

¹ **Title:** Carbon cycling in mature and regrowth forests globally: a macroecological synthesis based on the
² global Forest Carbon (ForC) database

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²⁵ ## [1] 0

²⁶ *NOTES TO COAUTHORS:*

- ²⁷ • “???” indicates a reference that we have entered in the .Rmd file, but not yet in the bibliography file.
²⁸ Don’t worry about those. (However, places with “REF” need references)
- ²⁹ • bold/ italic text indicates places where I know we need to go back and revisit/ fill in info

30 Summary

31 *Background.* Earth's climate is closely linked to forests, which strongly influence atmospheric carbon dioxide
32 (CO_2) and climate by their impact on the global carbon (C) cycle. However, efforts to incorporate forests
33 into climate models and CO_2 accounting frameworks have been constrained by a lack of accessible,
34 global-scale data on how C cycling varies across forest types and stand ages.

35 *Methods/Design.* Here, we draw from the Global Forest Carbon Database, ForC, to provide a macroscopic
36 overview of C cycling in the world's forests, giving special attention to stand age-related variation.

37 Specifically, we use 11923 *ForC* records from 865 geographic locations representing 34 C cycle variables to
38 characterize ensemble C budgets for four broad forest types (tropical broadleaf evergreen, temperate
39 broadleaf, temperate conifer, and taiga), including estimates for both mature and regrowth (age <100 years)
40 forests. For regrowth forests, we quantify age trends for all variables.

41 *Review Results/ Synthesis.* *ForC v3.0* yielded a fairly comprehensive picture of C cycling in the world's
42 major forest biomes, with broad closure of C budgets. The rate of C cycling generally increased from boreal
43 to tropical regions in both mature and regrowth forests, whereas C stocks showed less directional variation.
44 The majority of flux variables, together with most live biomass pools, increased significantly with stand age,
45 and the rate of increase again tended to increase from boreal to tropical regions.

46 *Discussion.* NEED TO WRITE THIS!!!

47 *Key words:* forest ecosystems; carbon cycle; stand age; productivity; respiration; biomass; global

48 **Background**

49 Forest ecosystems are shaping the course of climate change (IPCC1.5) through their influence on atmospheric
50 carbon dioxide (CO₂). Despite the centrality of forest C cycling in regulating atmospheric CO₂, important
51 uncertainties in climate models (???, ???, ???, Krause *et al* 2018) and CO₂ accounting frameworks (Pan *et*
52 *al* 2011) can be traced to lack of accessible, comprehensive data on how C cycling varies across forest types
53 and in relation to stand history. These require large-scale databases with global coverage, which runs
54 contrary to the nature in which forest C stocks and fluxes are measured and published. While remote sensing
55 measurements are increasingly useful for global- or regional-scale estimates of a few critical variables [e.g.,
56 aboveground biomass: (???); **REF**; gross primary productivity, *GPP*: Li and Xiao (2019); **REFS for**
57 **biomass change, net CO2 flux**], measurement of most forest C stocks and fluxes require intensive
58 on-the-ground data collection. Here, we provide a robust and comprehensive analysis of carbon cycling from
59 a stand to global level, and by biome and stand age, using the largest global compilation of forest carbon
60 data, which is available in our open source Global Carbon Forest database (ForC; Fig. 1).

61 A robust understanding of forest impacts on global C cycling is essential. Annual gross CO₂ sequestration in
62 forests (gross primary productivity, *GPP*) is estimated at >69 Gt C yr⁻¹ (???), or >7 times average annual
63 fossil fuel emissions from 2009-2018 (9.5 ± 0.5 Gt C yr⁻¹; ???). Most of this enormous C sequestration is
64 counterbalanced by CO₂ releases to the atmosphere through ecosystem respiration (*R_{eco}*) or fire, with forests
65 globally dominant as sources of both soil respiration (???) and fire emissions (REF). (check if
66 **deforestation statistic below includes natural fire, exclude here if it does.**) In recent years, the
67 remaining CO₂ sink averaged 3.2 ± 0.6 GtC yr⁻¹ from 2009-2018, offsetting 29% of anthropogenic fossil fuel
68 emissions (???). Yet, this sink is reduced by *deforestation/ forest losses to anthropogenic and natural*
69 *disturbances*. Recent net deforestation (*i.e.*, gross deforestation minus regrowth) has been a source of CO₂
70 emissions, estimated at ~1.1 Gt C yr⁻¹ from YEAR-YEAR (Pan *et al* 2011; **UPDATE**), reducing the net
71 forest sink to ~1.1-2.2 Gt C yr⁻¹ across Earth's forests (???).

72 The future of the current forest C sink is dependent both upon forest responses to climate change itself and
73 human land use decisions, which will feedback and strongly influence the course of climate change.
74 Regrowing forests in particular will play an important role (Pugh *et al* 2019), as these represent a large
75 (~#%) and growing proportion of Earth's forests (McDowell *et al* 2020). Understanding, modeling, and
76 managing forest-atmosphere CO₂ exchange is thus central to efforts to mitigate climate change [Grassi *et al*
77 (2017); Griscom *et al* (2017); **Cavaleri et al 2015**].

