $\bar{y}_i$ 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 $\bar{\boldsymbol{x}}_i$ 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 $\varepsilon_{it}$. 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 Figure 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 Figure 4.

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

## B. Supplementary Figures and Tables

| Country | Tower site code | Reference paper | Country | Tower site code | Reference Paper | Country | Tower site code | Reference paper |
|---|---|---|---|---|---|---|---|---|
| Belgium | BE-Vie | Aubinet et al. (2001) | French Guyana | GF-Guy | Bonal et al. (2008) | United States | US-Blo | Falge et al. (2002) |
| Brazil | BR-Sa1 | Hayek et al. (2018) | Germany | DE-Hai | Knohl et al. (2003) | | US-GBT | Zeller and Nikolov (2000) |
| | BR-Sa3 | Saleska et al. (2003) | | DE-Lkb | Lindauer et al. (2014) | | US-GLE | Frank et al. (2014) |
| Canada | CA-Gro | McCaughey et al. (2006) | | DE-Lnf | Anthoni et al. (2004) | | US-Ha1 | Barford et al. (2001) |
| | CA-NS1 | Goulden et al. (2006) | | DE-Obe | Bernhofer et al. (2008) | | US-KS1 | Dore et al. (2003) |
| | CA-NS2 | Bond-Lamberty et al. (2004) | | DE-Tha | Grünwald and Bernhofer (2007) | | US-Me1 | Irvine et al. (2007) |
| | CA-NS3 | Bond-Lamberty et al. (2004) | Ghana | GH-Ank | Chiti et al. (2010) | | US-Me2 | Law et al. (2004) |
| | CA-NS4 | Schmidt et al. (2011) | Italy | IT-CA1 | Sabbatini et al. (2016) | | US-Me3 | Sun et al. (2004) |
| | CA-NS5 | Bond-Lamberty et al. (2004) | | IT-CA3 | Sabbatini et al. (2016) | | US-Me4 | Law et al. (2004) |
| | CA-Oas | Chen et al. (2003) | | IT-Cp2 | Fares et al. (2014) | | US-Me5 | Law et al. (2004) |
| | CA-Obs | Chen et al. (2003) | | IT-Cpz | Garbulsky et al. (2008) | | US-Me6 | Ruehr et al. (2012) |
| | CA-Qfo | Bergeron et al. (2007) | | IT-Isp | Ferréa et al. (2012) | | US-MMS | Baldocchi et al. (2005) |
| | CA-SF1 | Amiro et al. (2006) | | IT-La2 | Marcolla et al. (2003) | | US-Oho | Chu et al. (2016) |
| | CA-TP1 | Arain and Restrepo-Coupe (2005) | | IT-Lav | Marcolla et al. (2003) | | US-PFa | Desai et al. (2008) |
| | CA-TP2 | Arain and Restrepo-Coupe (2005) | | IT-PT1 | Migliavacca et al. (2009) | | US-Prr | Kobayashi et al. (2014) |
| | CA-TP3 | Arain and Restrepo-Coupe (2005) | | IT-Ren | Montagnani et al. (2009) | | US-Syv | Desai et al. (2005) |
| | CA-TP4 | Arain and Restrepo-Coupe (2005) | | IT-Ro1 | Rey et al. (2002) | | US-UMd | Gough et al. (2013) |
| | CA-TPD | Schmidt et al. (2011) | | IT-Ro2 | Tedeschi et al. (2006) | | US-WCr | Desai et al. (2005) |
| Czech Republic | CZ-BK1 | Acosta et al. (2013) | | IT-SR2 | Gruening et al. (2013) | | US-Wi0 | Desai et al. (2008) |
| Denmark | DK-Sor | Pilegaard et al. (2011) | | IT-SRo | Chiesi et al. (2005) | | US-Wi1 | Desai et al. (2008) |
| Finland | FI-Hyy | Suni et al. (2003) | Netherlands | NL-Loo | Moors (2012) | | US-Wi2 | Desai et al. (2008) |
| | FI-Let | Koskinen et al. (2014) | Panama | PA-SPn | Wolf et al. (2011) | | US-Wi3 | Desai et al. (2008) |
| | FI-Sod | Thum et al. (2007) | Russian Federation | RU-Fyo | Kurbatova et al. (2008) | | US-Wi4 | Desai et al. (2008) |
| France | FR-Fon | Delpierre et al. (2016) | | RU-SkP | Maximov (2012) | | US-Wi5 | Schmidt et al. (2011) |
| | FR-LBr | Berbigier et al. (2001) | Switzerland | CH-Dav | Zielis et al. (2014) | | US-Wi8 | Desai et al. (2008) |
| | FR-Pue | Rambal et al. (2004) | | CH-Lae | Etzold et al. (2011) | | US-Wi9 | Schmidt et al. (2011) |

