Mapping Potential Carbon Capture from Global Natural Forest Regrowth

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Summary

Regrowing natural forests is a prominent natural climate solution, but accurate assessments of its potential are limited by uncertainty and variability around carbon accumulation rates. To assess why and where rates differ, we compiled 13,112 georeferenced measurements of carbon

accumulation. Climate explained variation in rates better than land use history, so we combined field data with 66 environmental covariate layers to create a global, 1-km resolution map of potential aboveground carbon accumulation rates for the first 30 years of forest regrowth. Our results indicate that on average default forest regrowth rates from the Intergovernmental Panel on Climate Change are underestimated by 32% and miss 8-fold variation within ecozones. Conversely, we conclude that previously reported maximum climate mitigation potential from natural forest regrowth is overestimated by 11% due to the use of overly high rates. Our results therefore provide a much needed and globally consistent method for assessing natural forest regrowth as a climate mitigation strategy.

Background

To constrain global warming, we must reduce emissions and capture excess carbon dioxide (CO_2) in the atmosphere[1,2]. Restoring forest cover, defined here as the transition from < 25% tree cover to > 25% tree cover where forests historically occurred, is a promising option for additional carbon capture[3] and has been prioritized in many national and international goals[4,5]. It is deployable, scalable, and provides important biodiversity and ecosystem services[6]. Yet the magnitude and distribution of climate mitigation opportunity from restoring forest cover is poorly described, with large confidence intervals around estimates[2,3]. To evaluate the appropriateness of forest cover restoration for climate mitigation, compared to the multitude of other potential climate mitigation actions, countries, corporations, and multilateral entities need more accurate assessments of its potential[7].

Mitigation potential from restoring forest cover (reported here in terms of $MgCO_2\ yr^{-1}$) is determined by the potential extent and location of new forest ("area of opportunity") and the rate at which those forests remove atmospheric CO_2 (reported here in terms of $MgC\ ha^{-1}\ yr^{-1}$). While there are now multiple estimates of area of opportunity based on diverse and often heavily debated criteria (e.g., references [3,8–11]), we lack spatially explicit and globally comprehensive estimates of accumulation rates. This is especially true for natural forest regrowth, defined here as the recovery of forest cover on deforested lands through spontaneous regrowth after cessation of prior disturbance or land use. Many countries do not have nationally specific forest carbon accumulation rates and instead rely on default rates from the Intergovernmental Panel on Climate Change (IPCC)[12,13]. Although these rates were recently updated[8,12], they nonetheless represent coarse estimates based on continent and ecological zone, and do not account for finer scale variation in rates due to more local land use history or environmental conditions.

We focus here on natural forest regrowth for several reasons, but there are many ways to restore forest or tree cover (Table S1) and all have value in specific contexts. Natural forest regrowth can cost less than intensive tree planting and also promote re-establishment of local biodiversity[14,15]. Reliance on natural forest regrowth, coupled with maintenance of natural disturbance regimes, also avoids perverse tree establishment in native grasslands[16]. Some reviews further suggest that naturally regrowing forests can recover as well as or better than actively restored forests[17–20]. However these reviews are likely biased towards more amenable sites for forest establishment and natural forest regrowth can be limited due to severe land degradation and/or distant seed sources[21]. Our comprehensive analysis across a range of starting conditions therefore provides a robust baseline for natural forest regrowth, elucidating fundamental constraints and drivers of carbon accumulation rates, and serving as a benchmark for alternative approaches to restoring forest cover.

Methods

To reduce uncertainty and better predict variation in carbon accumulation rates, we assembled a global dataset of carbon in naturally regrowing forests. We reviewed 11,360 primarily peer-reviewed studies to find those that described carbon or biomass accumulation due to any approach for returning forest cover to the landscape (Table S1). From those that described natural forest regrowth (N = 256 studies), we compiled 13,033 empirical measurements of carbon storage in above and belowground biomass, soil, litter, and coarse woody debris. We further filtered this dataset with more stringent criteria (see supplementary methods) to assess potential drivers of carbon accumulation rates (N = 5762 carbon measurements; 554 sites; 227 studies; Fig. 1). These potential drivers included climate, soil characteristics, and land use history. We next improved the geographic and environmental representativeness of our aboveground dataset by including available national forest inventory data from three continents (Fig. 1). We combined the aboveground point data with 66 global covariate layers that mapped variation in temperature, precipitation, seasonality, soil, topographical, and nitrogen deposition variables to develop a spatially explicit model of potential carbon accumulation rates across the globe. Throughout, we focus on the first thirty years of natural forest regrowth, because 2020 to 2050 represents a biophysically critical and policy-relevant window for both reaching net zero emissions and limiting the most negative effects of global warming[2,22].

Results

Potential drivers of carbon accumulation rates

Biome type, as a proxy for climatic and environmental variation, significantly influenced carbon accumulation in total plant pools (e.g., above and belowground biomass combined), but not soil, litter or coarse woody debris pools. Total plant carbon accumulated more rapidly in warmer and wetter biomes than in cooler and drier ones ($F_{5,2652.2} = 11.8$, $p < 0.0001$; Fig. 2; Table S2). In contrast, soil carbon accumulation rates did not vary significantly across biomes ($F_{6,126} = 1.0$, $p = 0.393$; Fig. S1) or with soil texture ($F_{9,128} = 0.2$, $p = 0.997$), underscoring the known challenges of generating default soil carbon accumulation rates[12]. In litter and coarse woody debris pools we did not observe measurable accumulation during the first 30 years of forest regrowth, despite differences among biomes in the absolute magnitude of these pools (Fig. S2; Fig. S3). Indeed, carbon stocks in these pools often declined with time, presumably due to decomposition of residual biomass from prior disturbance. We therefore did not further account for litter or coarse woody debris since natural forest regrowth did not directly drive near-term carbon dynamics in these pools.

The type of prior land use/disturbance significantly, but inconsistently, influenced carbon accumulation rates in both total plant and soil pools. The literature described seven land use/disturbance categories: pasture, long-term cropping, shifting cultivation, clear cut harvest, mining, fire, and other natural disturbances (e.g., hurricane windthrow, landslide). In all biomes except the Boreal, land use/disturbance type significantly influenced total plant carbon accumulation (Boreal: $F_{1,21.1} < 0.1$, $p = 0.910$; Temperate Conifer: $F_{4,32.1} = 31.3$, $p < 0.0001$; Temperate Broadleaf: $F_{5,314.7} = 23.6$ $p < 0.0001$; Tropical/Subtropical Dry: $F_{1,539.8} = 13.7$, $p = 0.0002$; Tropical/Subtropical Moist: $F_{5,539.8} =7.7$, $p < 0.0001$; Tropical/Subtropical Savanna: $F_{2,48.0} = 3.2$, $p = 0.0495$). However, within a biome, rates were often similar across land use/disturbance types (inset panels in Fig. 2). Moreover, across biomes, the specific effect of a given land use/disturbance type often differed. For example, former cropland showed the highest rates of total plant carbon accumulation in the Temperate Broadleaf biome, but only intermediate rates of recovery in the Tropical/Subtropical Moist biome. For soil, prior land use/disturbance data were limited to Temperate Broadleaf and Tropical/Subtropical Moist forests. Only the former showed a significant effect; specifically that disturbance due to cropping or timber harvest led to faster soil accumulation than disturbance by pasture ($F_{2,46} = 7.5$, $p = 0.001$). Overall, these results suggest that land use/disturbance type cannot be used to definitively predict carbon accumulation rates in naturally regrowing forests due to inconsistent effects across biomes for total plant carbon and limited data for soil.

Finally, disturbance intensity influenced carbon accumulation in plant biomass ($F_{2, 992.3} = 13.7$, $p < 0.0001$), but not soil ($F_{2,78} = 1.4$, $p = 0.237$). The literature-derived data included sites that experienced a range of disturbance intensities, from relatively mild (e.g., natural disturbance) to very intense (e.g., long term tillage for agriculture), so we categorized sites by low, medium or high disturbance intensity (Table S3). In general, total plant carbon accumulation rates were higher after the highest intensity of disturbance compared to the lowest intensity of disturbance (Figure S4), but this pattern was not consistent within biomes. Instead, within biomes, the highest carbon accumulation rates occurred in the category with the lowest starting biomass regardless of disturbance intensity (Table S4), reflecting standard sigmoidal growth curves.

Mapping global, near-term carbon accumulation potential

Given the significant biome effects and the limited predictive power of land use/disturbance history, we used 66 global environmental covariate layers, primarily related to climate (Table S5 and supplementary data), to develop a wall-to-wall map of potential aboveground carbon accumulation rates at a 1-km scale. We modeled only aboveground carbon accumulation, because the aboveground data represented the largest fraction of our literature-derived data (N = 2118), showed strong and well-explained variation across the globe, and avoided propagating uncertainty from root:shoot ratios. Focusing on aboveground carbon also allowed us to improve our geographic and environmental representation with available aboveground carbon data from national forest inventories in Australia, Sweden, and the United States (N = 10,994). However, to increase the utility of these maps for conservation and policy planning, we estimated total plant carbon (i.e., with belowground carbon included) *post hoc* using IPCC default root:shoot ratios[12] (see data availability).

We used an ensemble machine learning model to develop a predictive map of carbon accumulation rates in naturally regenerating forests over the next 30 years (Fig. 3a). We found that the best fit model included all 66 covariate layers (Table S5) Our ensemble model predicted the test data reasonably well (RMSE = 0.80 MgC ha^{-1} yr^{-1}, $R^2 = 0.45$). We had limited extrapolation, with covariate values at the field sites spanning most of the range of covariate values across the entire prediction area (Fig. S5). Also, the standard deviation across the ensemble model was ± 13% of the predicted value, on average. However, areas of substantial uncertainty remain. We observed the highest uncertainty in northern Africa and other savanna biomes, and lowest uncertainty in the tropics (Fig. 3b).

When we examined average carbon accumulation rates using the same spatial boundaries underlying the 2019 IPCC defaults (i.e., United Nations Food and Agriculture Organization (FAO) ecozones crossed by continent)[12], we found that our predicted rates were 32% higher on average than IPCC defaults for young forests (Table S6). However, this differed within and across biomes. Notably, our predicted rates were consistently higher in the Tropics (53% higher on average) compared to 2019 IPCC defaults (Fig. 4), even though some of our data were used to update these rates[8]. Our predicted rates are also on the high end of the range provided by the IPCC for the

Boreal, though incorporating albedo will limit the climate mitigation potential of natural forest regrowth in these locations[23].

Our map of potential carbon accumulation rates also demonstrated the value of improved spatial resolution, with over 8-fold variation within an average FAO ecozone and continent combination (i.e., the difference between the maximum and minimum predicted value relative to the minimum). Variation within countries was also substantial with an average of 1.7-fold difference in rates within a country (Table S7) and notable differences in rates at small spatial scales (see Colombia as an example, Fig. 5).

Climate mitigation potential of natural forest regrowth

Our map of potential near-term carbon accumulation rates also allowed us to refine estimates of global mitigation potential from natural forest regrowth. To do so, we combined our rate map with two scenarios of forest expansion based on recently published estimates. While there are multiple and diverse estimates of area of opportunity[3,8–11], we chose two that represented a policy-relevant scenario and a maximum biophysical potential. The first "national commitments" scenario sums country-level commitments to the Bonn Challenge and nationally determined contributions (NDCs) to the Paris Agreement (349 Mha)[11]. The second "maximum" scenario is a spatially-resolved estimate of maximum biophysical area (678 Mha) that excludes grassland biomes to avoid negative biodiversity consequences, the Boreal to avoid potentially adverse warming effect due to changes in albedo, current croplands to safeguard human needs for food, and rural and urban population centers[3] (Fig. 3c). Using our maps of potential aboveground carbon accumulation, we estimate that natural forest regrowth across 349 and 678 M ha could capture between 3.98 and 5.86 $PgCO_2\ yr^{-1}$ in aboveground biomass and a further 1.36 and 1.99 $PgCO_2\ yr^{-}$

^{1} in belowground biomass over 30 years. Carbon accumulation in soil may be negligible or negative (Fig. S2). However, if we use the global average from our literature-derived data (0.42 MgC ha^{-1} yr^{-1}) for the shallower 0-30 cm profile where additional soil accumulation is expected to occur[24], then these estimates rise to a total of 5.87 and 8.89 PgCO$_2$ yr^{-1}. Under the national commitments scenario[11], ten countries held 69% of the global mitigation potential, whereas under the maximum scenario[3], the top ten countries held 61% of the potential (Table S7). However, these countries differed between scenarios and in general mitigation potential depended heavily on area of opportunity. These two scenarios are illustrative and alternative scenarios would provide different results, but regardless the mitigation potential of any scenario can easily be estimated using the wall-to-wall map presented here.

Discussion

There is high enthusiasm for natural forest regrowth as a climate mitigation strategy, given its potential to capture carbon while also providing additional benefits such as habitat for biodiversity[6], which is needed to stem the equally urgent biodiversity crisis[25]. Here we provide a consistent method for quantifying potential carbon accumulation in naturally regrowing forests over the next 30 years, at global and local scales. We find that current IPCC default rates are on average 32% lower than our predicted rates and most notably 53% lower in the tropics, suggesting that tropical countries using IPCC default rates may be underestimating the mitigation potential of natural forest regrowth. Moreover, the default IPCC rates miss 8-fold variation within ecozones.

This improved spatial resolution allows us to better match area of opportunity with potential carbon accumulation rates and refine prior estimates of climate mitigation potential. We find that the maximum biophysical potential for natural forest regrowth to mitigate climate change is 8.89 $PgCO_2$ yr^{-1}, which is 11% lower than previously reported due to the overestimation of rates (derived from Bonner et al.[26]). Nevertheless, regrowth of natural forest remains the single largest natural climate solution even with our more conservative estimate[3].

Achieving 8.89 Pg CO_2 yr^{-1} under our maximum biophysical scenario is challenging and would require dietary shifts towards a plant-based diet, which could release large areas of current grazing lands back to forest, as well as croplands that are used to produce fodder for livestock[27,28]. Even 5.87 $PgCO_2$ yr^{-1} under the more policy-relevant national commitments scenario will be difficult to achieve, with some countries committing to restore more forest area than is available[10] and/or relying on approaches other than natural forest regrowth to restore forests[11]. These challenges do not undermine the utility of our map, however, which can be used to estimate mitigation potential for any available area of opportunity.