78 Despite the importance of forests, comprehensive global studies have historically been limited by the scattered
79 and more local nature of research studies. Primary research articles typically cover only a small numbers of
80 sites at a time. The rare exceptions that span regions or continents with rare exceptions spanning regions or
81 continents are typically coordinated through research networks such as ForestGEO (Anderson-Teixeira *et al*
82 2015, e.g., Lutz *et al* 2018) or FLUXNET [Baldocchi *et al* (2001); e.g., **FLUXNET_REF**]. The result of
83 decades of research on forest C cycling is that tens of thousands of records have been distributed across
84 literally thousands of scientific articles –often behind paywalls– along with variation in data formats, units,
85 measurement methods, *etc..* In this format, the data are effectively inaccessible for many global-scale
86 analyses, including those attempting to benchmark model performance with global data (Clark *et al* 2017,
87 Luo *et al* 2012), quantify the the role of forests in the global C cycle (*e.g.*, Pan *et al* 2011), or use
88 book-keeping methods to quantify actual or scenario-based exchanges of CO₂ between forests and the
89 atmosphere [Griscom *et al* (2017); **REFS**]. Scattered data are not conducive for advancing science nor for

making decisions about how to best manage our forests as a tool for constraining the climate crisis.

To address the need for global-scale analyses of forest C cycling, we recently developed *ForC* (Anderson-Teixeira *et al* 2016, pp @anderson-teixeira_forc_2018). *ForC* contains published estimates of forest ecosystem C stocks and annual fluxes (>50 variables), with the different variables capturing the unique ecosystem pools (e.g., woody, foliage, and root biomass; dead wood) and flux types (e.g, gross and net primary productivity; soil, root, and ecosystem respiration). These data are ground-based measurements, and *ForC* contains associated data required for interpretation (e.g., stand history, measurement methods). These data have been amalgamated from original peer-reviewed publications, either directly or via intermediary data compilations. Since its most recent publication (Anderson-Teixeira *et al* 2018), *ForC* has grown to include two additional large databases: the Global Soil Respiration Database (SRDB; Bond-Lamberty and Thomson 2010) and the Global Reforestation Opportunity Assessment database (GROA; Cook-Patton *et al* 2020) that also synthesized published forest C data. Following these additions, *ForC* currently contains 39762 records from 10608 plots and 1532 distinct geographic areas representing all forested biogeographic and climate zones. This represents an 129% increase in records from the prior publication (Anderson-Teixeira *et al* 2018).

Here, we analyze the more extensive *ForC* data (Fig. 1) to provide a robust overview of stand-level carbon cycling of the world's major forest biomes and how it varies with stand age. Our primary goal is to provide a data-driven summary of our current state of knowledge on broad trends in forest C cycling. Specifically, we address three broad questions:

1. How thoroughly can we represent C budgets for each of the world's major forest biomes (*i.e.*, tropical, temperate broadleaf and deciduous, boreal) based on the current *ForC* data?
2. How do C cycling vary across the world's major forest biomes?
3. How does C cycling vary with stand age (in interaction with biome)?

While components of these questions have been previously addressed (Luyssaert *et al* 2007, Anderson-Teixeira *et al* 2016, Cook-Patton *et al* 2020, Banbury Morgan *et al* n.d.), our analysis represents by far the most comprehensive analysis of C cycling in global forests, and will serve as a foundation for improved understanding of global forest C cycling and highlight where key sources of uncertainty still reside.

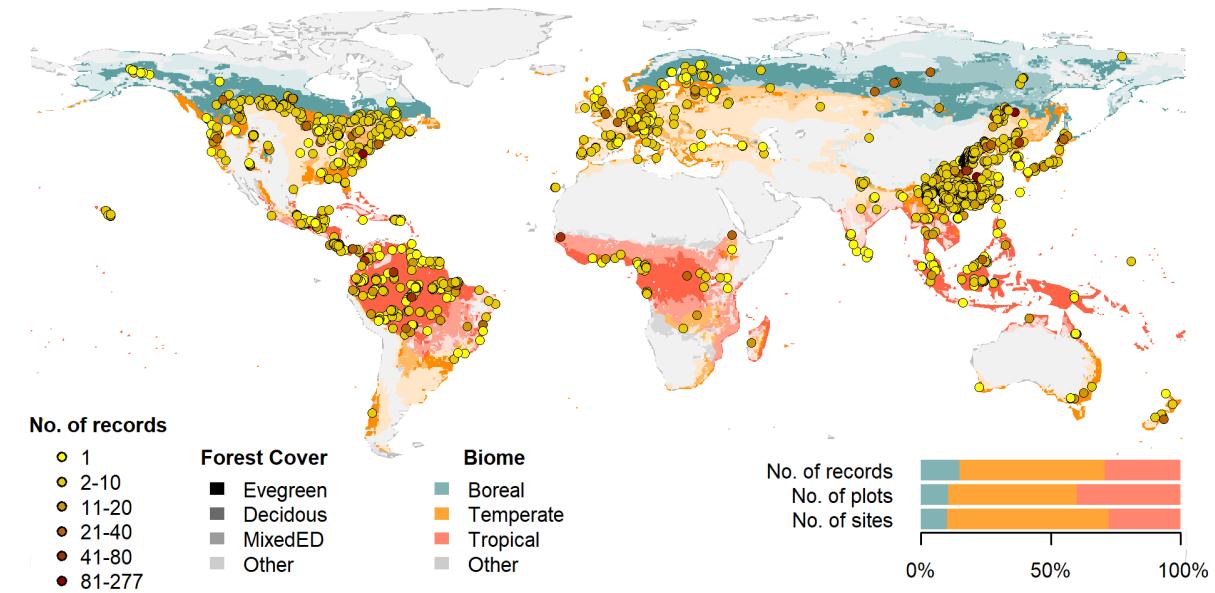


Figure 1 | Map of sites included in this analysis. Symbols are colored according to the number of records at each site. Underlying map shows coverage of evergreen, deciduous, and mixed forests (from SYNMAP; Jung et al. 2006) and biomes. Distribution of sites, plots, and records among biomes is shown in the inset.