**Table B.1 | FLUXNET micrometeorological measurement towers in forests included in the regression analysis by country (NASA 2015).**

| Model | (1) |
|---|---|
| Dependent variable | NEE |
| Average temperature | -2.20*** |
| | (0.46) |
| Average temperature squared | 0.07** |
| | (0.03) |
| Precipitation | -0.00 |
| | (0.00) |
| Latitude | -0.06 |
| | (0.29) |
| Elevation | -0.00 |
| | (0.00) |
| 2000 (reference) | |
| 2001 | 3.80 |
| | (2.60) |
| 2002 | -1.21 |
| | (3.38) |
| 2003 | -1.77 |
| | (3.98) |
| 2004 | -2.15 |
| | (3.69) |
| 2005 | -1.42 |
| | (3.65) |
| 2006 | -0.10 |
| | (3.62) |
| 2007 | -3.53 |
| | (3.84) |
| 2008 | -1.75 |
| | (3.73) |
| 2009 | -1.45 |
| | (4.02) |
| 2010 | 0.34 |
| | (3.83) |
| 2011 | -1.63 |
| | (3.90) |
| 2012 | -1.24 |
| | (3.90) |
| 2013 | -0.93 |
| | (3.80) |
| 2014 | -2.46 |
| | (3.92) |
| Constant | 5.60 |
| | (19.49) |
| n x T | 607 |
| n | 78 |
| adjusted $R^2$ | 0.15 |

**Table B.2 | Linear OLS regression of net ecosystem exchange.** NEE = net ecosystem exchange in $tCO_2ha^{-1}yr^{-1}$. ** = $p < 0.01$, *** = $p < 0.001$. Unstandardized regression coefficients with standard errors in brackets. All standard errors are clustered by tower site, and robust with respect to heteroscedasticity and autocorrelation. Years covered: 2000-2014. Table B.3 gives a descriptive overview of all variables in model 1. Table B.1 lists all 78 micrometeorological measurement towers of FLUXNET in forests included in model 1.

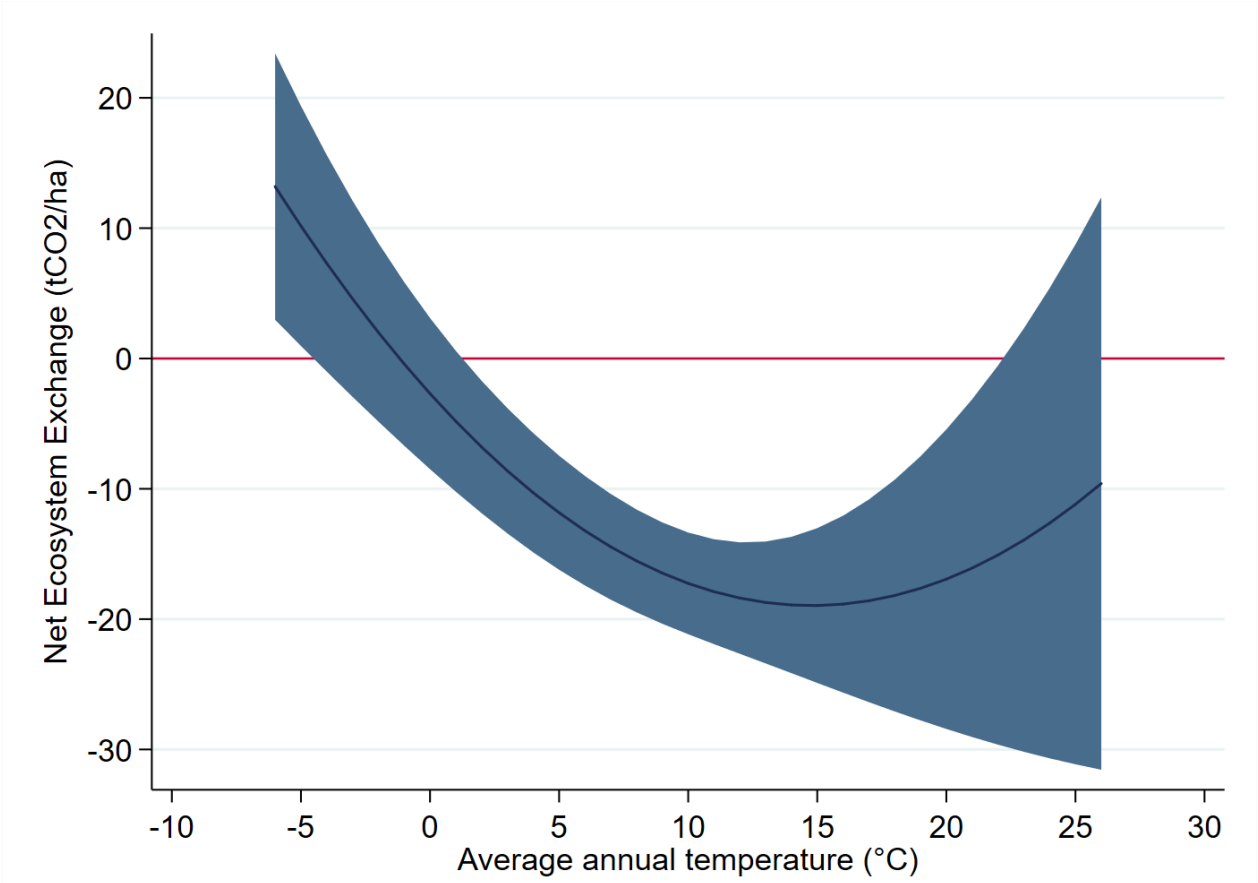


**Figure B.1 | Predicted values of net ecosystem exchange (NEE) by annual average temperature.** NEE of $CO_2$ as predicted by the OLS regression model presented in Table B.2 (dark blue line) with 95% confidence intervals (blue area). Negative numbers on the y-axis indicate net absorption of $CO_2$ by forests, positive numbers net $CO_2$ release.