The urgency of the growing climate crisis means that the global community needs to simultaneously deploy multiple climate mitigation strategies to constrain global warming[1,2]. This includes strong reductions in emissions, since natural climate solutions, including the regrowth of natural forests, are not a substitute for reducing fossil fuel emissions[29], but rather an essential complement, especially while carbon capture technologies remain expensive and under development[30]. Regrowing natural forest is also not a substitute for protecting existing forests, which store enormous pools of carbon[31]. In general, there is no “panacea” approach to climate mitigation and most, if not all, options (e.g., transformations in our energy sector, carbon taxes) will require enormous political will and financial resources to realize. Natural forest regrowth has high mitigation potential, but may impose land use trade-offs[3,9]. Our results can help local decisionmakers optimize areas of opportunity for natural forest regrowth by pinpointing areas of high potential carbon accumulation to consider alongside other important feasibility criteria, such as costs, livelihoods, and social suitability. Our analyses of potential carbon accumulation rates over the next 30 years also provide an important complement to other global biomass mapping efforts which focus on longer term carbon storage. Recent analyses estimate potential carbon storage in mature forests[10,32,33] or to 2100[11], but the next thirty years represent an important and policy-relevant window for limiting the climate crisis[2,22]. Our analyses estimate how much carbon can be captured during this critical window, enabling comparison of natural forest regrowth to other near-term climate mitigation actions.

There are several sources of uncertainty in our analysis. The first results from limited field site coverage, and variation in data quality and methodology. Although our data compilation far exceeds prior efforts with an initial consideration of 11360 publications, confidence in our results necessarily depend on data availability, which vary considerably across studies and geographies (Fig. 1). The dataset employed here spanned 43 countries, but 96% of the data derived from only ten countries (United States, Sweden, Mexico, Brazil, Costa Rica, Colombia, China, Indonesia, Bolivia and Panama, in descending order). Data may be limited because researchers have not collected the data, the data are not publicly available (e.g., many national forest inventories), or because some forest types are still fairly intact with limited opportunity to quantify regrowth. Despite the patchy plot data, we found that plots covered most of the environmental conditions across the prediction area, with the main exceptions being the Sahel and northeast Asia (Fig. S5).

Increased data collection, ideally in a coordinated fashion to increase comparability across sites and using repeated plot measurements to improve robustness, would ameliorate some of these issues. To facilitate coordination and enable updates to our analyses as new data becomes available, we deliberately merged our efforts with the global Forest Carbon Database (ForC) to support the further development of a single, robust, and transparent repository for forest carbon data[34]. Future data collection should not only prioritize aboveground carbon data in northern Africa and northeast Asia, but also soil carbon data. Although our review encompasses and expands upon all existing reviews of soil carbon accumulation (see supplementary methods), data did not substantially elucidate how soil carbon changes with natural forest regrowth. Our global default of 0.42 MgC ha^{-1} yr^{-1} for soil carbon accumulation is similar to that observed by others (e.g.,[24,35]), but further research is clearly merited.

Another source of uncertainty stems from using historical forest growth to predict future carbon accumulation rates. As global warming ramps up, rates in a given location may increase or decrease depending on factors such disturbance frequency, CO_2 fertilization, or increased respiration due to higher temperatures[10,36]. Moreover, there are other known factors that influence natural forest regrowth that we did not capture in our analysis. For example, residual vegetation can also accelerate forest regrowth by providing roosting sites for seed-dispersers[37] or shade for late-successional species[38]. Others have observed an increased likelihood of regrowth near rivers or existing forest fragments, far from roads or on steep (less-accessible) slopes, and in areas protected from browsing[39–42]. Our global map provides a good starting point, but project-level planning will require detailed site assessments, as well as additional research to refine how local factors and future climate will impact carbon accumulation rates in a given location.

Further work is also needed to characterize how other approaches to restoring forest cover impact carbon accumulation rates and storage. We focused on natural forest regrowth, where natural processes rather than management actions predominantly drive carbon accumulation. However, the permanence of natural forest regrowth (and the carbon stored therein) cannot be assumed[43], especially if secondary forests are less valued than plantation forests. Rates from naturally regrowing forests also do not capture how silvicultural practices can enhance tree establishment and carbon accumulation[44] or how harvested wood products from sustainably managed forests can provide life cycle benefits through substitution effects and carbon storage in long-lived wood products[45]. While additional work is needed to characterize climate mitigation potential of alternative management schemes, we now provide a robust baseline by which to characterize any additional benefit of assisted regeneration and/or active planting and management[17–21].

As countries, corporations, and multilateral entities develop plans to deploy natural forest regrowth as a climate mitigation strategy, our global, 1-km resolution map of potential aboveground carbon accumulation rates provides essential information for targeting activities towards areas with the highest potential carbon accumulation, for estimating the potential carbon return on investment, and for further refining how forests influence terrestrial carbon cycles at local, national, and global scales. It will allow governments that have NDCs related to natural forest regrowth to quickly estimate potential carbon accumulation and prioritize more detailed assessments in regions with higher carbon accumulation rates. We reduce the uncertainty and variability around carbon accumulation rates to facilitate comparisons of natural forest regrowth with other climate mitigation options and confirm that regrowing natural forests has the potential to greatly contribute to stabilizing global warming.

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Author Contributions:

SCP, BG, NH, DG, KL, SS, and LX designed the study with input from all co-authors. SCP contributed to and led all other facets of the study. SML, KJAT, RDB, PWE, HG, KDH, CL, RL, KP, SR, SW, CW, WW, and BG contributed to database compilation, analyses, and manuscript preparation. NH, KL, DG, TC, DR, SS, LX and JV constructed the global maps and contributed to manuscript preparation. GL, RL, VH, KP, and SR contributed to database compilation and manuscript preparation. RLC, RAH, YM, PM, AP, and JDP contributed to manuscript preparation.

Data Availability

The literature-based dataset (both raw and filtered), detailed descriptions of the environmental covariates, and code for constructing the global maps and assessing uncertainty are all available at https://github.com/forc-db/groa. Spatial data for both aboveground carbon accumulation rates and uncertainty (scaled and unscaled by mean pixel value), as well as belowground carbon accumulation rates can be downloaded from Global Forest Watch (www.globalforestwatch.org) and Microsoft's Azure platform. While SCP and NH welcome discussions around potential collaborations, the data are freely available.

Figures

Fig. 1 Distribution of sites after final filtering of the literature-based dataset (blue) and inclusion of the field inventory data (green). We compiled data from forest (dark gray) and savanna biomes (light gray). We restricted savanna data to portions of these grassland-forest matrices with forest cover > 25%.

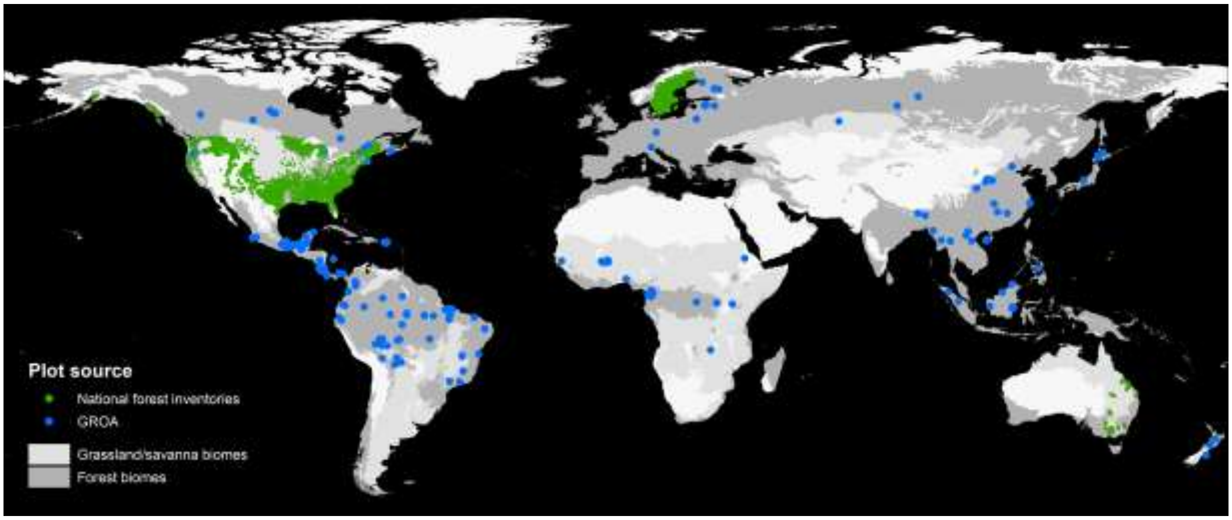


Figure 2. Total plant carbon (MgC ha^{-1}) through time (scatterplots) and average carbon accumulation rates as a function of prior land use/disturbance (inset: mean MgC ha^{-1} yr^{-1} ± 95% C.I.). Lines represent overall modeled fit (± 95% C.I., Table S2) regardless of disturbance. Studies commonly provided information on seven disturbance/land use types: fire ("F", closed squares), other natural disturbance ("D", open squares, e.g., hurricane windthrow), clear cut harvest of land in forest use ("H", open circles), shifting cultivation ("SC", open diamonds), pasture ("PA", open triangles), permanent cropland ("C", closed triangles), and mining ("M", closed circles). Small gray points indicate no known disturbance type. Savanna results only apply to portions of these grassland-forest matrices with forest cover > 25%.

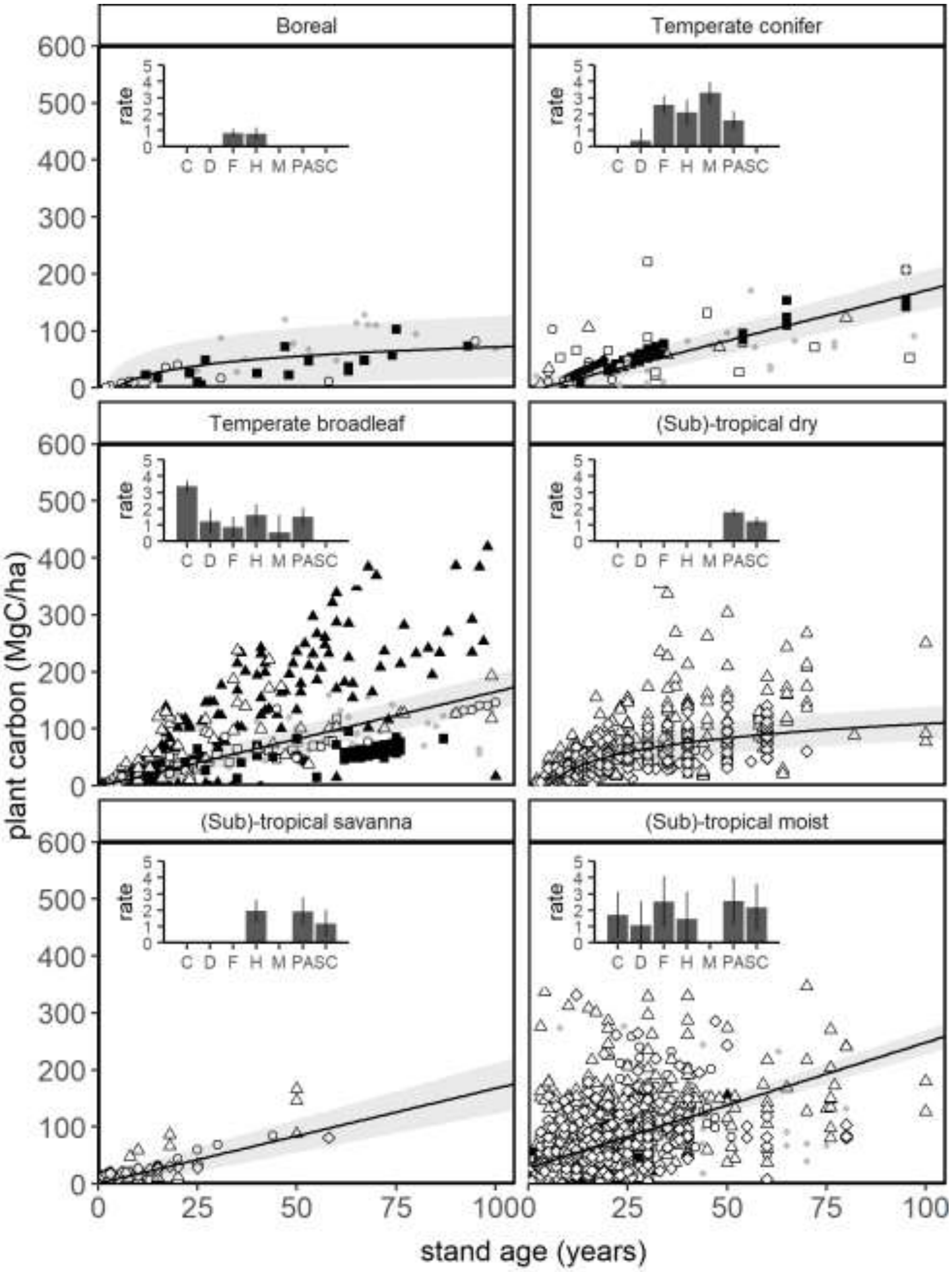


Fig. 3 (a) Predicted aboveground carbon accumulation rates (MgC ha^{-1} yr^{-1}) in naturally regrowing forests in forest (solid colors) and savanna biomes (hatched colors). We denote savanna biomes differently to note that many of these areas are not appropriate for forest and that restoration of forest cover should proceed with particular caution in these biomes. Note that the map only predicts accumulation rates if natural forest $\leq$30 years were growing there; it does not exclude currently forested areas or non-forestable parts of these biomes. b) The ratio of model uncertainty relative to best-fit model value per 1-km pixel. Higher ratios denote greater variation across random forest decision trees. c) Modeled accumulation rates filtered to the area of opportunity in Griscom et al.[3] to demonstrate where these rates might apply.