117 Methods/ Design

118 This review synthesizes data from the *ForC* database (Fig. 1; <https://github.com/forc-db/ForC>;
 119 Anderson-Teixeira *et al* 2016, pp @anderson-teixeira_forc_2018). *ForC* amalgamates numerous
 120 intermediary data sets (*e.g.*, Luyssaert *et al* 2007, Bond-Lamberty and Thomson 2010, Cook-Patton *et al*
 121 2020) and original studies. Original publications were referenced to check values and obtain information not
 122 contained in intermediary data sets, although this process has not been completed for all records. The
 123 database was developed with goals of understanding how C cycling in forests varies across broad geographic
 124 scales and as a function of stand age. As such, there has been a focus on incorporating data from regrowth
 125 forests (*e.g.*, Anderson *et al* 2006, Martin *et al* 2013, Bonner *et al* 2013) and obtaining stand age data when
 126 possible (83% of records in v.2.0; Anderson-Teixeira *et al* 2018). Particular attention was given to developing
 127 the database for tropical forests (Anderson-Teixeira *et al* 2016), which represented roughly one-third of
 128 records in *ForC* v.2.0* (Anderson-Teixeira *et al* 2018). Since publication of *ForC* v.2.0, we added the
 129 following data to *ForC*: the Global Database of Soil Respiration Database (*SRDB* v.##, 9488 records;
 130 Bond-Lamberty and Thomson 2010), the Global Reforestation Opportunity Assessment database (*GROA*
 131 v1.0, 10116 records; Cook-Patton *et al* 2020, Anderson-Teixeira *et al* 2020). We've also added data from
 132 individual publications (detailed list at [https://github.com/forc-
 133 db/ForC/blob/master/database_management_records/ForC_data_additions_log.csv](https://github.com/forc-db/ForC/blob/master/database_management_records/ForC_data_additions_log.csv)), with a particular
 134 focus on productivity (Banbury Morgan *et al* n.d., *e.g.*, Taylor *et al* 2017), dead wood, and ForestGEO sites
 135 (*e.g.*, Lutz *et al* 2018, p @johnson_climate_2018). We note that there remains a significant amount of
 136 relevant data that is not yet included in *ForC*, particularly biomass data from national forest inventories

137 (e.g.,; **REFS**). The database version used for this analysis has been tagged as a new release on Github (**XX**)
138 and assigned a DOI through Zenodo (DOI: TBD).

139 To facilitate analyses, we created a simplified version of ForC, *ForC-simplified*
140 (https://github.com/forc-db/ForC/blob/master/ForC_simplified), which we analyzed here. In generating
141 *ForC-simplified*, all measurements originally expressed in units of dry organic matter (*OM*) were converted
142 to units of C using the IPCC default of $C = 0.47 * OM$ (IPCC 2006). Duplicate or otherwise conflicting
143 records were reconciled as described in APPENDIX S1, resulting in a total of 32499 records (81.7% size of
144 total database). Records were filtered to remove plots that had undergone significant anthropogenic
145 management or major disturbance since the most recent stand initiation event. Specifically, we removed all
146 plots flagged as managed in ForC-simplified (18.9%). This included plots with any record of managements
147 manipulating CO₂, temperature, hydrology, nutrients, or biota, as well as any plots whose site or plot name
148 contained the terms “plantation”, “planted”, “managed”, “irrigated”, or “fertilized”. Plots flagged as
149 disturbed in ForC-simplified (5.7%) included stands that had undergone any notable anthropogenic thinning
150 or partial harvest. We retained sites that were grazed or had undergone low severity natural disturbances
151 (<10% mortality) including droughts, major storms, fires, and floods. We removed all plots for which no
152 stand history information had been retrieved (7.3%). In total, this resulted in 23199 records (58.3% of the
153 records in the database) being eligible for inclusion in the analysis.

154 We selected 23 annual flux and 11 C stock variables for inclusion in the analysis. These different flux and
155 stock variables (Table 1) represent different pools (e.g., aboveground biomass, dead wood, ecosystem total)
156 and levels of combination (e.g., total aboveground net primary productivity (*ANPP*) versus the ANPP of
157 individual elements such as foliage, roots, and branches. Note that two flux variables, aboveground
158 heterotrophic (R_{het-ag}) and total (R_{het}) respiration, were included for conceptual completeness but had no
159 records in *ForC* (Table 1). Records for these variables represented 67.5% of the total records eligible for
160 inclusion. For this analysis, we combined some of ForC’s specific variables (e.g., multiple variables for net
161 primary productivity, such as measurements including or excluding fruit and flower production and herbivory)
162 into more broadly defined variables. Specifically, net ecosystem exchange (measured by eddy-covariance;
163 **FLUXNET REF**) and biometric estimates of *NEP* were combined into the single variable *NEP* (Table 1).
164 Furthermore, for *NPP*, *ANPP*, and *ANPP_{litterfall}*, *ForC* variables specifying inclusion of different
165 components were combined. Throughout ForC, for all measurements drawing from tree census data (e.g.,
166 biomass, productivity), the minimum diameter breast height (DBH) threshold for tree census was $\leq 10\text{cm}$.
167 All records were measured directly or derived from field measurements (as opposed to modeled).