| Variable | mean | within ($\bar{x}_i$) | | | between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$) | | | N (nxT) | n | Description |
|---|---|---|---|---|---|---|---|---|---|---|
| | | sd | min. | max. | sd | min. | max. | | | |
| Net ecosystem exchange | -13.98 | 6.28 | -41.86 | 13.55 | 15.52 | -67.40 | 10.21 | 674 | 94 | Net ecosystem exchange (NEE) of $CO_2$. NEE is the sum of Gross Primary Productivity (GPP, i.e. biomass stored) and ecosystem respiration (release of $CO_2$ from soil and plant). Negative numbers indicate net absorption, positive numbers net release of $CO_2$. Unit: t per ha. |
| Average temperature | 8.87 | 0.73 | 6.52 | 11.21 | 7.42 | -4.62 | 25.89 | 693 | 94 | Average annual air temperature derived from daily averages. Unit: °C. |
| Precipitation | 0.92 | 0.19 | 0.19 | 1.59 | 0.56 | 0.16 | 3.11 | 693 | 94 | Annual precipitation. Sum of daily data. Unit: 1000 mm. |
| Latitude | 44.39 | 0 | 44.39 | 44.39 | 12.93 | 2.9 | 67.4 | 693 | 94 | In degrees north or south from equator. |
| Elevation | 527.62 | 0 | 527.62 | 527.62 | 596.38 | 1 | 3197 | 625 | 78 | Elevation of site. Unit: m above sea level. |

**Table B.3 | Variable description of FLUXNET data of micrometeorological measurement towers in forests.** Data source is FLUXNET, a global network of micrometeorological tower sites with long-term measurement. FLUXNET is operated by the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) of the National Aeronautics and Space Administration (NASA) of the United States. Years covered: 2000-2014.