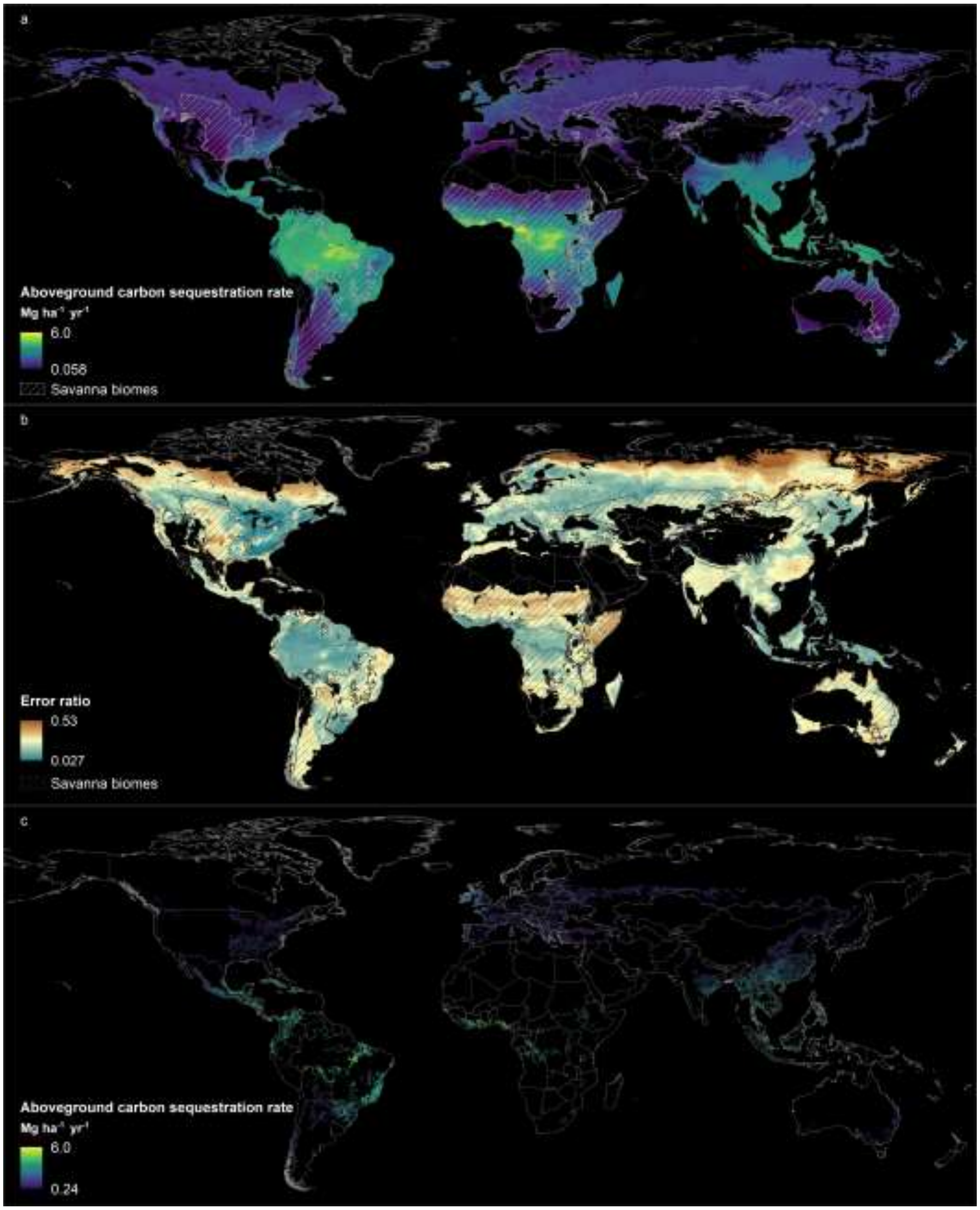


Fig. 4. Average predicted rate of carbon accumulation per ecozone (open circles) compared to 2019 IPCC defaults, which are given as a single number (closed circle) or a range (thick black bars). Colored bars indicate the range between the minimum and maximum modeled rate per ecozone and continent (Boreal = dark purple, Temperate = light purple, Subtropical = light green, Tropical = dark green). Ecozone and continental forest types are listed below the x-axis (NA = North America, NZ = New Zealand, SA = South America)

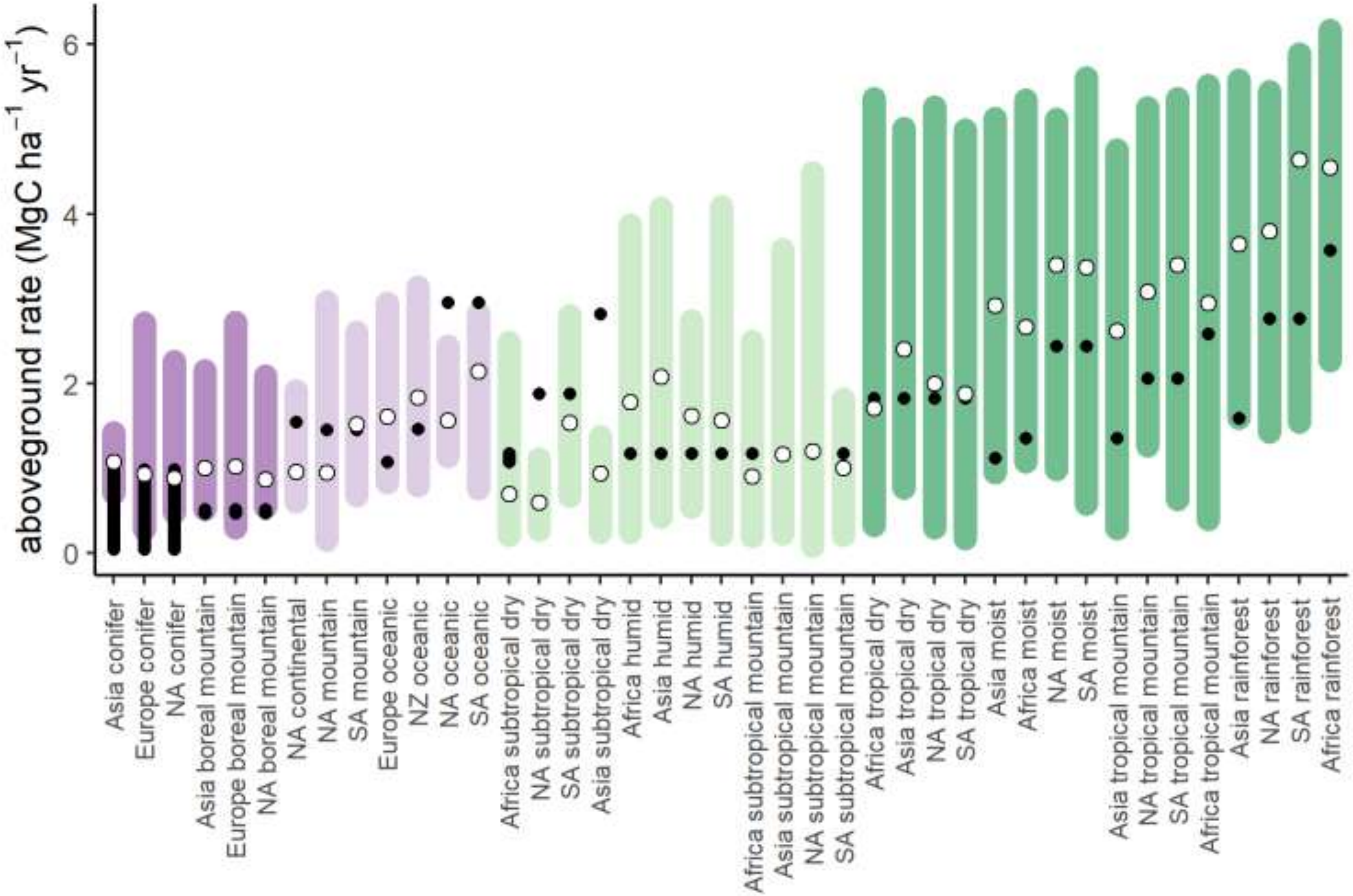
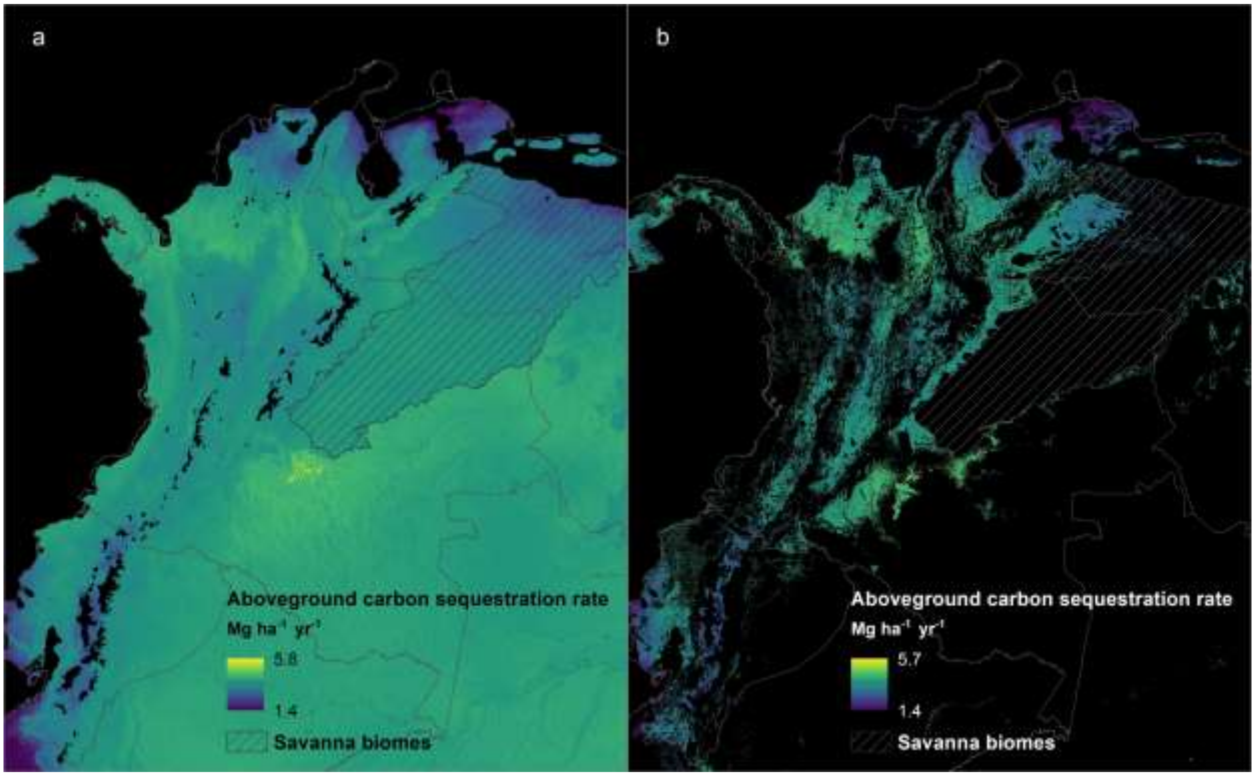


Fig. 5. (a) Map of predicted carbon accumulation rates in Colombia, as an example of country-level variation in rates. (b) Map of predicted rates filtered to the area of opportunity in Griscom et al.[3] to demonstrate where these rates might apply.



Methods and Supplementary Results

Assembling a global carbon database

We systematically reviewed the literature (19 April 2017) with a Web of Science keyword search of studies published since 1975: TOPIC: (biomass OR carbon OR agb OR recover* OR accumulat*) AND (forest) AND (restorat* OR reforest* OR afforest* OR plantation* OR agroforest* OR secondary*). We included "agb" for aboveground biomass. We included "afforest*" because afforestation sometimes describes establishing forest cover in places where forests historically occurred, but we eliminated studies that described tree planting in grasslands (also called "afforestation"), as these efforts are often not successful[46], and reduce biodiversity and ecosystem integrity[47,48].

The initial search yield 10,937 peer-reviewed studies, which we augmented to 11,360 with additional peer-reviewed studies referenced therein or datasets from distinguished institutions (Oak Ridge National Laboratory, International Centre for Research in Agroforestry, and Chinese Academy of Forestry). We reviewed all abstracts to identify accessible studies that quantified forest regrowth after clearing historically forested land (N = 5,464) and fully reviewed these to find any that quantified carbon or biomass stocks (N ~1400). We categorized the latter by approach for restoration of forest or tree cover (Table S1) and focused initially on natural forest regrowth given the need for improved natural forest regrowth data and the immense time required to build this dataset. However, other approaches are currently being reviewed.

To be included, studies had to provide (a) empirical measures of carbon (or biomass) in above- or belowground plant, litter, coarse woody debris and/or soil pools, (b) stand age with at least one stand between 5 and 30 years, and (c) a latitude and longitude, or a discernible geolocation (e.g., an identifiable place name). Papers focusing on soils did not need to include other carbon pools but had to include mineral soils deeper than 10 cm, as well as a reference measurement (e.g., a younger stand or an adjacent non-forest plot) to assess changes in soil carbon. We included measurements in shallower soils if present in papers with 30 cm or deeper data. deeper data. Similarly, we extracted all available data from stands between 0 and 100 years for studies when included in studies with the correct age range (5 to 30 years), excluding studies with only very young forests because of the stochastic nature of early forest establishment, as well as papers with only forests greater than 30 years given our 2020 to 2050 focus.

To avoid duplicated measurements, we gave priority to primary studies and included the earliest instance of repeatedly published data. Our dataset fully encompasses all relevant primary studies from many other reviews (e.g.,[17,35,49–56]) and the Forest Carbon Database (ForC)[34]. For these, we obtained the original studies to confirm numbers, correct errors, and acquire additional variables. However, we preferentially extracted data from three reviews rather than the primary source when authors acquired and reanalyzed original datasets, some of which were previously unpublished (Poorter et al.[57]) or were published in Russian or Chinese[58,59]. Guo and Ren[58] notably provided 5730 measurements across China that we included in the larger dataset, but ultimately excluded by our more stringent filtering (details below).