168 For this analysis, we grouped forests into four broad biome types based on climate zones and dominant
169 vegetation type (tropical broadleaf, temperate broadleaf, temperate needleleaf, and boreal needleleaf) and
170 two age classifications (young and mature). Climate zones (Fig. 1) were defined based on site geographic
171 coordinates according to Köppen-Geiger zones (Rubel and Kottek 2010). We defined the tropical biome as
172 including all equatorial (A) zones, temperate biomes as including all warm temperate (C) zones and warmer
173 snow climates (Dsa, Dsb, Dwa, Dwb, Dfa, and Dfb), and the boreal biome as including the colder snow
174 climates (Dsc, Dsd, Dwc, Dwd, Dfc, and Dfd). Any forests in dry (B) and polar (E) Köppen-Geiger zones
175 were excluded from the analysis. We defined leaf type (broadleaf / needleleaf) was based on descriptions in
176 original publications (prioritized) or values extracted from a global map based on satellite observations
177 (SYNMAP; ???). For young tropical forests imported from *GROA* but not yet classified by leaf type, we
178 assumed that all were broadleaf, consistent with the rarity of naturally regenerating needleleaf forests in the

Table 1. Carbon cycle variables included in this analysis, their sample sizes, and summary of biome differences and age trends.

Variable	Description	N records			biome differences*	age trend†
		records	plots	geographic areas		
Annual fluxes						
<i>NEP</i>	net ecosystem production or net ecosystem exchange (+ indicates C sink)	329	146	88	n.s.	+; xB
<i>GPP</i>	gross primary production ($NPP + R_{auto}$ or $R_{eco} - NEE$)	303	115	84	TrB > TeB \geq TeN \geq BoN	+; xB
<i>NPP</i>	net primary production ($ANPP + BNPP$)	214	112	74	TrB > TeB \geq TeN $>$ BoN	n.s.
<i>ANPP</i>	aboveground <i>NPP</i>	343	236	131	TrB > TeB \geq TeN $>$ BoN	+; xB
<i>ANPP_{woody}</i>	woody production ($ANPP_{stem} + ANPP_{branch}$)	64	53	37	n.s.	+
<i>ANPP_{stem}</i>	woody stem production	217	190	117	TrB > TeN \geq TeB \geq BoN	n.s.
<i>ANPP_{branch}</i>	branch turnover	69	59	42	TrB > TeB \geq TeN	n.s.
<i>ANPP_{foliage}</i>	foliage production, typically estimated as annual leaf litterfall	162	132	88	TrB > TeB \geq TeN $>$ BoN	+
<i>ANPP_{litterfall}</i>	litterfall, including leaves, reproductive structures, twigs, and sometimes branches	82	70	55	n.s.	+
<i>ANPP_{repro}</i>	production of reproductive structures (flowers, fruits, seeds)	51	44	34	n.t.	n.t.
<i>ANPP_{folivory}</i>	foliar biomass consumed by folivores	20	12	11	n.t.	n.t.
<i>M_{woody}</i>	woody mortality—i.e., B_{ag} of trees that die	18	18	18	n.t.	n.t.
<i>BNPP</i>	belowground NPP ($BNPP_{coarse} + BNPP_{fine}$)	148	116	79	TrB > TeN \geq TeB \geq BoN	+
<i>BNPP_{coarse}</i>	coarse root production	77	56	36	TeN \geq TrB	n.s.
<i>BNPP_{fine}</i>	fine root production	123	99	66	n.s.	+
<i>R_{eco}</i>	ecosystem respiration ($R_{auto} + R_{het}$)	213	98	70	TrB > TeB \geq TeN	+
<i>R_{auto}</i>	autotrophic respiration ($(R_{auto-ag} + R_{root})$)	24	23	15	n.t.	n.t.
<i>R_{auto-ag}</i>	aboveground autotrophic respiration (i.e., leaves and stems)	2	2	1	n.t.	n.t.
<i>R_{root}</i>	root respiration	181	139	95	TrB \geq TeB	+
<i>R_{soil}</i>	soil respiration ($(R_{het-soil} + R_{root})$)	627	411	229	TrB > TeB $>$ TeN \geq BoN	n.s.
<i>R_{het-soil}</i>	soil heterotrophic respiration	197	156	100	TrB > TeB \geq TeN	n.s.
<i>R_{het-ag}</i>	aboveground heterotrophic respiration	0	0	0	-	-
<i>R_{het}</i>	heterotrophic respiration ($(R_{het-ag} + R_{het-soil})$)	0	0	0	-	-
Stocks						
<i>B_{tot}</i>	total live biomass ($B_{ag} + B_{root}$)	188	157	87	TrB \geq TeB $>$ BoN	+; xB
<i>B_{ag}</i>	aboveground live biomass ($B_{ag-wood} + B_{foliage}$)	4466	4072	621	TrB \geq TeN \geq TeB $>$ BoN	+; xB
<i>B_{ag-wood}</i>	woody component of aboveground biomass	115	102	64	TeN $>$ TrB \geq BoN	+; xB
<i>B_{foliage}</i>	foliage biomass	134	115	72	TeN $>$ TrB \geq BoN \geq TeB	+; xB
<i>B_{root}</i>	total root biomass ($(B_{root-coarse} + B_{root-fine})$)	2329	2298	360	n.s.	+; xB
<i>B_{root-coarse}</i>	coarse root biomass	134	120	73	TeN $>$ TeB \geq BoN	+; xB
<i>B_{root-fine}</i>	fine root biomass	226	180	109	n.s.	+; xB
<i>DW_{tot}</i>	deadwood ($DW_{standing} + DW_{down}$)	79	73	42	n.t.	+; xB
<i>DW_{standing}</i>	standing dead wood	36	35	22	n.t.	n.t.
<i>DW_{down}</i>	fallen dead wood, including coarse and sometimes fine woody debris	278	265	37	n.t.	+; xB
<i>OL</i>	organic layer / litter/ forest floor	474	413	115	n.s.	+; xB