| Rank | Country | Sum score of quintiles | $CO_2$ emissions | $CO_2$ p.c. emissions | Forest land share | NEE per ha | NEE | NEE potential | GDP p.c. |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Japan | 33 | 5 | 5 | 5 | 4 | 5 | 4 | 5 |
| 2 | Spain | 33 | 5 | 4 | 4 | 5 | 5 | 5 | 5 |
| 3 | South Korea | 32 | 5 | 5 | 5 | 5 | 4 | 3 | 5 |
| 4 | France | 32 | 5 | 4 | 3 | 5 | 5 | 5 | 5 |
| 5 | United States | 31 | 5 | 5 | 3 | 3 | 5 | 5 | 5 |
| 6 | Australia | 31 | 5 | 5 | 2 | 4 | 5 | 5 | 5 |
| 7 | Mexico | 30 | 5 | 4 | 3 | 4 | 5 | 5 | 4 |
| 8 | Argentina | 30 | 5 | 4 | 2 | 5 | 5 | 5 | 4 |
| 9 | Italy | 30 | 5 | 4 | 3 | 5 | 4 | 4 | 5 |
| 10 | Germany | 30 | 5 | 5 | 3 | 4 | 4 | 4 | 5 |
| 11 | Turkey | 30 | 5 | 4 | 2 | 5 | 5 | 5 | 4 |
| 12 | Brazil | 29 | 5 | 3 | 5 | 2 | 5 | 5 | 4 |
| 13 | Peru | 29 | 4 | 3 | 5 | 4 | 5 | 5 | 3 |
| 14 | New Zealand | 29 | 3 | 5 | 4 | 4 | 4 | 4 | 5 |
| 15 | China | 29 | 5 | 5 | 3 | 3 | 5 | 5 | 3 |
| 16 | Poland | 29 | 5 | 5 | 3 | 4 | 4 | 4 | 4 |
| 17 | Iran, Islamic Rep. | 29 | 5 | 5 | 1 | 5 | 4 | 5 | 4 |
| 18 | Venezuela, RB | 29 | 5 | 4 | 5 | 2 | 5 | 4 | 4 |
| 19 | South Africa | 28 | 5 | 5 | 1 | 5 | 4 | 5 | 3 |
| 20 | Turkmenistan | 28 | 4 | 5 | 2 | 5 | 4 | 4 | 4 |
| 21 | Malaysia | 28 | 5 | 5 | 5 | 2 | 4 | 3 | 4 |
| 22 | Belarus | 28 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| 23 | Czech Republic | 28 | 4 | 5 | 4 | 4 | 3 | 3 | 5 |
| 24 | Greece | 28 | 4 | 4 | 3 | 5 | 4 | 4 | 4 |
| 25 | Bulgaria | 28 | 4 | 5 | 4 | 5 | 3 | 3 | 4 |
| 26 | United Kingdom | 27 | 5 | 4 | 2 | 4 | 3 | 4 | 5 |
| 27 | Portugal | 27 | 4 | 4 | 4 | 5 | 3 | 3 | 4 |
| 28 | Chile | 27 | 4 | 4 | 3 | 3 | 5 | 4 | 4 |
| 29 | Serbia | 27 | 5 | 5 | 3 | 5 | 3 | 3 | 3 |
| 30 | Bolivia | 27 | 3 | 3 | 5 | 4 | 5 | 5 | 2 |
| 31 | Romania | 27 | 4 | 4 | 3 | 4 | 4 | 4 | 4 |
| 32 | Indonesia | 26 | 5 | 3 | 5 | 1 | 5 | 4 | 3 |
| 33 | Finland | 26 | 4 | 5 | 5 | 1 | 4 | 2 | 5 |
| 34 | Austria | 26 | 4 | 5 | 4 | 3 | 3 | 2 | 5 |
| 35 | Hungary | 26 | 4 | 4 | 3 | 5 | 3 | 3 | 4 |
| 36 | Belgium | 26 | 4 | 5 | 3 | 5 | 2 | 2 | 5 |
| 37 | Kazakhstan | 26 | 5 | 5 | 1 | 3 | 3 | 5 | 4 |
| 38 | Ukraine | 26 | 5 | 4 | 2 | 4 | 4 | 5 | 2 |
| 39 | Colombia | 26 | 4 | 3 | 5 | 2 | 5 | 4 | 3 |
| 40 | Slovenia | 25 | 3 | 5 | 5 | 4 | 2 | 1 | 5 |
| 41 | Thailand | 25 | 5 | 4 | 3 | 1 | 4 | 4 | 4 |
| 42 | Croatia | 25 | 3 | 4 | 4 | 5 | 3 | 2 | 4 |
| 43 | India | 25 | 5 | 3 | 3 | 2 | 5 | 5 | 2 |
| 44 | Vietnam | 25 | 5 | 3 | 5 | 2 | 4 | 4 | 2 |
| 45 | Sweden | 25 | 4 | 4 | 5 | 1 | 4 | 2 | 5 |
| 46 | Morocco | 25 | 4 | 3 | 2 | 5 | 4 | 4 | 3 |
| 47 | Slovak Republic | 25 | 3 | 5 | 4 | 4 | 2 | 2 | 5 |
| 48 | Bosnia and Herzegovina | 24 | 3 | 5 | 4 | 4 | 3 | 2 | 3 |
| 49 | Angola | 24 | 3 | 2 | 4 | 3 | 5 | 5 | 2 |
| 50 | Netherlands | 24 | 4 | 5 | 2 | 5 | 1 | 2 | 5 |
| 51 | Ecuador | 24 | 3 | 3 | 5 | 3 | 4 | 3 | 3 |
| 52 | Ireland | 24 | 3 | 5 | 2 | 4 | 2 | 3 | 5 |
| 53 | Estonia | 24 | 3 | 5 | 5 | 3 | 2 | 1 | 5 |
| 54 | Latvia | 23 | 2 | 4 | 5 | 3 | 3 | 2 | 4 |
| 55 | Zambia | 23 | 2 | 1 | 5 | 3 | 5 | 5 | 2 |
| 56 | Zimbabwe | 23 | 3 | 2 | 4 | 3 | 5 | 5 | 1 |
| 57 | Norway | 23 | 4 | 5 | 3 | 1 | 3 | 2 | 5 |
| 58 | Botswana | 23 | 2 | 3 | 2 | 3 | 4 | 5 | 4 |
| 59 | Uruguay | 23 | 2 | 3 | 2 | 5 | 3 | 4 | 4 |
| 60 | Azerbaijan | 23 | 3 | 4 | 2 | 5 | 2 | 3 | 4 |
| 61 | Myanmar | 23 | 3 | 1 | 4 | 3 | 5 | 5 | 2 |
| 62 | Uzbekistan | 22 | 4 | 3 | 1 | 5 | 3 | 4 | 2 |
| 63 | Paraguay | 22 | 2 | 2 | 4 | 3 | 4 | 4 | 3 |
| 64 | Russian Federation | 22 | 5 | 5 | 5 | 1 | 1 | 1 | 4 |
| 65 | Namibia | 22 | 1 | 3 | 2 | 4 | 4 | 5 | 3 |
| 66 | Lithuania | 22 | 3 | 4 | 4 | 3 | 2 | 2 | 4 |
| 67 | Syrian Arab Republic | 22 | 4 | 3 | 1 | 5 | 1 | 3 | 5 |
| 68 | Denmark | 22 | 3 | 4 | 2 | 4 | 2 | 2 | 5 |
| 69 | Lao PDR | 22 | 1 | 2 | 5 | 3 | 5 | 4 | 2 |
| 70 | Canada | 22 | 5 | 5 | 4 | 1 | 1 | 1 | 5 |
| 71 | Tanzania | 22 | 2 | 1 | 5 | 3 | 5 | 5 | 1 |
| 72 | Iraq | 21 | 4 | 4 | 1 | 4 | 2 | 3 | 3 |