Beyond geolocation, stand age (years), type of carbon pool, and carbon or biomass estimate (Mg ha^{-1}), we also extracted any available data on type and intensity of prior land use or disturbance. We used geolocation to extract biome designations from Dinerstein et al.[60,61]. While we acquired data from presumably forested portions of Tropical and Temperate savannas (e.g., Miombo forests in Africa, Cerrado forests in Brazil, Pinyon-Juniper forests in the United States), we note that it is not ecological appropriate to increase forest cover in many areas of savannas and that we do not advocate expansion of trees on natural low tree cover savannas[47,48]. We did not include mangroves since they are highly dynamic systems that require complex accounting for *in situ* versus exported soil carbon accumulation[62].

The resulting dataset includes 13033 carbon or biomass data points. We aggregated data by site (N = 2330) and plot (N = 6674), where sites have unique geolocations and plots are spatial units within sites that have unique attributes (e.g., age, prior land use; see metadata for additional details). We then further winnowed these data along stricter criteria to exclude (a) locations with inappropriate geolocations, such as in the ocean or a non-forest biome according to the biome spatial layer[60,61], (b) stands less than one year old because they are not (yet) undergoing natural forest regrowth, (c) Mediterranean forests and temperate savanna because sample size was too low ($N < 10$ for any single pool), (d) studies with only shallow soil measurements (30 cm or less) because carbon in top soil is highly dynamic and can dramatically underestimate overall soil carbon[63], and (e) Guo and Ren[58] data because it contained many old stands with little to no plant biomass which we could not explain (Fig. S6). The final dataset used in these analyses spanned 3058 unique forest plots, 554 sites, 121 ecoregions, and most forest and savanna biomes (Fig. 1).

Standardizing data across publications

For studies that reported biomass only, we converted to carbon (MgC ha^{-1}) using 0.47 as a default conversion factor for above- and belowground pools (combined and described as the “total plant carbon” pool)[64], 0.37 for litter biomass[65], and 0.50 for coarse woody debris biomass[66]. If a study used different default conversion factors, we adjusted their carbon numbers to match the above defaults for consistency.

Most soil organic carbon (SOC) data (72%; N = 1065 of 1485) were already in units of MgC ha^{-1} $depth^{-1}$ and the remainder we converted from SOC concentration (g $100g^{-1}$) or soil organic matter (SOM). For SOM concentration data (N = 38), we estimated SOC concentration as SOM/2 based on Pribyl[67], which found that the median ratio between SOM and SOC across 481 data points from 24 empirical studies was 1.97, with a mean of 2.20. We converted SOC concentration to MgC ha^{-1} $depth^{-1}$ with empirical bulk density data where given (N = 355) or depth-specific bulk density data from SoilGrids[68] (N = 65). SoilGrids provides bulk density modeled at 15, 30, 60 cm and we used the value nearest in depth to the SOC concentration measure. Modeled bulk density was higher but within the range of empirical estimates (1.29 ± 0.13 versus 0.98 ± 0.31 Mg m^{-3}, mean ± s.d.). To convert to MgC ha^{-1} $depth^{-1}$, we used one bulk density value for each site and reference pairing, using measured bulk density from the pre-forest site if available, measured bulk density from the youngest nearby site as the next option, or SoilGrids bulk density from the pre-forest site in the absence of other data.

After converting biomass data to carbon, we standardized within pools. Aboveground carbon measures typically included foliage, but we retained two measures that excluded foliage, since foliage is a small fraction of overall carbon. Studies differed in whether they included understory (e.g., lianas, shrubs). For those without, we added average understory carbon per biome based on our dataset (1.2 to 4.0 MgC ha^{-1}). We did not, however, adjust for differences in diameters at breast height (dbh; nominally 1.3 m above ground level). Although studies used different dbh thresholds, ranging from 0 to 10 cm, minimum dbh did not explain variation in aboveground biomass ($F_{1,459.2} = 0.5$, $p = 0.4608$) and we assumed that authors used a dbh threshold that captured the majority of biomass at their sites. We summed above- and belowground plant carbon using empirically measured belowground carbon when present (N = 444) or standard root-to-shoot ratios

(R:S)[69] when absent (N = 2346). Where it was possible to compare, we found that estimated belowground carbon was 1.8 MgC ha^{-1} higher than measured values, since the field measurements typically only quantified biomass to a specific depth and/or roots greater than a specific diameter. This produced 2790 independent plot measurements of total plant carbon. For dead pools (litter and coarse woody debris), measurements often included additional pools, but we did not attempt to parse litter and/or coarse woody debris from these combined measurements because these pools are highly variable and site-specific[65]. Thus, we only retained single pool measurements (N = 473 litter and 298 coarse woody debris). Finally, for soil, we adjusted data to the nearest of two standard depths (30 and 60 cm). For plots with multiple depth measures, we used the slope from a fitted log-log curve for cumulative SOC stocks as a function of depth to estimate SOC at standard depths, but for plots without multiple depth measures, we used a biome-specific slope coefficient[70]. If standardizing depths resulted in duplicate measures – for example, when a study reported SOC at 20 and 40 cm, leading to two predicted values at 30 cm – we calculated the average. Depth-standardized SOC was 1% lower than the empirical measure of SOC and highly correlated (R^2 = 0.84).

For plant, litter and coarse woody debris (CWD) pools, we analyzed carbon stocks (MgC ha^{-1}) as a function of stand age, as these pools can have zero carbon at initiation of regrowth. However, SOC changes are relative to a non-zero baseline so we first converted SOC stock data to rates (MgC ha^{-1} yr^{-1}). For repeated measure designs, we calculated a single rate per plot based on SOC change from initial conditions. For the remaining studies, we used linear regression to fit SOC as a function of stand age within each chronosequence, treating any reference plot (e.g., an adjacent treeless cropland) as age zero (N = 5 data points on average per regression). We only compared forest and reference plots with the same prior land use[35]. This produced a single rate estimate per chronosequence, and these rates became the foundational data for the soil analyses. We ultimately derived 138 SOC rates from chronosequences (N = 129) and repeated measures (N = 9). Most rates quantified changes at 0-30 cm (N = 83) and then 0-60 cm (N = 55).

Potential drivers of carbon accumulation rates

To assess fundamental drivers of variation in carbon accumulation rates, we examined differences in rates (a) across biomes as a proxy for major climatic differences, (b) across soil texture categories (soil only), and as a function of (c) type of prior disturbance or land use, and (d) intensity of prior disturbance or land use.

First, to examine differences in plant, litter, and coarse woody debris carbon among biomes, we used mixed effects models (R v. 3.5.1 packages *lme4* and *lmertest*) to examine carbon stocks as a function of stand age, biome, and stand age × biome with site (or plot nested within site) as a random intercept. We were primarily interested in the interaction term here and below, since it describes how the effect of age on carbon stocks (i.e., carbon accumulation rate) is modified by the predictor variable, which in this case is biome. We compared a linear model to one with ln-transformed stand age, selecting the model that minimized the Aikake Information Criterion (AIC). For litter and coarse woody debris, carbon either declined non-linearly from initial starting conditions and/or remained roughly constant with stand age (Fig. S3). We therefore did not further examine carbon accumulation in these pools, because residual dead matter from previous disturbance obscured any signal of additional accumulation. However, we did examine variation across biomes by removing stand age from the model. We found that litter and CWD carbon stocks were generally higher in Boreal and Temperate biomes compared to other biomes (Fig. S2; litter: $F_{5,138.7} = 8.5$, $p < 0.0001$; CWD: $F_{4,125.7} = 5.9$, $p = 0.0002$). For soil, we used linear regression to model carbon accumulation rates as a function of biome identity. We also included depth as a categorical predictor (depth and depth × biome) and found that, although stocks generally declined with depth of measurement as expected, rates of carbon accumulation did not ($F_{1,126} < 0.1$, $p = 0.956$).

Second, we examined how soil carbon accumulation might differ by soil texture. We used SoilGrids data on clay, silt and sand percentages to estimate the soil texture category (e.g., sand, loam, clay, etc.) at each site where texture data were not provided. We used linear regression to analyze soil carbon accumulation as a function of texture, and again found that texture was not a significant predictor of variation ($F_{9,128} = 0.2$, $p = 0.9997$)

Third, we examined how prior land use or disturbance influenced carbon stocks through time for disturbance types with > 3 data points per biome. When studies listed multiple disturbance or land use types for a single plot, we noted the most recent type where discernable. Otherwise, we used the type that was most likely to negatively impact forest regrowth (natural disturbance < harvest = shifting cultivation < crop < pasture, based on *pers. obs.*). We conducted separate analyses per biome, as each biome was associated with different disturbance types. For plant biomass (N = 2600), we used mixed effects linear regression, modeling carbon as a function of stand age and prior land use, plus their interaction, with site (or plot nested within site) as a random intercept. For soil (N = 132), we used an analysis of variance with prior land use and depth as the predictors of SOC.

Finally, we examined how the intensity of prior disturbance influences carbon stocks through time. Unfortunately, studies provided fewer details about the intensity of prior land use (N = 1567 and 91 for plant biomass and SOC respectively). Three co-authors in this study (HPG, KDH, CL) independently categorized disturbance intensity into low, medium, and high categories using a disturbance rubric (Table S3), assigning the final category based on majority agreement among scorers. Given data scarcity, we only categorized intensity of prior land use for four disturbance types: pasture, shifting cultivation, long-term cropland, and clear-cut harvest. We conducted our statistical analysis across disturbance types, using mixed effects to model total plant carbon as a function of stand age and disturbance intensity, plus their interaction, with site or plot nested within site and biome as random intercepts. We used a similar model for soil with only disturbance intensity as the predictor and biome as a random intercept. We also ran similar models, though without the biome random effect, for each biome with sufficient data.

Mapping global, near-term forest carbon accumulation potential

To develop maps of aboveground carbon accumulation, we extracted the literature-derived data with a separate measurement for aboveground carbon and stand age of 30 years or less (N = 2118). We supplemented these data with three national forest inventories: Australia, Sweden, and the United States. The Australia data were collected between 2006 and 2017 from naturally regenerating stands of known age (N = 54)[33]. These stands were located across contrasting biomes, ranging from relatively productive temperate regions to water-stressed semi-arid regions. Biomass data only include new tree growth and do not include remnant trees. The Swedish National Forest Inventory plot data were collected between 2007 and 2017 (N = 5458)[71]. The United States data are from the United States Department of Agriculture (USDA) Forest Service's Forest Inventory and Assessment (FIA) program (N = 5482)[33]. Due to privacy concerns, FIA data are made available only after a fraction of plots are randomly swapped with others' coordinates. Although these security procedures shifted the geolocation of plot data and predictor variables by ~ 1 km, including the FIA data improved the predictive power of the model. We used plots that had (a) been remeasured at time one (T_1) and time two (T_2) to estimate a rate of carbon accumulation, (b) no treatment at T_2 or T_1 (TRTCD = 0) to restrict data to natural forest regrowth, (c) no trees recorded as alive in T_2 that were recorded as dead in T_1 (DEAD_TO_LIVE_COUNT = 0) to remove erroneous measurements, (d) no recorded disturbance in T_2 or T_1 (DSTRBCD = 0), (e) aboveground biomass at T_2 (AG_LIVE_BIO_MGHA > 0) to avoid harvested or burned plots, and (f) a stand age at T_2 between 0 and 30 years (30 > STDAGE > 0). We also only included plots where more than 50% of the area was comprised of the same forest type, owner class, land class, and other properties at T_1 and T_2 to ensure consistency within a site (CONDPROP_UNADJ > 0.5).

Combined, all literature-derived and national inventory data represented 13,112 plot measurements. We then calculated carbon accumulation rate by dividing aboveground carbon by stand age, providing an average rate over the first 30 years of growth. We removed plots that did not fall into forest or savanna biomes or had no recorded biomass to avoid plots that had likely been harvested (N = 685 or 5.2% of data). We also removed any points that had rates greater than three standard deviations above the mean (N = 153 or 1.2% of data). Finally, when there were multiple point estimates within each of our ~ 1 km pixels, we calculated the average rate to use in model development (N = 10,216). Averaging within pixels improved model performance compared to models with no averaging.

To create a spatially predictive model of carbon accumulation, we first sampled our prepared stack of 66 environmental covariates at each of the point locations within the literature-derived and national inventory datasets. These layers included climate, soil nutrient, soil chemical, soil physical, radiation, topographic, and nitrogen deposition variables (Table S5). We did not use variables that represent current vegetation condition (e.g., leaf area index or percent forest cover) or satellite-derived indices such as Normalized Difference Vegetation index (NDVI), as these do not represent fundamental biophysical controls on carbon accumulation rates for the future accumulation of plant biomass. We resampled and reprojected these covariate map layers to a unified pixel grid in EPSG:4326 (WGS84) at 30 arc-seconds resolution (~1km at the equator), downsampling higher resolution data using mean aggregation method and resampling those with a lower original resolution using simple upsampling (i.e., without interpolation). We chose this resolution to balance pixel-level uncertainty, which is proportionately larger in smaller pixels, with utility for local decision-makers. If multiple resolutions were available for a covariate, we used the resolution closest to 30 arc-seconds. Covariates represent different time periods but were all between 1970 and 2017. This time period allows us to capture long-term average conditions under current and historical climate.

We then split the total number of points into a training set and a test set using an 80/20 random split, stratified by data source (i.e., the literature-derived data and each national inventory) and by biome. We used the training set to determine the best machine learning algorithm and set of hyper-parameters, and to train the final model. We used the test set to assess out-of-sample error, as well as model performance with novel data (details below).

We compared four machine learning algorithms (random forest (RF)[72], a gradient boosting decision tree called XGBoost[73], support vector machines[74], and multi-layer perceptron)[75], along with four feature selection methods (support vector machine feature selection, RF-based feature selection, principal component analysis, and no feature selection), leading to 16 different combinations of feature selection methods and machine learning algorithms (or “model pipelines"). Each model pipeline first applied feature scaling to the data (standard scaling for the continuous variables and one-hot encoding of biome as our only categorical variable), then selected features using the feature selection algorithm, and finally trained the machine learning model on the transformed data. For each machine learning algorithm, we also defined a suite of hyperparameters to test over, often leading to over 1,000 tested hyperparameter combinations. We conducted the machine learning steps in Microsoft Azure.