* Tr: Tropical, TeB: Temperate Broadleaf, TeN: Temperate Needleleaf, B: Boreal, n.s.: no significant differences, n.t.: not tested

† + or -: significant positive or negative trend, xB: significant age x biome interaction, n.s.: no significant age trend, n.t.: not tested

tropics (REF). We also classified forests as “young” (< 100 years) or “mature” (≥ 100 years or classified as “mature”, “old growth”, “intact”, or “undisturbed” in original publication). Assigning stands to these

181 groupings required the exclusion of records for which *ForC* lacked geographic coordinates (0.4% of sites in
182 full database) or records of stand age (5.7% of records in full database). We also excluded records of stand
183 age = 0 year (0.8% of records in full database). In total, our analysis retained 76.1 of the focal variable
184 records for forests of known age. Numbers of records by biome and age class are given in Table S1.

185 Data were summarized to produce schematics of C cycling across the eight biome by age group combinations
186 identified above. To obtain the values reported in the C cycle schematics, we first averaged any repeated
187 measurements within a plot. Values were then averaged across geographically distinct areas, defined as plots
188 clustered within 25 km of one another (*sensu* Anderson-Teixeira *et al* 2018), weighting by area sampled if
189 available for all records. This step was taken to avoid pseudo-replication and to combine any records from
190 sites with more than one name in ForC.

191 We tested whether the C budgets described above “closed”—*i.e.*, whether they were internally consistent.
192 Specifically, we first defined relationships among variables: for example, $NEP = GPP - R_{eco}$,
193 $BNPP = BNPP_{coarse} + BNPP_{fine}$, $DW_{tot} = DW_{standing} + DW_{down}$). **(issue #44-but just delete
194 this chunk if not resolved before submission)** Henceforth, we refer to the variables on the left side of
195 the equation as “aggregate” fluxes or stocks, and those that are summed as “component” fluxes or stocks,
196 noting that the same variable can take both aggregate and component positions in different relationships.
197 We considered the C budget for a given relationship “closed” when component variables summed to within
198 one standard deviation of the aggregate variable.

199 To test for differences across mature forest biomes, we also examined how stand age impacted fluxes and
200 stocks, employing a mixed effects model [‘lmer’ function in ‘lme4’ R package version **x.xx; REF**] with biome
201 as fixed effect and plot nested within geographic.area as random effects on the intercept. When Biome had a
202 significant effect, we looked at a Tukey’s pairwise comparison to see which biomes were significantly different
203 from one another. This analysis was run for variables with records for at least seven distinct geographic areas
204 in more than one biome, excluding any biomes that failed this criteria (Table 1).

205 To test for age trends in young (<100yrs) forests, we employed a mixed effects model with biome and
206 $\log_{10}[\text{stand.age}]$ as fixed effects and plot nested within geographic.area as a random effect on the intercept.
207 This analysis was run for variables with records for at least three distinct geographic areas in more than one
208 biome, excluding any biomes that failed this criteria (Table 1). When the effect of stand age was significant
209 at $p \leq 0.05$ and when each biome had records for stands of at least 10 different ages, a biome \times stand.age
210 interaction was included in the model.

211 To facilitate the accessibility of our results and data, and to allow for rapid updates as additional data
212 become available, we have automated all database manipulation, analyses, and figure production in R
213 (**version, citation**).

214 **Review Results/ Synthesis**

215 **Data Coverage**

216 Of the 39762 records in *ForC* v3.0, 11923 met our strict criteria for inclusion in this study (Fig. 1). These
217 records were distributed across 5062 plots in 865 distinct geographic areas. Of the 23 flux and 11 stock
218 variables mapped in these diagrams, *ForC* contained sufficient mature forest data for inclusion in our
219 statistical analyses (*i.e.*, records from ≥ 7 distinct geographic areas) for 20 fluxes and 9 stocks in tropical

220 broadleaf forests, 15 fluxes and 8 stocks in temperate broadleaf forests, 14 fluxes and 7 stocks in temperate
221 conifer forests, and 8 fluxes and 7 stocks in boreal forests. For regrowth forests (<100 yrs), *ForC* contained
222 sufficient data for inclusion in our statistical analyses (*i.e.*, records from ≥ 3 distinct geographic areas) for 11
223 fluxes and 10 stocks in tropical broadleaf forests, 16 fluxes and 10 stocks in temperate broadleaf forests, 16
224 fluxes and 10 stocks in temperate conifer forests, and 14 fluxes and 9 stocks in boreal forests.

225 **C cycling in mature forests**

226 Average C cycles for mature tropical broadleaf, temperate broadleaf, temperate conifer, and boreal forests \geq
227 100 years old and with no known major natural or anthropogenic disturbance are presented in Figures 2-5
228 (and available in tabular format in the *ForC* release accompanying this publication:

229 [`ForC/numbers_and_facts/ForC_variable_averages_per_Biome.csv`](#).

230 For variables with records from ≥ 7 distinct geographic areas, these ensemble C budgets were generally
231 consistent. That is, component variables summed to within one standard deviation of their respective
232 aggregate variables in all but one instance. In the temperate conifer biome, the average composite measure of
233 root biomass (B_{root}) was less than the combined average value of coarse and fine root biomass ($B_{root-coarse}$
234 and $B_{root-fine}$, respectively). This lack of closure was driven by very high estimates of $B_{root-coarse}$ from
235 high-biomass forests of the US Pacific Northwest.