**Table B.4 | Full country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015.**

| Rank | Country | Sum score of quintiles | $CO_2$ emissions | $CO_2$ p.c. emissions | Forest land share | NEE per ha | NEE | NEE potential | GDP p.c. |
|---|---|---|---|---|---|---|---|---|---|
| 73 | Congo, Rep. | 21 | 2 | 2 | 5 | 2 | 5 | 3 | 2 |
| 74 | Israel | 21 | 4 | 5 | 1 | 4 | 1 | 1 | 5 |
| 75 | Switzerland | 21 | 3 | 4 | 3 | 3 | 2 | 1 | 5 |
| 76 | Gabon | 21 | 2 | 3 | 5 | 2 | 4 | 1 | 4 |
| 77 | Algeria | 21 | 4 | 4 | 1 | 3 | 2 | 4 | 3 |
| 78 | Congo, Dem. Rep. | 20 | 2 | 1 | 5 | 2 | 5 | 4 | 1 |
| 79 | Cameroon | 20 | 3 | 2 | 4 | 2 | 4 | 3 | 2 |
| 80 | Panama | 20 | 2 | 3 | 5 | 2 | 3 | 1 | 4 |
| 81 | Georgia | 20 | 2 | 3 | 4 | 3 | 3 | 2 | 3 |
| 82 | Lebanon | 20 | 3 | 4 | 2 | 5 | 1 | 1 | 4 |
| 83 | Saudi Arabia | 20 | 5 | 5 | 1 | 2 | 1 | 1 | 5 |
| 84 | Pakistan | 20 | 4 | 2 | 1 | 4 | 2 | 5 | 2 |
| 85 | Central African Republic | 20 | 1 | 1 | 4 | 2 | 4 | 3 | 5 |
| 86 | Macedonia, FYR | 20 | 2 | 4 | 4 | 4 | 2 | 1 | 3 |
| 87 | Cuba | 20 | 3 | 3 | 3 | 2 | 2 | 2 | 5 |
| 88 | Papua New Guinea | 20 | 2 | 2 | 5 | 2 | 5 | 2 | 2 |
| 89 | Mozambique | 20 | 2 | 1 | 5 | 2 | 5 | 4 | 1 |
| 90 | Albania | 19 | 1 | 3 | 3 | 5 | 2 | 2 | 3 |
| 91 | Dominican Republic | 19 | 3 | 3 | 4 | 3 | 2 | 1 | 3 |
| 92 | Tunisia | 19 | 3 | 3 | 1 | 4 | 2 | 3 | 3 |
| 93 | Philippines | 19 | 4 | 2 | 3 | 2 | 3 | 3 | 2 |
| 94 | Egypt, Arab Rep. | 19 | 5 | 3 | 1 | 3 | 1 | 3 | 3 |
| 95 | Nepal | 18 | 2 | 1 | 3 | 5 | 3 | 3 | 1 |
| 96 | Ethiopia | 18 | 2 | 1 | 2 | 3 | 4 | 5 | 1 |
| 97 | Costa Rica | 18 | 2 | 3 | 5 | 2 | 2 | 1 | 3 |
| 98 | Libya | 18 | 4 | 5 | 1 | 3 | 1 | 2 | 2 |
| 99 | Honduras | 17 | 2 | 2 | 4 | 2 | 3 | 2 | 2 |
| 100 | Bangladesh | 17 | 4 | 2 | 2 | 2 | 2 | 3 | 2 |
| 101 | Nigeria | 17 | 4 | 2 | 1 | 1 | 3 | 4 | 2 |
| 102 | Kenya | 17 | 3 | 2 | 1 | 2 | 3 | 5 | 1 |
| 103 | Ghana | 17 | 3 | 2 | 4 | 1 | 3 | 2 | 2 |
| 104 | Afghanistan | 17 | 2 | 1 | 1 | 5 | 2 | 5 | 1 |
| 105 | Cambodia | 17 | 2 | 2 | 5 | 1 | 3 | 2 | 2 |
| 106 | Somalia | 17 | 1 | 1 | 2 | 1 | 3 | 4 | 5 |
| 107 | Guatemala | 17 | 3 | 2 | 3 | 2 | 3 | 2 | 2 |
| 108 | Moldova | 17 | 2 | 3 | 2 | 5 | 1 | 2 | 2 |
| 109 | Cote d'Ivoire | 16 | 2 | 2 | 3 | 1 | 3 | 3 | 2 |
| 110 | Jordan | 16 | 3 | 3 | 1 | 4 | 1 | 1 | 3 |
| 111 | Swaziland | 16 | 1 | 2 | 4 | 4 | 1 | 1 | 3 |
| 112 | Madagascar | 16 | 1 | 1 | 2 | 3 | 4 | 4 | 1 |
| 113 | Jamaica | 15 | 2 | 3 | 3 | 2 | 1 | 1 | 3 |
| 114 | Malawi | 15 | 1 | 1 | 3 | 3 | 3 | 3 | 1 |
| 115 | Sri Lanka | 15 | 3 | 2 | 3 | 1 | 2 | 1 | 3 |
| 116 | Nicaragua | 15 | 2 | 2 | 3 | 2 | 2 | 2 | 2 |
| 117 | Uganda | 14 | 2 | 1 | 2 | 2 | 2 | 4 | 1 |
| 118 | Mongolia | 14 | 3 | 4 | 1 | 1 | 1 | 1 | 3 |
| 119 | Burundi | 14 | 1 | 1 | 2 | 3 | 1 | 1 | 5 |
| 120 | Liberia | 14 | 1 | 1 | 4 | 2 | 3 | 2 | 1 |
| 121 | Senegal | 14 | 2 | 2 | 4 | 1 | 2 | 2 | 1 |
| 122 | Armenia | 14 | 1 | 3 | 2 | 3 | 1 | 1 | 3 |
| 123 | Yemen, Rep. | 13 | 3 | 2 | 1 | 3 | 1 | 2 | 1 |
| 124 | Lesotho | 13 | 1 | 1 | 1 | 5 | 1 | 2 | 2 |
| 125 | Guinea | 13 | 1 | 1 | 3 | 1 | 3 | 3 | 1 |
| 126 | Benin | 13 | 2 | 2 | 4 | 1 | 2 | 1 | 1 |
| 127 | El Salvador | 13 | 2 | 2 | 2 | 2 | 1 | 1 | 3 |
| 128 | Kyrgyz Republic | 12 | 2 | 2 | 1 | 1 | 1 | 3 | 2 |
| 129 | Rwanda | 11 | 1 | 1 | 2 | 4 | 1 | 1 | 1 |
| 130 | Guinea-Bissau | 11 | 1 | 1 | 5 | 1 | 1 | 1 | 1 |
| 131 | Chad | 11 | 1 | 1 | 1 | 1 | 2 | 4 | 1 |
| 132 | Sierra Leone | 11 | 1 | 1 | 4 | 1 | 2 | 1 | 1 |
| 133 | Tajikistan | 11 | 1 | 2 | 1 | 2 | 1 | 3 | 1 |
| 134 | Gambia, The | 11 | 1 | 1 | 5 | 1 | 1 | 1 | 1 |
| 135 | Burkina Faso | 10 | 1 | 1 | 2 | 1 | 2 | 2 | 1 |
| 136 | Mauritania | 10 | 1 | 2 | 1 | 1 | 1 | 2 | 2 |
| 137 | Niger | 9 | 1 | 1 | 1 | 1 | 1 | 3 | 1 |
| 138 | Mali | 9 | 1 | 1 | 1 | 1 | 1 | 3 | 1 |
| 139 | Haiti | 8 | 1 | 1 | 1 | 2 | 1 | 1 | 1 |
| 140 | Eritrea | 8 | 1 | 1 | 2 | 1 | 1 | 1 | 1 |
| 141 | Togo | 7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