We used the Python scikit-learn package and the “gridsearchCV” function to define and train model pipelines using three-fold cross-validation and choose the best hyperparameter combination for each model pipeline[76]. We used the cross-validation root-mean-square error (RMSE) to choose the best feature selection method and machine learning algorithm with defined hyperparameters. Cross-validation is an important step in training and comparing machine learning algorithms, as it creates pseudo-training sets that can be used to estimate the out-of-sample error and reduce over-fitting to the training set, while still keeping the final test set completely independent of the model. In three-fold cross-validation, the training set is randomly split into three equally sized subsets. Two subsets combine to form a new training subset, and the last subset serves as a validation set to assess the model performance. We trained the model pipeline on the training subset, stored the RMSE of the model predictions over the validation set, and then repeated the process twice more with the remaining combinations of training and validation subsets. The final cross-validation score is the average of the validation RMSEs across each model pipeline, and we used average cross-validation RMSE to compare model pipelines and selected the model pipeline with the lowest cross-validation RMSE as our best trained model pipeline. In our case, the best trained model pipeline was the random forest machine learning algorithm with no feature selection.

After determining the best performing algorithm and set of hyperparameters, we used a Monte Carlo approach to create an ensemble model for our final predictions and uncertainty analysis. We generated the ensemble model by first drawing 100 independent bootstrapped samples with replacement of our training data, stratified on the data source and biome. Next, we trained separate random forest models using the best performing set of hyperparameters on each of the 100 bootstrapped samples of the training data. Our final model is the ensemble of the 100 random forest models, where the ensemble model prediction is the average of the predictions of the 100 random forest models. To asses our out-of-sample error, we applied this final ensemble model to our test set. The ensemble model had an RMSE of 0.798 Mg C ha^{-1} yr^{-1} and an R^2 of 0.445 on our independent test set.

To create a final global map of aboveground carbon accumulation and associated uncertainty, we sampled all environmental covariate layers over all pixels in forest and savanna biomes and applied the best trained model to each pixel's covariates. Although the trained model works over any area, we constrained it to forest and savanna biomes. Because our model is an ensemble of 100 random forest models with each random forest model trained on an independent bootstrapped sample of the training data, we can use the standard deviation of the 100 random forest models' predictions to estimate model uncertainty in each pixel. Therefore, for each pixel we have the model's prediction and standard deviation across the 100 models. We also tested the extent of extrapolation in our models by examining how many of the Earth's pixels exist outside the range of our sampled data for each of the 66 global covariate layers. We first extracted the minimum and maximum values of each covariate layer across our sampling pixels to determine sample range. We then used the final model to evaluate the number of variables that fell outside the sample range, across all terrestrial pixels. Next, we created a per-pixel representation of the relative proportion of interpolation and extrapolation (Fig. S5). This revealed that our samples covered most environmental conditions on Earth, with 88% of Earth's pixels values falling within the sampled range of at least 90% of all bands. Across all pixels, the average fraction of the pixel values falling within the sampled range of the covariates was 97%.

We compared our predicted rates with the latest 2019 IPCC default rates for young forest (<20 years)[12] by estimating the average pixel value, as well as the minimum and maximum pixel value within each ecozone by continent combination. Whenever a range was provided for IPCC values, we used the average of the lower and upper bound of the range to compare to our predicted rates.

Climate mitigation potential of natural forest regrowth

To estimate the constrained maximum mitigation potential of natural forest regrowth, we combined the Griscom et al.[3] area map with our map of potential aboveground carbon accumulation and a map of potential belowground plant carbon accumulation. We created the latter by applying default root:shoot ratios to the aboveground pixels[12]. This Griscom et al.[3] extent raster identifies more area of opportunity than is available, because there are a series of non-spatial deductions that they applied later in their analyses. We therefore proportionally scaled mitigation opportunity within each country so that the final area summed to their reported 678 Mha area of opportunity. The Griscom et al.[3] analysis assumes that a small fraction of their area of opportunity would have plantations, so we adjusted their mitigation estimate to reflect a scenario of 100% natural forest regrowth (10.56 $PgCO_2$ yr^{-1}).

Lewis et al.[11] compiled national commitments to the Bonn Challenge and from nationally determined contributions to the Paris Agreement. Although that publication focused on tropical countries, we acquired the global compilation to use here. Two countries (Niger and Burkina Faso) included commitments that we did not include, because those countries fall outside of our potential rates map. To estimate the mitigation potential of these national commitments, we used the same average predicted rates per country from the overlay of Griscom et al.[3] for above- and belowground carbon accumulation. Thus, this assumes that the 349 Mha of opportunity under this scenario represents an average subset of the area identified as biophysically possible in Griscom et al. [3].

Supplementary Figures

Figure S1. Observed variation in live plant carbon accumulation rates and soil carbon accumulation (mean ± 95% confidence intervals) among biomes, from the literature-derived dataset. We did not have plant biomass data for (sub)-tropical conifer forests.

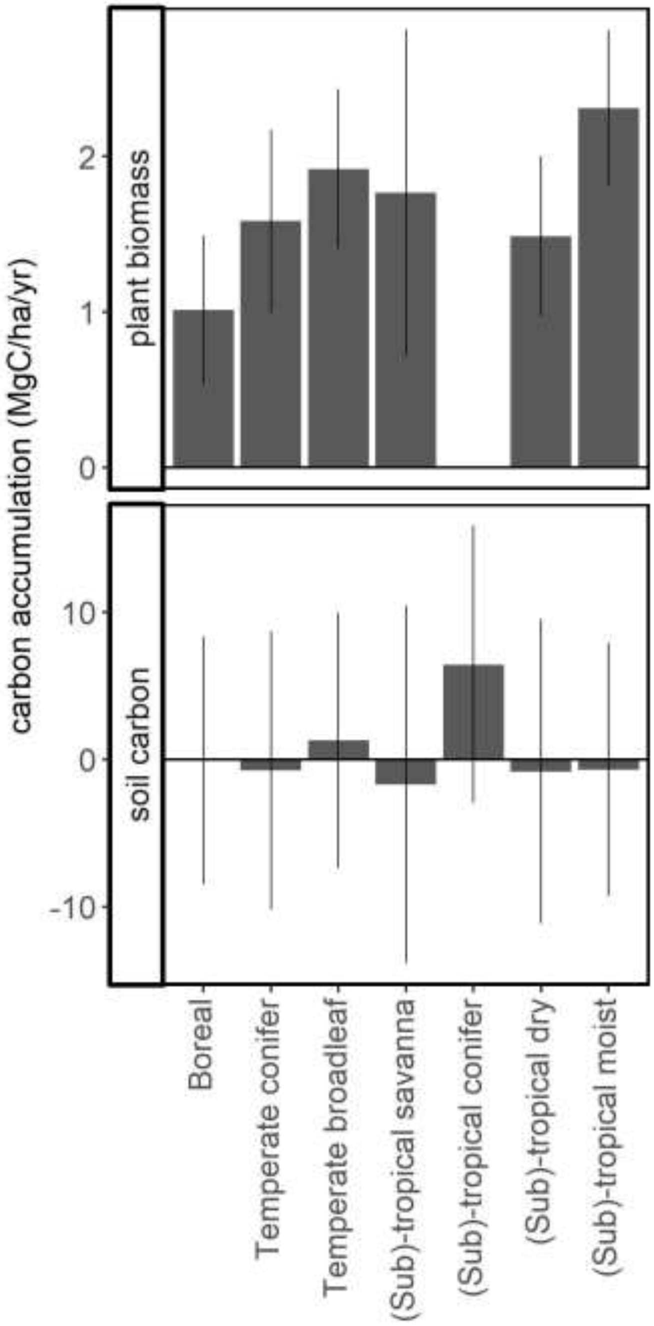


Figure S2: Carbon pools (mean ± SE) in coarse woody debris (gray) and litter (black).

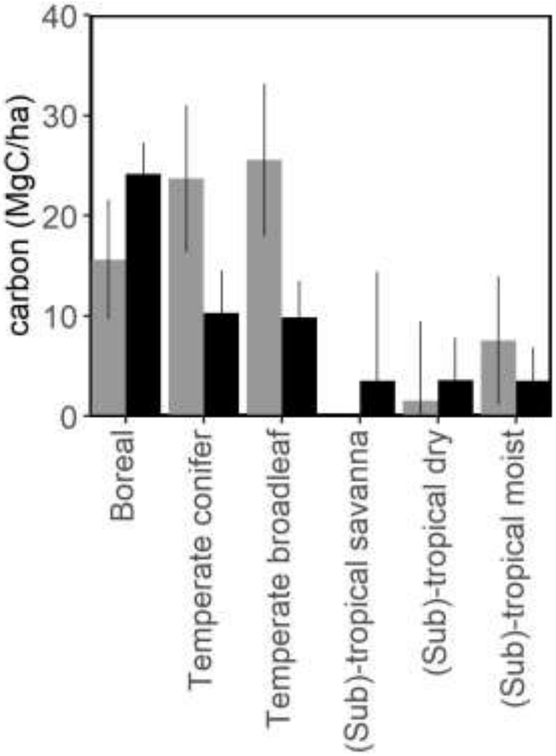


Figure S3: Coarse woody debris (gray) and litter (black) carbon pools over time in each biome. We did not find studies describing litter or coarse woody debris pools in temperate savannas, or coarse woody debris in tropical savannas.

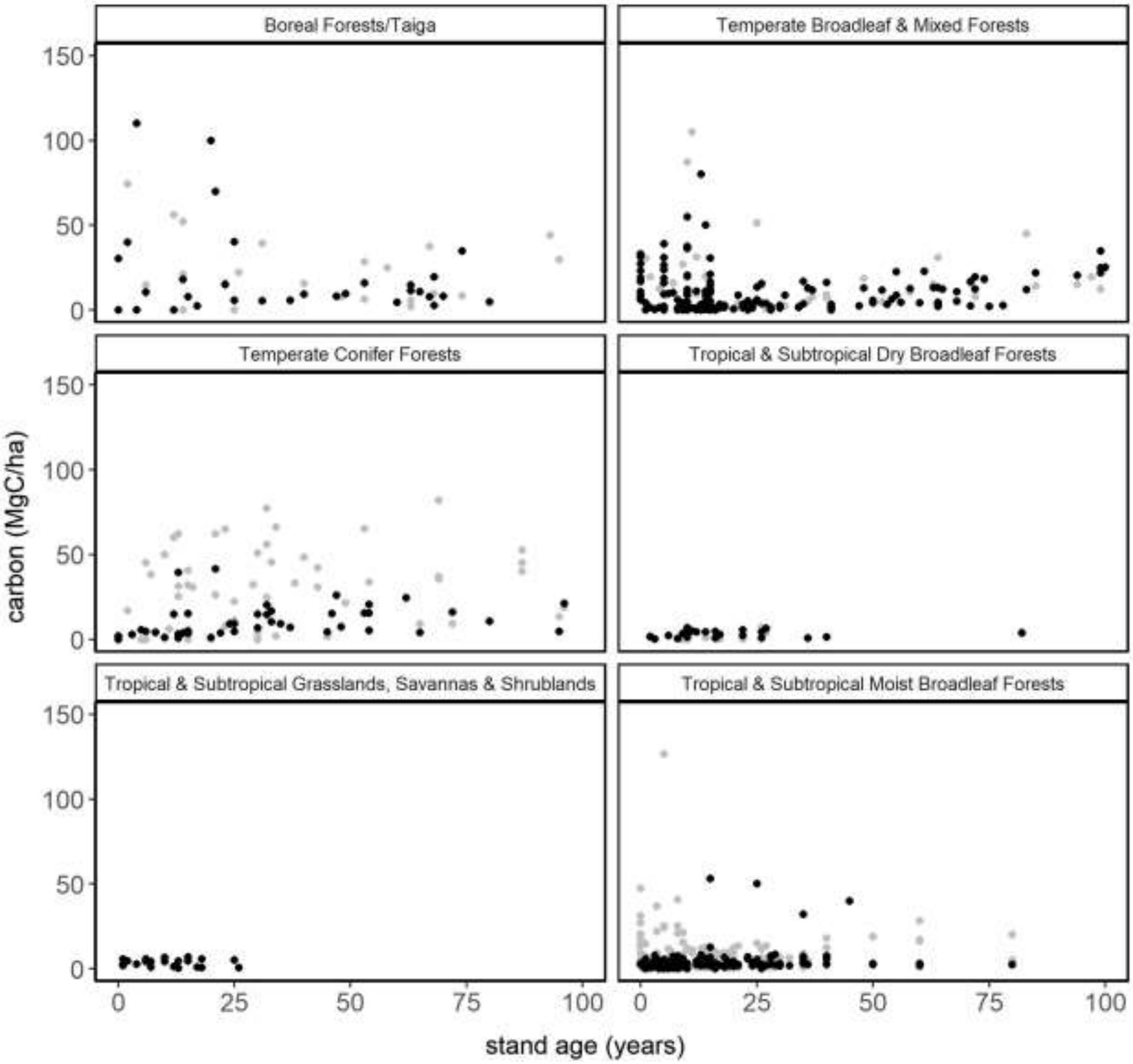


Figure S4: Carbon accumulation in plots with high intensity disturbance (black circles, black line) versus low intensity disturbance (gray circles, gray line). The most disturbed categories had lower residual biomass at the initiation of regrowth (e.g., 0 MgC ha^{-1} versus 28 MgC ha^{-1} in the least disturbed category; t-value = 5.9, $p < 0.0001$), suggesting that the higher rate in the most disturbed category is due to standard sigmoidal growth rates in forests.