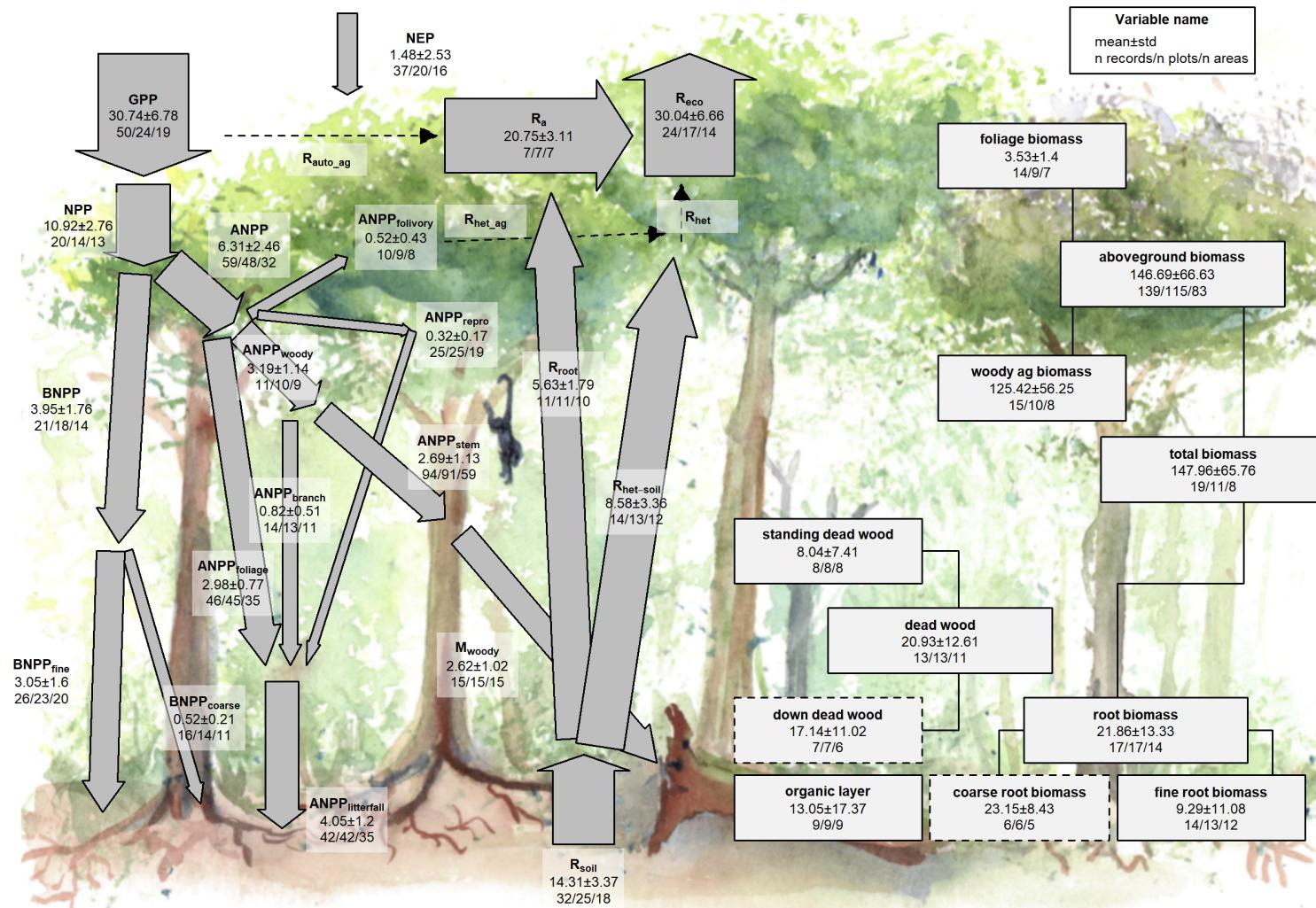


Figure 2 | C cycle diagram for mature tropical broadleaf forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are mean \pm std, where geographically distinct areas are treated as the unit of replication. Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux. Asterisk after variable name indicates lack of C cycle closure.