**Table B.4, continued | Full country ranking of climate responsibility, forests' mitigation contribution and potential, and economic capabilities in 2015.** p.c. = per capita, NEE = net ecosystem exchange, GDP = gross domestic product. Numbers represent the quintiles the countries rank if not indicated otherwise. Data sources: $CO_2$ emissions: EDGAR – Emissions Database for Global Atmospheric Research; forest land share: FAO – Food and Agriculture Organization of the UN; NEE: own calculations based on FLUXNET data; GDP: IMF – International Monetary Fund.

| Model | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | Forest land share | | | | | |
| Agricultural land | -0.21* | -0.08 | -0.03 | -0.04 | 0.05 | 0.03 |
| | (0.10) | (0.10) | (0.10) | (0.11) | (0.13) | (0.12) |
| Population | | -0.27** | -0.28** | -0.27** | -0.17* | -0.18* |
| | | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) |
| Urban population | | -0.00 | -0.02 | -0.01 | -0.12 | -0.11 |
| | | (0.09) | (0.09) | (0.09) | (0.09) | (0.08) |
| GDP per capita | | | 0.10* | 0.09* | 0.10* | 0.09* |
| | | | (0.04) | (0.03) | (0.04) | (0.04) |
| Industry | | | -0.10* | -0.08* | -0.09* | -0.10* |
| | | | (0.04) | (0.04) | (0.04) | (0.04) |
| Services | | | -0.08 | -0.08$^{+}$ | -0.09$^{+}$ | -0.09$^{+}$ |
| | | | (0.05) | (0.04) | (0.05) | (0.05) |
| Forest products trade balance | | | | 0.02 | 0.02 | 0.03 |
| | | | | (0.03) | (0.02) | (0.02) |
| Protected forest area | | | | | 0.06* | 0.06* |
| | | | | | (0.03) | (0.03) |
| Mean temperature | | | | | | -0.10* |
| | | | | | | (0.04) |
| Droughts | | | | | | 0.00 |
| | | | | | | (0.00) |
| n x T | 2494 | 2494 | 2255 | 2255 | 1781 | 1744 |
| n | 98 | 98 | 96 | 96 | 88 | 88 |
| adjusted $R^2$ within | 0.06 | 0.15 | 0.22 | 0.20 | 0.27 | 0.28 |

**Table B.5 | Country and time fixed effects regressions of forest land share.** $^{+}$ = $p < 0.10$, * = $p < 0.05$, ** = $p < 0.01$. Unstandardized regression coefficients with standard errors in brackets. All six models include the years 1990-2015 and contain dummy variables for each year in order to control for overall time-trends. All standard errors are clustered by country and year, and robust with respect to heteroscedasticity and autocorrelation.