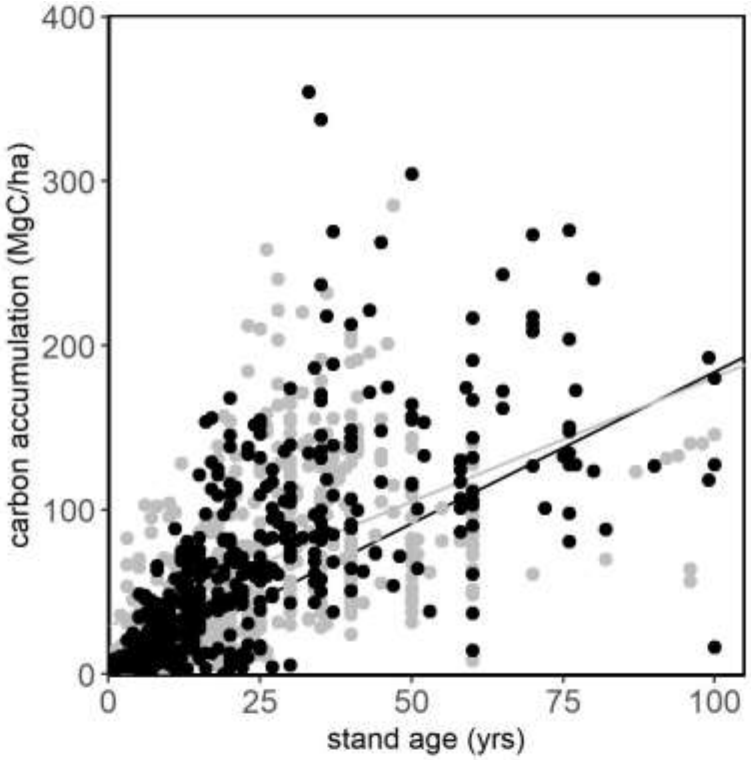


Fig. S5: Map of extent of extrapolation per pixel across all covariate layers. A value of 1 indicates that 100% of pixels fall within the sample range (i.e., there is no extrapolation).

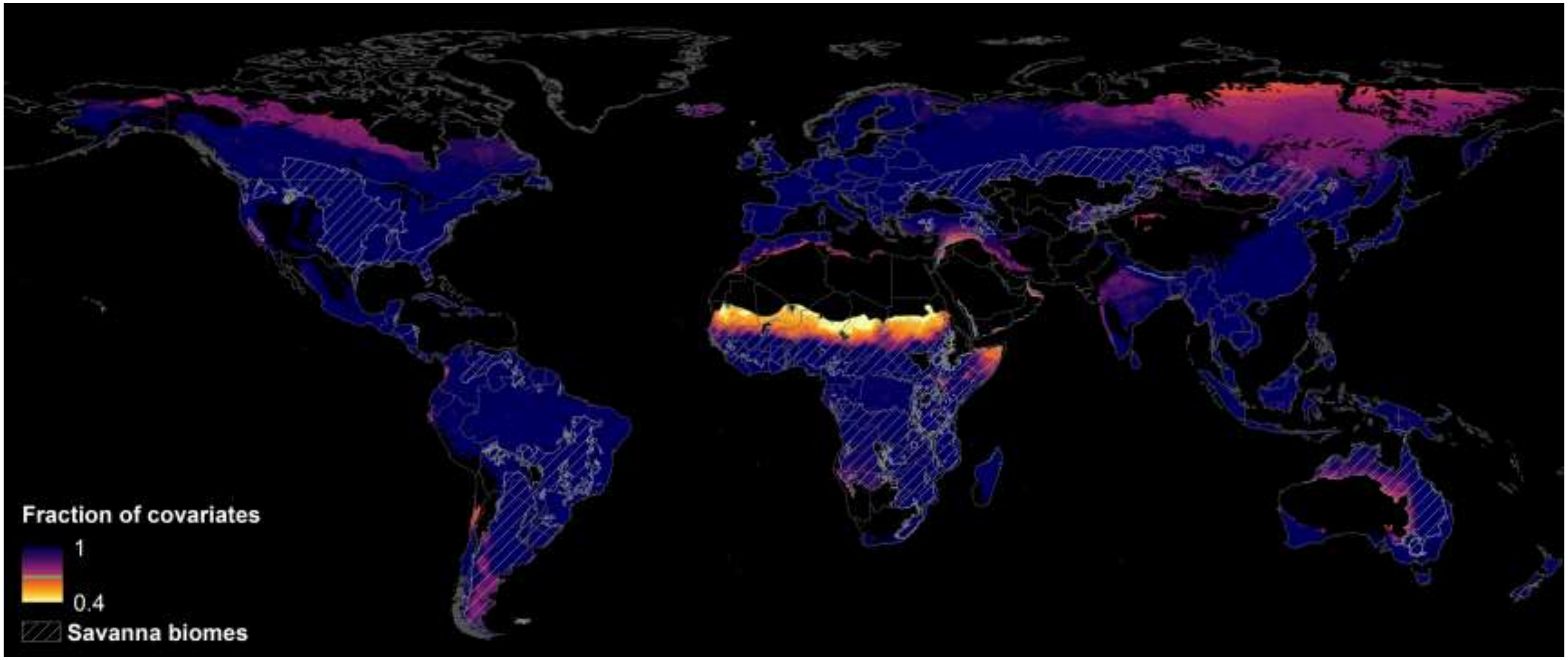
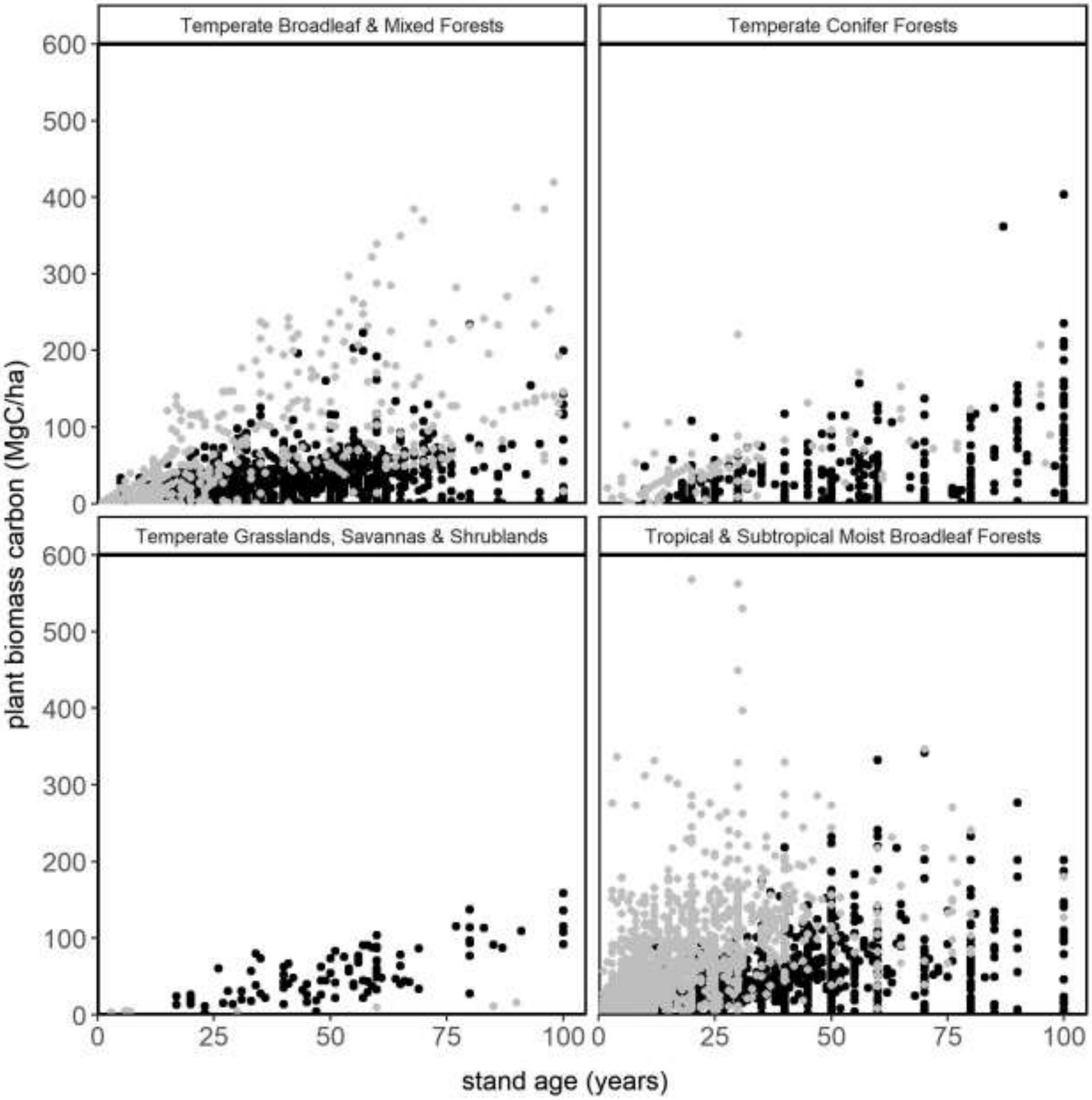


Fig. S6: Total plant carbon through time from Guo and Ren[58] (black circles) compared to other studies (gray circles).



Supplementary Tables

Table S1: General approaches for restoring forest or tree cover, based on aggregation of existing taxonomies and expert consultation at a workshop at Oxford University, UK in February 2017. These approaches will not necessarily reach > 25% forest cover.

Land-use	**Type with Definitions**
Semi-natural forest, protected or with some selective logging	**Natural forest regrowth** involves allowing forests to spontaneously regrow without any silvicultural interventions, though may involve removing disturbance factors (e.g., fire breaks, fencing, control of feral animals such as camels and goats, reduced grazing pressure)[77]. This includes both succession after abandonment and forest recovery following logging, fire or disturbances.
	Assisted natural regeneration aims to accelerate natural forest regrowth and/or guide successional trajectories through activities that enhance tree growth, such as removing invasive grasses, liana cutting, and/or other practices[78]. We also include enrichment planting in this category.
	Active restoration includes smaller tree configurations (e.g., applied nucleation methods), as well as large scale tree planting endeavors to restore native forests. Species may be mixed at the stand scale or in patches at the landscape scale. This strategy may also involve extensive natural forest regrowth following initial planting.
Timber plantations	**Mixed species plantations** include at least two species intermixed on large areas in timbers stands and may involve a mix of native and non-native species.
	Monoculture plantations include plantation forests where the same species is grown on large areas in even-aged stands[79]. We include estimates for individual species that are commonly employed, as well as a more general estimate for species that are more infrequent. This includes both native and non-native species.
Agroforestry	**Intensive tree monocrops** include all non-timber monocultures, such as fruit or nut tree monocultures, oil palm plantations, and other commodity crops.
	Multistrata systems are those with a mix of under- and overstory species, and include home gardens and shade-grown cropping systems like cacao (*Theobroma cacao* L.) and coffee (*Coffea* sp.) combined with shade-, timber- or commercial tree crops[80].
	Tree intercropping includes agricultural systems where woody species are grown in crop fields, in scattered or systematic arrangements. These species may be used for fruit, fodder, fuelwood or timber[80].
	Silvopastoral systems include grazing under scattered or planted trees, as well as tree-fodder systems[80].
Transitional land use	The **transitional land use** strategy involves incorporating a range of agroforestry and/or plantation approaches in early stages of reforestation, as a transitional phase towards native forest restoration, to overcome socioeconomic and ecological obstacles to restoring these lands[81].

Table S2: Best fit equations per biome for carbon accumulation in total plant pools (MgC ha^{-1}) as a function of stand age (year) based on the literature-derived data. Parameters are slope ± standard error (SE) and intercept ± SE. We also provide the number of literature-derived data points per regression (N). The rate column indicates an average rate for the first 30 years of stand development based on predicted total plant carbon at age 30.

Biome	**Best fit equation**	**N**	**rate**
Boreal Forest	(23.2 ± 3.2) × ln(age) + (-35.7 ± 12.6)	45	1.45
Temperate Broadleaf & Mixed Forests	(1.7 ± 0.1) × age + (-0.7 ± 6.5)	418	1.63
Temperate Conifer Forests	(1.8 ± 0.1) × age + (-5.5 ± 6.8)	104	1.58
Tropical & Subtropical Dry Broadleaf Forests	(35.9 ± 1.7) × ln(age) + (-56.6 ± 7.4)	552	2.19
Tropical & Subtropical Savannas (forested portions)	(1.7 ± 0.2) × age + (1.0 ± 7.0)	57	1.70
Tropical & Subtropical Moist Broadleaf Forests	(2.2 ± 0.1) × age + (28.4 ± 2.8)	1614	3.15

Table S3: Schema for categorizing intensity of land use/disturbance. Other land use/disturbance types (mining, fire, and other natural disturbance (e.g., hurricane windthrow, landslide) did not have sufficient data.

Disturbance/ land use	**Low intensity**	**Medium intensity**	**High intensity**
Shifting cultivation	Most shifting cultivation with < 3 cycles and < 15 years of use	Long-term shifting cultivation with ≥ 3 cycles, ≥ 15 years of use	NA
Long term crop	NA	Minimal input (e.g., herbicides, fertilizers) with < 10 years of usage	Most crop systems and ≥ 10 years
Pasture	NA	Minimal input (e.g., herbicides, fertilizers), < 10 years of usage	Most pasture systems
Harvest	Single harvest, no fire	Multiple harvests or harvest and burn	NA

Table S4: Biome-level effects of disturbance intensity on carbon accumulation in total plant biomass (MgC ha^{-1} yr^{-1}) as a function of stand age. Intensity categories are low (L), medium (M), and high (H) based on Table S3. For all biomes, the greatest carbon accumulation rate (e.g., slope parameter) was observed in the intensity category with the lowest starting biomass (e.g., intercept parameter).

biome	**intensity**	**best fit equation** (parameters ± SE)	**Statistic** (age × intensity)	**N**
Temperate Broadleaf	L	(1.6 ± 0.2) × (age) + (-8.6 ± 28.8)	$F_{2,62.0} = 1.4$, $p = 0.248$	21
	M	(0.9 ± 0.7) × (age) + (12.7 ± 49.1)		5
	H	(1.2 ± 0.2) × (age) + (17.1 ± 14.6)		63
Temperate Conifer	L	(-58.5 ± 22.8) × ln(age) + (206.9 ± 63.9)	$F_{1,3.3} = 15.0$, $p = 0.024$	3
	H	(29.9 ± 5.5) × ln(age) + (-36.8 ± 20.8)		6
(Sub)-tropical Dry	L	(28.1 ± 4.3) × ln(age) + (-42.6 ± 19.3)	$F_{2,71.1} = 37.7$, $p < 0.0001$	292
	M	(17.0 ± 7.0) × ln(age) + (-18.3 ± 24.8)		22
	H	(62.8 ± 3.6) × ln(age) + (-124.2 ± 12.4)		126
(Sub)-tropical Moist	L	(2.5 ± 0.2) × (age) + (35.8 ± 6.1)	$F_{2,746.7} = 10.3$, $p < 0.0001$	282
	M	(2.6 ± 0.2) × (age) + (19.3 ± 1.9)		443
	H	(1.9 ± 0.1) × (age) + (23.3 ± 3.6)		255
(Sub)-tropical Savanna	L	(1.4 ± 0.3) × (age) + (-0.1 ± 9.9)	$F_{1,39.2} = 7.1$, $p = 0.010$	36
	H	(0.4 ± 0.3) × (age) + (3.0 ± 9.2)		12

Table S5: Environmental covariates used in the machine-learning model. Additional metadata including the date of the data, original resolution, transformations, and links to data sources are available in the supplementary data section.