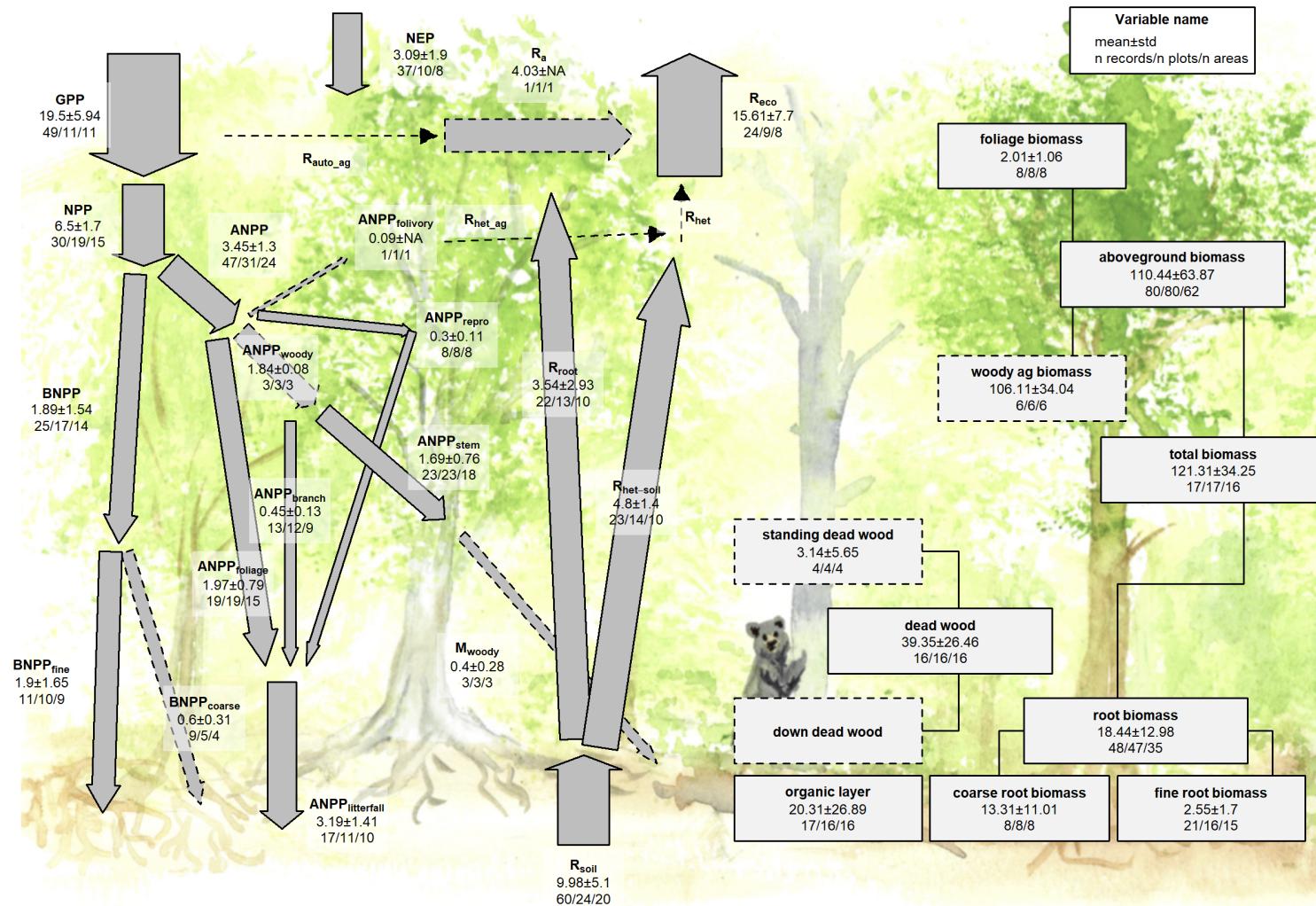


Figure 3 | C cycle diagram for mature temperate broadleaf forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are mean \pm std, where geographically distinct areas are treated as the unit of replication. Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux. Asterisk after variable name indicates lack of C cycle closure.