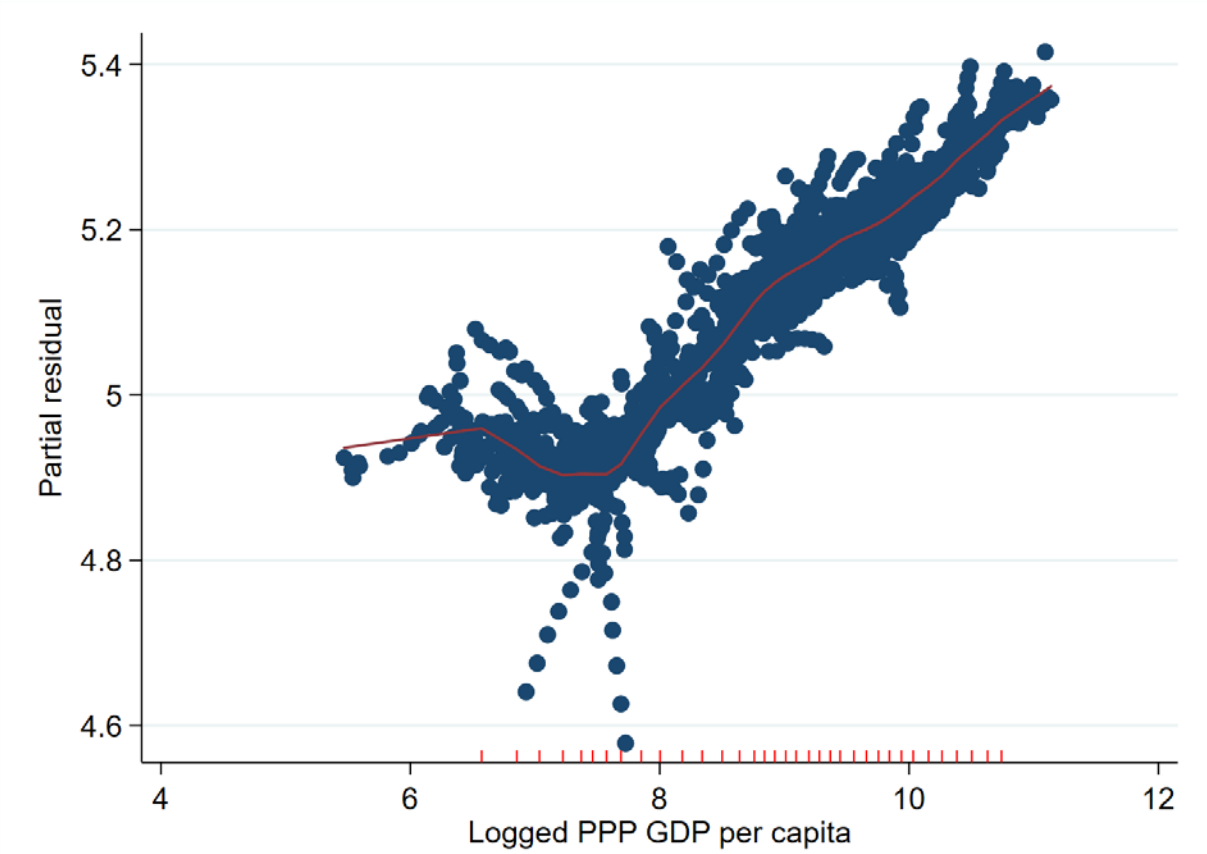


**Figure B.2 | Partial residual plot for GDP p.c. of model 6 in Figure 4 and Table B.5.** Partial residual for every country year (blue filled circles) and the smoothed mean (red curve) as calculated from the fixed effects regression with penalized splines (Ruppert et al. 2003) for logged GDP per capita. Red ticks on the x-axis represent knots. The plot demonstrates that the effect of GDP growth on forest land share growth is almost flat for poor countries with logged PPP GDP p.c. of less than ca. 8.0, and positive and virtually linear for richer countries. Thus, the effect is positive and linear for the vast majority of observations.