Covariate	**Source**
Aridity Index	[82]
Probability of occurrence of R horizon	[68]
Absolute depth to bedrock (in cm)	[68]
Biome	[60]
Bulk density (fine earth) (kg/cubic-meter)	[68]
Cation Exchange Capacity of the soil (mmol(c)/kg)	[68]
Clay content (mass fraction)	[68]
Annual mean radiation (W/square-meter)	[83]
Highest weekly radiation (W/square-meter)	[83]
Lowest weekly radiation (W/square-meter)	[83]
Radiation seasonality (C of V)	[83]
Radiation of wettest quarter (W/square-meter)	[83]
Radiation of driest quarter (W/square-meter)	[83]
Radiation of warmest quarter (W/square-meter)	[83]
Radiation of coldest quarter (W/square-meter)	[83]
Annual mean moisture index	[83]
Highest weekly moisture index	[83]
Lowest weekly moisture index	[83]
Moisture index seasonality (C of V)	[83]
Mean moisture index of wettest quarter	[83]
Mean moisture index of driest quarter	[83]
Mean moisture index of warmest quarter	[83]
Mean moisture index of coldest quarter	[83]
Coarse fragments volumetric (%)	[68]
Annual Evapotranspiration	[82]
Aspect	[84]
Elevation	[84]
Hillshade	[84]
Slope (m)	[84]
NHx Deposition	[85]
NOy Deposition	[85]
Soil organic carbon density (kg/cubic-meter)	[68]
Soil organic carbon stock in (tons/ha)	[68]
Soil organic carbon content (g/kg)	[68]
Soil pH x 10 in H2O	[68]
Soil pH x 10 in KCl	[68]
Average Monthly Shortwave Radiation 1982 - 2015	[86]
Silt content (mass fraction)	[68]
Sand content (mass fraction)	[68]
Monthly Average Climate water deficit (mm)	[87]

Covariate	**Source**
Monthly Average Palmer Drought Severity Index	[87]
Monthly Average Runoff (mm)	[87]
Monthly Average Soil moisture (mm)	[87]
Monthly Average Vapor pressure (kPa)	[87]
Monthly Average Vapor pressure deficit (kPa)	[87]
Monthly Average Wind-speed at 10m (m/s)	[87]
Annual mean temperature (°C)	[88]
Mean diurnal temperature range (mean(period max-min)) (°C)	[88]
Isothermality	[88]
Temperature seasonality (C of V)	[88]
Max temperature of warmest week (°C)	[88]
Min temperature of coldest week (°C)	[88]
Temperature annual range (°C)	[88]
Mean temperature of wettest quarter (°C)	[88]
Mean temperature of driest quarter (°C)	[88]
Mean temperature of warmest quarter (°C)	[88]
Mean temperature of coldest quarter (°C)	[88]
Annual precipitation (mm)	[88]
Precipitation of wettest week (mm)	[88]
Precipitation of driest week (mm)	[88]
Precipitation seasonality (C of V)	[88]
Precipitation of wettest quarter (mm)	[88]
Precipitation of driest quarter (mm)	[88]
Precipitation of warmest quarter (mm)	[88]
Precipitation of coldest quarter (mm)	[88]
Available soil water capacity until wilting point (volumetric fraction)	[68]

Table S6. 2019 IPCC default rates (MgC ha^{-1} yr^{-1}) for aboveground biomass accumulation in young forests[12], converted to carbon using 0.47[64]. We also include predicted average, minimum, and maximum rates (MgC ha^{-1} yr^{-1}) from our map across the same area. The final column indicates the percent difference of the average predicted rate relative to the IPCC rate in each forest ecozone, where a positive value indicates that the predicted rate is higher than the IPCC rate.

Ecozone	Continent	IPCC	Predicted rate Average (Min - Max)	% Diff
Boreal coniferous forest	Asia	0 - 1	1.08 (0.71 - 1.43)	110
Boreal coniferous forest	Europe	0 - 1	0.94 (0.29 - 2.72)	81
Boreal coniferous forest	North America	0 - 1	0.89 (0.48 - 2.26)	72
Boreal mountain system	Asia	0.5 - 0.5	1.01 (0.52 - 2.16)	104
Boreal mountain system	Europe	0.5 - 0.5	1.03 (0.3 - 2.72)	108
Boreal mountain system	North America	0.5 - 0.5	0.87 (0.55 - 2.09)	76
Subtropical dry forest	Africa	1.1 - 1.2	0.7 (0.22 - 2.49)	-38
Subtropical dry forest	North America	1.9	0.6 (0.28 - 1.11)	-68
Subtropical dry forest	South America	1.9	1.54 (0.67 - 2.81)	-18
Subtropical dry forest	Asia	2.8	0.94 (0.25 - 1.37)	-67
Subtropical humid forest	Africa	1.2	1.78 (0.25 - 3.87)	52
Subtropical humid forest	Asia	1.2	2.08 (0.43 - 4.07)	77
Subtropical humid forest	North America	1.2	1.62 (0.55 - 2.74)	38
Subtropical humid forest	South America	1.2	1.56 (0.22 - 4.09)	33
Subtropical mountain system	Africa	1.2	0.91 (0.21 - 2.49)	-23
Subtropical mountain system	Asia	1.2	1.17 (0.23 - 3.58)	0
Subtropical mountain system	North America	1.2	1.21 (0.09 - 4.49)	3
Subtropical mountain system	South America	1.2	1.01 (0.22 - 1.82)	-14
Temperate continental forest	North America	1.6	0.96 (0.61 - 1.92)	-38
Temperate mountain system	North America	1.5	0.95 (0.15 - 2.97)	-35
Temperate mountain system	South America	1.5	1.53 (0.68 - 2.6)	5
Temperate oceanic forest	Europe	1.1	1.62 (0.84 - 2.95)	50
Temperate oceanic forest	New Zealand	1.5	1.84 (0.8 - 3.14)	26
Temperate oceanic forest	North America	3	1.57 (1.15 - 2.44)	-47
Temperate oceanic forest	South America	3	2.15 (0.76 - 2.82)	-27
Tropical dry forest	Africa	1.8	1.71 (0.33 - 5.36)	-6
Tropical dry forest	Asia	1.8	2.4 (0.77 - 5.01)	31
Tropical dry forest	North America	1.8	2 (0.3 - 5.26)	9
Tropical dry forest	South America	1.8	1.88 (0.17 - 4.99)	3
Tropical moist forest	Asia	1.1	2.93 (0.95 - 5.13)	159
Tropical moist forest	Africa	1.4	2.67 (1.08 - 5.34)	96
Tropical moist forest	North America	2.4	3.4 (0.99 - 5.11)	39
Tropical moist forest	South America	2.4	3.37 (0.59 - 5.61)	38
Tropical mountain system	Asia	1.4	2.63 (0.29 - 4.76)	93
Tropical mountain system	North America	2.1	3.08 (1.27 - 5.25)	49
Tropical mountain system	South America	2.1	3.4 (0.63 - 5.36)	65
Tropical mountain system	Africa	2.6	2.95 (0.4 - 5.51)	14

Ecozone	**Continent**	**IPCC**	**Predicted rate Average (Min - Max)**	**% Diff**
Tropical rainforest	Asia	1.6	3.64 (1.6 - 5.57)	128
Tropical rainforest	North America	2.8	3.8 (1.43 - 5.45)	37
Tropical rainforest	South America	2.8	4.64 (1.55 - 5.89)	67
Tropical rainforest	Africa	3.6	4.55 (2.28 - 6.16)	27

Table S7: Country-level summaries of carbon accumulation rates (MgC ha^{-1} yr^{-1}) and mitigation potential from natural forest regrowth (TgCO$_2$ yr^{-1}) under two scenarios for natural forest regrowth. The first scenario represents a biophysical maximum[3] and another based on national commitments[11]. The rate column includes rates from pixels that overlap with area of opportunity pixels in Griscom et al[3]. We only list countries that are a million hectares or larger.

Geography	**Mean (min-max) aboveground rate,** MgC ha^{-1} yr^{-1}	**Mean belowground rate,** MgC ha^{-1} yr^{-1}	**Mitigation, maximum scenario,** TgCO$_2$ yr^{-1}	**Mitigation, commitment scenario,** TgCO$_2$ yr^{-1}
Afghanistan	0.99 (0.85 - 1.09)	0.33	0.1	-
Albania	1.26 (0.95 - 1.61)	0.67	9.83	-
Algeria	0.96 (0.36 - 1.52)	0.53	7.78	-
Angola	2.89 (2.38 - 4.58)	1.34	4.9	-
Argentina	0.93 (0.2 - 2.94)	0.36	79.65	6.27
Armenia	0.85 (0.61 - 1.04)	0.39	1.62	-
Australia	1.03 (0.22 - 3.61)	0.39	149.84	-
Austria	1.2 (0.85 - 1.49)	0.55	7.58	-
Azerbaijan	0.85 (0.59 - 1.33)	0.36	4.42	7.28
Bangladesh	3.34 (2.55 - 3.83)	0.92	0.1	12.87
Belarus	1.03 (0.81 - 1.24)	0.47	30.37	-
Belgium	1.65 (1.29 - 2.13)	0.76	3.47	-
Belize	4.38 (3.18 - 5.03)	1.04	5.64	-
Benin	4.94 (3.96 - 5.3)	1.83	0.67	13.17
Bhutan	2.22 (1.46 - 3.81)	0.68	2.32	-
Bolivia	2.83 (0.8 - 5.55)	0.98	61.46	93.08
Bosnia and Herzegovina	1.22 (1.06 - 1.49)	0.59	11.51	-
Brazil	3.95 (1.33 - 5.84)	1.2	1830.52	471.77
Bulgaria	0.93 (0.7 - 1.24)	0.43	18.02	-
Burundi	4.06 (3.32 - 4.58)	1.08	0.61	40.76
Cabo Verde	1.32 (1.1 - 1.63)	0.85	1.59	-
Cambodia	3.69 (2.54 - 4.98)	1.58	51.94	-
Cameroon	5.01 (3.52 - 6.13)	1.79	47.11	319.26
Canada	0.96 (0.48 - 2.26)	0.44	38.8	-
Central African Republic	4.77 (3.63 - 5.67)	1.68	10.36	88.23
Chad	1.36 (1 - 1.52)	0.76	0.32	46.59
Chile	1.73 (0.68 - 2.81)	0.9	25.89	6.7
China	1.9 (0.57 - 4.93)	0.48	1062.15	409.73
Colombia	4.27 (2.24 - 5.52)	1.29	394.38	44.24
Congo, Rep.	4.9 (3.26 - 5.78)	1.82	74	52.32
Congo, Dem. Rep.	4.43 (2.03 - 5.78)	1.63	221	403.55
Costa Rica	3.51 (2.05 - 4.37)	1.07	28.81	22.62

Geography	**Mean (min-max) aboveground rate,** MgC ha^{-1} yr^{-1}	**Mean belowground rate,** MgC ha^{-1} yr^{-1}	**Mitigation, maximum scenario,** TgCO$_2$ yr^{-1}	**Mitigation, commitment scenario,** TgCO$_2$ yr^{-1}
Croatia	1.19 (0.89 - 1.58)	0.6	11.67	-
Cuba	3.02 (2.19 - 4.48)	0.71	72.96	-
Czech Republic	1.11 (0.88 - 1.39)	0.51	7.09	-
Cote d'Ivoire	4.86 (3.22 - 5.75)	1.8	155.2	129.74
Denmark	1.74 (1.36 - 2.24)	0.8	2.4	-
Dominican Republic	3.2 (1.83 - 4.11)	1.05	36.08	-
Ecuador	3.53 (2.15 - 4.87)	1.16	85.05	9.38
El Salvador	2.66 (2.19 - 3.19)	0.93	10.52	14.71
Equatorial Guinea	4.77 (4.16 - 5.38)	1.77	0.22	-
Eritrea	1.14 (1.03 - 1.24)	0.31	0	-
Estonia	1.41 (1.2 - 1.65)	0.65	7.16	-
Ethiopia	2.62 (0.97 - 4.34)	0.79	73.4	210.65
Finland	1.31 (0.7 - 1.59)	0.6	0.81	-
France	1.49 (0.74 - 4.9)	0.68	120.69	98.46
Gabon	4.72 (3.72 - 5.68)	1.75	12.61	-
Georgia	1.21 (0.67 - 1.63)	0.4	8.25	0.39
Germany	1.41 (1.02 - 2.21)	0.65	27.71	-
Ghana	4.87 (3.34 - 5.78)	1.85	72.74	52.37
Greece	1.02 (0.58 - 1.44)	0.57	41.86	-
Guatemala	3.58 (2.03 - 5.05)	1.13	55.35	-
Guinea	4.6 (2.71 - 5.43)	1.69	12.8	49.18
Guinea-Bissau	2.8 (2.55 - 3.03)	0.96	1.1	-
Guyana	4.24 (3.42 - 5.18)	0.91	4.01	-
Haiti	3.34 (1.93 - 4.37)	1.09	21.49	-
Honduras	3.02 (1.97 - 4.4)	1.06	57.43	16.49
Hungary	0.94 (0.83 - 1.18)	0.43	7.52	-
India	2.12 (0.51 - 4.35)	0.93	392.2	267.19
Indonesia	4.38 (1.92 - 5.17)	1.59	130.99	686.45
Iran	0.94 (0.5 - 1.42)	0.2	6.78	-
Ireland	2.33 (1.77 - 2.89)	1.07	66.11	-
Israel	0.95 (0.44 - 1.07)	0.39	0.16	-
Italy	1.13 (0.63 - 1.66)	0.6	53.24	-
Jamaica	3.47 (2.42 - 4.16)	1.17	5.27	-
Japan	1.5 (1.16 - 3.18)	0.5	30.89	-
Jordan	0.54 (0.46 - 0.62)	0.17	0	-
Kazakhstan	0.8 (0.53 - 0.92)	0.36	5.04	-
Kenya	2.7 (1.42 - 4.28)	0.74	10.38	72.23
Korea, Dem. Rep.	1.36 (1.12 - 1.58)	0.62	14.75	-
Korea, Rep.	1.55 (1.37 - 1.76)	0.39	2.77	54.1

Geography	**Mean (min-max) aboveground rate,** MgC ha^{-1} yr^{-1}	**Mean belowground rate,** MgC ha^{-1} yr^{-1}	**Mitigation, maximum scenario,** TgCO$_2$ yr^{-1}	**Mitigation, commitment scenario,** TgCO$_2$ yr^{-1}
Kyrgyzstan	0.71 (0.55 - 0.89)	0.33	0.33	-
Laos	3.63 (2.72 - 4.34)	1.14	45.35	144.44
Latvia	1.31 (1.03 - 1.6)	0.6	9.2	-
Lebanon	1.04 (0.8 - 1.31)	0.56	0.8	0.59
Liberia	5.1 (4.29 - 5.66)	1.89	5.36	27.14
Libya	0.79 (0.37 - 1.23)	0.36	0.16	-
Lithuania	1.2 (0.94 - 1.53)	0.55	8.45	-
Madagascar	3.03 (1.65 - 4.09)	0.81	17.45	62.48
Malawi	2.7 (2.31 - 3.55)	0.55	0.6	60.57
Malaysia	4.59 (3.68 - 5.57)	1.7	1.85	-
Mexico	2.69 (0.28 - 5.23)	0.84	450.82	151.92
Moldova	0.85 (0.71 - 0.98)	0.39	2.32	0.98
Mongolia	0.89 (0.77 - 1.05)	0.41	6.67	3.78
Montenegro	1.28 (1.05 - 1.66)	0.64	4.63	-
Morocco	0.95 (0.29 - 1.67)	0.53	4.71	-
Mozambique	2.97 (1.92 - 4.27)	1.12	0.45	16.53
Myanmar	3.13 (1.41 - 4.9)	0.92	226	-
Nepal	2.02 (1.28 - 3.18)	0.61	18.2	7.88
Netherlands	1.69 (1.53 - 1.89)	0.78	6.63	0.85
New Zealand	2.48 (1.01 - 3.08)	0.69	26.58	6.93
Nicaragua	3.07 (2.1 - 4.21)	0.95	76.98	43.99
Nigeria	5.28 (4.02 - 5.9)	1.95	112.63	842.32
Norway	1.19 (0.93 - 1.63)	0.54	0.03	7.88
Pakistan	1.04 (0.58 - 1.38)	0.34	2.39	11.63
Panama	4.03 (3.05 - 5)	1.16	48.53	20.58
Papua New Guinea	3.94 (2.54 - 4.88)	1.42	8.53	-
Paraguay	2.14 (0.56 - 4)	0.67	111.09	-
Peru	3.97 (1.93 - 5.36)	1.26	37.89	66.35
Philippines	4.29 (2.87 - 5.19)	1.43	153.44	-
Poland	1.14 (0.86 - 1.87)	0.53	26.12	-
Portugal	1.33 (0.77 - 2.84)	0.72	31.06	-
Romania	0.95 (0.71 - 1.37)	0.44	24.99	-
Russian Federation	1.01 (0.59 - 1.56)	0.47	298.94	-
Rwanda	4.38 (4.16 - 4.55)	1.18	0	43.91
Senegal	2.65 (1.96 - 2.9)	0.53	0.02	-
Serbia	1.02 (0.82 - 1.32)	0.47	15.17	-
Sierra Leone	4.52 (3.47 - 5.1)	1.61	1.72	-
Slovakia	0.99 (0.86 - 1.39)	0.46	3.98	-
Slovenia	1.34 (1.03 - 1.6)	0.62	2.9	-
Solomon Islands	3.66 (2.89 - 4.21)	1.35	0.03	-

Geography	**Mean (min-max) aboveground rate,** MgC ha^{-1} yr^{-1}	**Mean belowground rate,** MgC ha^{-1} yr^{-1}	**Mitigation, maximum scenario,** TgCO$_2$ yr^{-1}	**Mitigation, commitment scenario,** TgCO$_2$ yr^{-1}
Somalia	1.81 (1.21 - 2.49)	0.59	4.5	-
South Africa	1.63 (0.46 - 3.81)	0.56	6.97	-
South Sudan	2.07 (1.49 - 2.32)	1.1	0.08	-
Spain	1.04 (0.4 - 2.94)	0.55	79.16	-
Sri Lanka	3.86 (2.44 - 4.44)	1.34	3.17	3.24
Suriname	4.22 (3.64 - 4.91)	0.85	1.29	-
Sweden	1.22 (0.67 - 2.3)	0.56	0.37	-
Switzerland	1.31 (0.78 - 1.57)	0.6	3.2	-
Syria	0.98 (0.32 - 1.34)	0.49	0.88	-
Tajikistan	0.89 (0.72 - 1)	0.41	0.1	-
Tanzania	2.11 (1.32 - 4.39)	0.82	48.73	-
Thailand	3.81 (2.45 - 5.53)	1.52	213.82	-
The Former Yugoslav Republic of Macedonia	0.97 (0.65 - 1.26)	0.49	6.1	-
Timor-Leste	3.32 (2.24 - 3.82)	1.19	6.54	-
Togo	4.59 (3.71 - 5.53)	1.6	10.55	-
Tunisia	0.91 (0.34 - 1.27)	0.5	1.06	-
Turkey	0.9 (0.42 - 1.62)	0.51	119.38	-
Uganda	3.5 (1.48 - 4.74)	1.19	4.33	53.97
Ukraine	0.96 (0.78 - 1.52)	0.44	51.16	56.76
United Kingdom	1.93 (1.34 - 2.78)	0.89	100.08	18.95
United States	1.15 (0.16 - 4.32)	0.43	321.16	109.86
Uruguay	1.55 (0.82 - 2.42)	0.3	0	-
Uzbekistan	0.83 (0.65 - 0.93)	0.38	0.02	-
Vanuatu	3.53 (2.71 - 4.04)	1.3	2.1	-
Venezuela	3.6 (1.63 - 5.14)	1.08	186.46	-
Vietnam	3.32 (2.39 - 4.71)	0.9	110.73	292.96
Zambia	2.42 (1.24 - 2.83)	0.5	2.59	1.43
Zimbabwe	1.4 (1.27 - 1.52)	0.79	0.06	-

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Metadata

Database structure

The dataset includes three levels: full citation information (Table M1), variables specific to sites (Table M2), and stand ("plot")-level carbon and biomass data with associated covariates (Table M3). Individual measurements are nested within plots, where plots are defined as stands with unique qualities (e.g., a single age, land use or combination) Plots are nested within sites. Sites are defined by having a unique latitude and longitude, though the specificity of geolocation varied across studies with some reporting highly precise locations for each stand and others giving a single geolocation for a larger region.

We followed a few general rules for data extraction. If multiple publications described the same geolocation, we coded all data with a single site to avoid pseudoreplication. If a range was given for a variable, we calculated the average, but excluded data with large ranges, such as a forest age that spanned more than 10 years or a geolocation that spanned more than a degree latitude or longitude. Finally, for graphical data we used WebPlotDigitizer[89] to extract the variables.

Note that we make available our full dataset, which includes some variables that we did not include in our final analysis but may be useful for future work. For some fields, data are missing, because studies did not provide all details (e.g., type of prior disturbance).

Table M1: Explanation of variables in literature dataset.

Column name	Description
study.id	unique numeric identifier for each publication
citations.author	last name of first author
citations.year	year of publication
citations.journal	citation information including journal, volume and page number
citations.title	full title from publication

Table M2: Explanation of variables in site datasheet.

Column name	Description
site.id	unique numeric identifier for each geolocation
study.id	unique numeric identifier for each publication
site.sitename	text description of site name
site.state	sub-national jurisdiction such as state, province etc., if given
site.country	country name
lat_dec	latitude in decimal degrees
long_dec	longitude in decimal degrees
other reference	other publications or resources used to fill out site information
elevation	height above sea level in meters, if given
AMT	annual mean temperature in degrees Celsius, if given
AMP	annual mean precipitation in millimeters, if given
soil.classification	soil order converted to US system of nomenclature, if given

Table M3: Explanation of variables in measurement datasheet.

Column name	**Description**
measurement.id	unique identifier for each carbon/biomass measurement
plot.id	unique identifier for distinct spatial unit(s) within a site, e.g., if a study reported a single mean aboveground biomass measure for 12 year old stands, this would receive a single plot.id whereas if separate measures are given for a 12 year old stand that was previously pasture versus a 12 year old stand that was previously cropped then each of those would a distinct plot.id.
site.id	unique numeric identifier for each geolocation
study.id	unique numeric identifier for each publication
refor.type	reforestation type or reference condition; SNR = spontaneous natural regeneration (or “natural forest regrowth”), TMC = intensive tree monocrop (reference), C = cropland (reference), PA = pasture (reference)
species	name of dominant species, if given
prior	type of most recent disturbance, if given; C = crop; SC = shifting cultivation/fallow; H = clearcut harvest of land in forest use; F = fire; D = non-fire disturbance such as landslide or hurricane; PA = pasture; M = mining; TMC = tree monocrop (e.g., banana or rubber plantation)
stand.age	age of forest stand; crop and pasture = 0, otherwise age is as given in study; age range is between 0 and 100 years
date	year data were collected, if given
n	number of plots (e.g. distinct spatial units) per measurement
sub_n	number of subplots per plot, e.g., soil samples pooled for a single measure
plot.size	largest plot dimension in m^2 (e.g., plot size used to measure largest diameter trees)
variables.name	name of carbon pool; variables include aboveground_biomass/carbon; understory_biomass/carbon; litter_biomass/carbon; deadwood_biomass/carbon; belowground_biomass/carbon; soil organic carbon (SOC)/percent soil organic matter (SOM_per)/percent soil organic carbon (soil_perC); or combinations of above if study did not parse data by pool, see “Definitions of Pools”
mean_ha	value of biomass or carbon estimate per hectare in Mg/ha
covar_1	type of covariate (see “Definitions of Pools”)
coV1_value	value of covariate 1
covar_2	type of covariate (see “Definitions of Pools”)
coV2_value	value of covariate 2
covar_3	type of covariate (see “Definitions of Pools”)
coV3_value	value of covariate 3
density	number of individual trees per hectare, if given

Column name	Description
sand.silt.clay	soil texture, if given; sand%:silt%:clay% or text description (e.g., clay, sandy clay, sandy clay loam, loamy sand, silty clay, silt loam)
pH	pH, if given
allometry	direct harvest = direct harvest of all biomass at a site; site-specific harvest = based on trees harvested at the site; species-specific = based on species; forest-type-specific = based on similar forest in the region; biome-specific = based on general equations for a biome (e.g., [90])

Definitions of Pools

1. Aboveground_biomass/carbon refers to aboveground tree biomass excluding understory biomass/carbon. If the two pools are combined, we note the presence of the latter by adding "+ understory_biomass/carbon" to the variables.name column. A minimum diameter at breast height (min_dbh, covariate 1) is typically listed with this measurement with a "0" indicating all trees were sampled. Alternatively, studies sometimes measured only trees above a certain height, in which case we note minimum height (min_height, covariate 1). Note that aboveground_biomass_woody indicates only stem and branch biomass, not foliage.

2. Understory_biomass/carbon typically refers to herbaceous biomass, shrubs, lianas, and/ trees saplings shorter than breast height. Possible covariates (covariate 1) include maximum height (max_height) or maximum dbh (max_dbh) measured.

3. Belowground_biomass/carbon refers to root biomass. We did not include studies that only quantified fine root biomass. Possible covariates (covariate 1) include minimum root diameter measured (root_diameter_min) or maximum depth of sampling (max_depth). If a study only quantified roots up to a specific size, we noted this in root_diameter_max

(covariate 2). We extracted but did not include in our analyses, data quantifying root biomass where there was no estimate of aboveground biomass.

4. Soil biomass/carbon was reported as soil organic carbon density (SOC), percent soil organic matter (SOM_per), or soil organic carbon concentration (soil_perC), depending on the study. If a study reported soil organic carbon concentration, we also included bulk_density (covariate 3) where it was given. For all soil measures, we noted the maximum depth (max_depth, covariate 1) and minimum depth (min_depth, covariate 2) of measurement and analyzed data as the sum of all shallower soil profiles.

5. Litter_biomass/carbon refers to litter and CWD_biomass/carbon refers to coarse woody debris. We parsed data where possible according to IPCC guidelines[91], where coarse woody debris includes wood lying on the surface, dead roots and stumps larger than or equal to 10cm. Litter includes all non-living biomass that is distinguishable from mineral soil, typically 2mm or greater and less than 10cm.

Studies included in database

The references list first author, year, title and citation information for all studies (N = 257) in the larger database (N = 13033 measurements). We included data from peer-reviewed publications or datasets from respected institutions with asterisks denoting the latter.

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