| Variable | mean | within ($\bar{x}_i$) | | | between ($x_{it} - \bar{x}_i + \bar{\bar{x}}$) | | | N (nxT) | n | Description | Data Source |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | sd | min. | max. | sd | min. | max. | | | | |
| Forest land share | 32.77 | 2.02 | 18.34 | 50.01 | 23.83 | 0 | 98.60 | 4690 | 181 | Forest is determined both by the presence of trees and the absence of other predominant land uses. Forest area is land under natural or planted stands of trees of at least 5 meters in situ or with the potential of growth to this height, with an area of more than 0.5ha and width of more than 20m, and a canopy cover of at least 10%, whether productive or not, and excludes tree stands in agricultural production systems and trees in urban parks and gardens. Unit: % of land area. | FAO |
| Agricultural land | 40.37 | 2.87 | 19.71 | 57.93 | 21.12 | 0.53 | 84.40 | 4650 | 182 | Agricultural land refers to the share of land area that is arable, under permanent crops, and under permanent pastures. Unit: % of land area. | FAO |
| Population | 34.12 | 12.17 | -191.34 | 249.11 | 127.76 | 0.02 | 1272.37 | 4754 | 183 | Total population. Unit: 1 million. | UNPD, WB |
| Urban population | 52.83 | 3.37 | 39.20 | 69.73 | 23.32 | 8.93 | 100 | 4806 | 185 | Urban population refers to people living in urban areas as defined by national statistical offices. Unit: % of total population. | UNPD, FAO, WB |
| GDP p. c. | 11.29 | 4.85 | -16.87 | 47.98 | 11.75 | 0.54 | 62.31 | 4384 | 177 | Gross domestic product (GDP) per capita (p.c.) based on purchasing power parity (PPP). PPP GDP is GDP converted to international dollars using PPP rates. Unit: 1000 international dollars. | IMF |
| Industry, value added | 28.17 | 4.50 | -5.59 | 60.52 | 11.04 | 7.20 | 75.96 | 4092 | 174 | Industry corresponds to the International Standard Industrial Classification (ISIC) divisions 10-45. The origin of value added is determined by the ISIC, revision 3. Unit: % of GDP. | WB |
| Services, value added | 55.57 | 5.41 | 22.75 | 99.17 | 13.46 | 22.77 | 82.07 | 4075 | 173 | Services correspond to ISIC divisions 50-99. The industrial origin of value added is determined by the ISIC, revision 3. Unit: % of GDP. | WB |
| Forest products trade balance | 0.16 | 1.53 | -24.07 | 27.69 | 2.03 | -2.09 | 24.27 | 4171 | 174 | Forest products trade balance is the ratio of exports to imports of forest goods as share of GDP. | FAO |
| Protected forest area | 37.40 | 34.56 | -640.36 | 469.28 | 142.59 | 0 | 1630.39 | 3289 | 149 | Protected forest area is designated primarily for conservation of biological diversity and natural and associated cultural resources. Protection and maintenance is managed through legal or other effective means. Unit: $km^2$. | FAO |
| Mean temperature | 18.98 | 0.49 | 15.61 | 21.29 | 8.21 | -5.97 | 28.90 | 4225 | 169 | Mean annual air temperature derived from quality controlled monthly observational data from thousands of weather stations worldwide. Unit: °C. | WB |
| Droughts | 0.20 | 0.36 | -0.60 | 1.16 | 0.24 | 0 | 1 | 1963 | 160 | Dummy, 1, if a drought occurred at least once a year. A drought is classified if at least one of the following criteria is met: 10 or more people dead, 100 or more people affected, declaration of a state of emergency, call for international assistance. | CRED |

**Table B.6 | Drivers of national forest land share: variable description.** CRED = Centre for Research on the Epidemiology of Disasters, FAO = Food and Agriculture Organization of the United Nations, IMF = International Monetary Fund, UNPD = United Nations Population Division, WB = World Bank; All variables in the models are included by taking the natural logarithm allowing for the estimation of elasticities. Years covered: 1990-2015.

| | | |
|---|---|---|
| Algeria*# | Hungary*# | Peru*# |
| Argentina*# | India*# | Philippines*# |
| Australia*# | Indonesia*# | Poland*# |
| Austria*# | Iran, Islamic Rep.*# | Portugal*# |
| Bangladesh*# | Ireland*# | Romania*# |
| Belarus*# | Israel | Russian Federation*# |
| Belgium*# | Italy*# | Senegal*# |
| Brazil*# | Jamaica*# | Serbia*# |
| Bulgaria*# | Japan* | Slovak Republic*# |
| Burkina Faso*# | Kenya*# | Slovenia*# |
| Cambodia*# | Lao PDR* | South Africa*# |
| Cameroon*# | Latvia*# | South Korea*# |
| Canada*# | Lebanon*# | Spain*# |
| Chile*# | Liberia | Sri Lanka* |
| China*# | Lithuania*# | Swaziland*# |
| Colombia*# | Malawi*# | Sweden*# |
| Congo, Rep.*# | Malaysia*# | Switzerland*# |
| Costa Rica* | Mali*# | Tajikistan*# |
| Croatia*# | Mexico*# | Tanzania*# |
| Czech Republic*# | Mongolia*# | Thailand*# |
| Denmark*# | Morocco*# | Tunisia*# |
| Dominican Republic* | Mozambique*# | Turkey*# |
| Ecuador*# | Myanmar*# | Uganda*# |
| Estonia*# | Namibia*# | Ukraine*# |
| Ethiopia* | Nepal*# | United Kingdom* |
| Finland*# | Netherlands*# | United States*# |
| France* | New Zealand*# | Uruguay*# |
| Gabon*# | Nicaragua*# | Uzbekistan*# |
| Gambia, The*# | Niger*# | Venezuela, RB*# |
| Georgia*# | Norway*# | Vietnam*# |
| Germany*# | Panama*# | Zambia*# |
| Ghana*# | Papua New Guinea*# | Zimbabwe*# |
| Guatemala*# | Paraguay*# | |

**Table B.7 | Countries included in the analyses.** All 98 countries are full members of the United Nations, have sufficient quality of forest area data (tier 2 and 3; FAO 2016) and are included in the models 1, and 2 of Table B.5. Due to missing values in the further added variables, the models 3 and 4 include the 96 countries indicated by '*', and for the models 5 and 6 of Table B.5 the 88 countries marked by '#'.

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