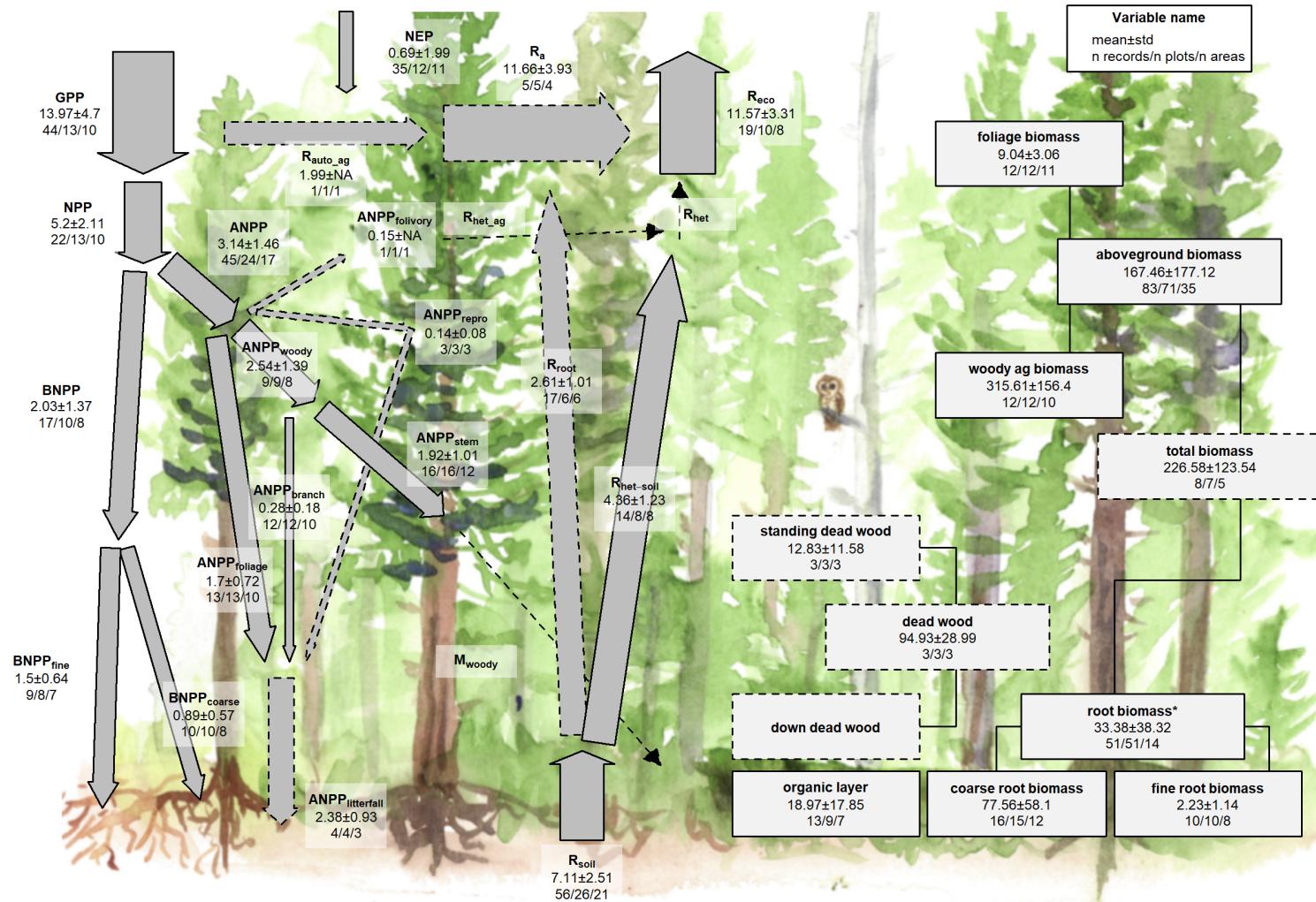


Figure 4 | C cycle diagram for mature temperate conifer forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are mean \pm std, where geographically distinct areas are treated as the unit of replication. Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux. Asterisk after variable name indicates lack of C cycle closure.

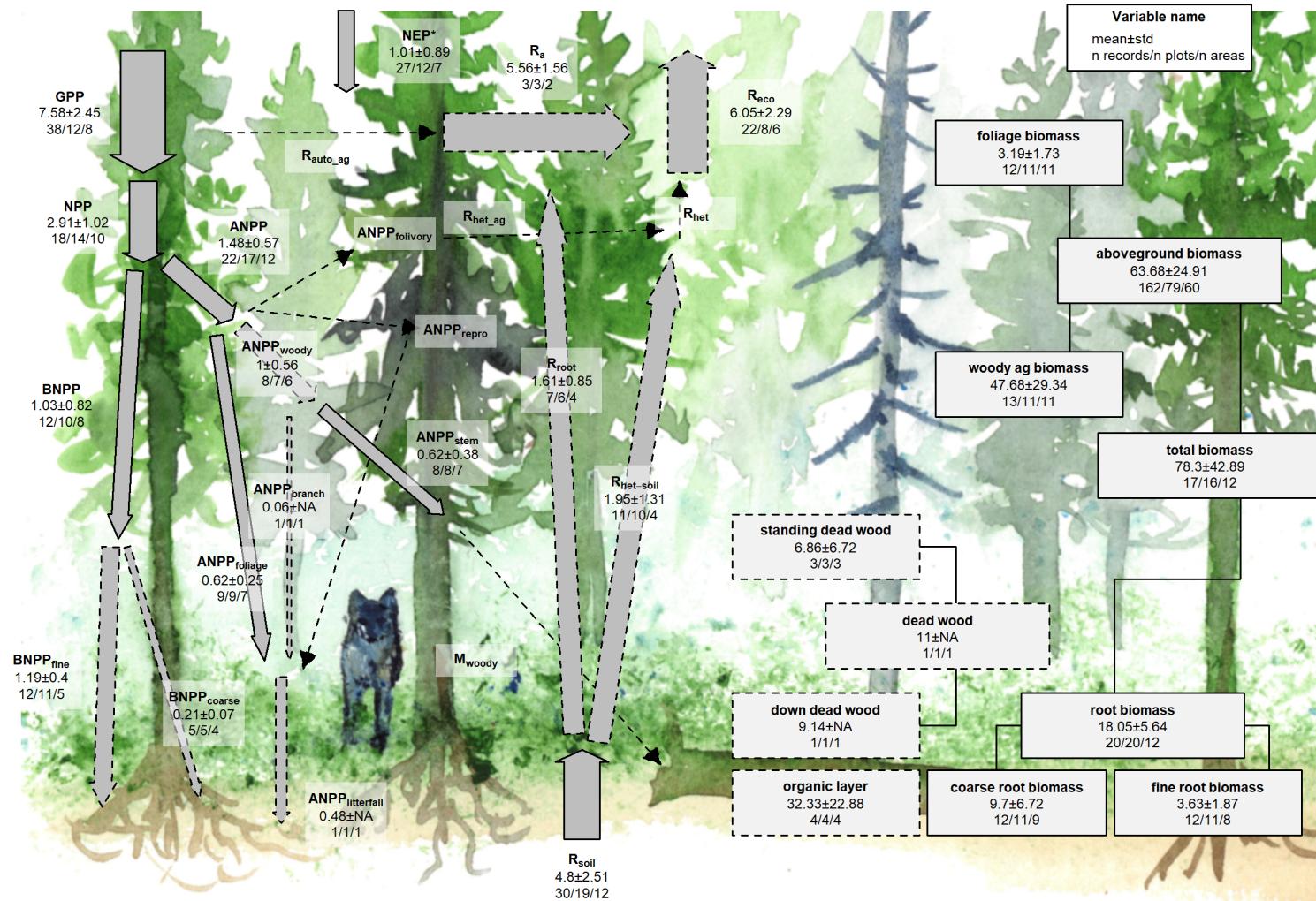


Figure 5 | C cycle diagram for mature boreal conifer forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are mean \pm std, where geographically distinct areas are treated as the unit of replication. Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux. Asterisk after variable name indicates lack of C cycle closure.

236 There were sufficient data to assess mature forest biome differences for 15 flux variables, and significant
237 differences among biomes were detected for 12 variables (Table 1). In all of these cases—including C fluxes
238 into, within, and out of the ecosystem—C fluxes were highest in tropical forests, intermediate in temperate
239 (broadleaf or conifer) forests, and lowest in boreal forests (Table 1, Figs. 6, S1-S15). Differences between
240 tropical and boreal forests were always significant, with temperate forests intermediate and significantly
241 different from one or both. Fluxes tended to be numerically greater in temperate broadleaf than conifer
242 forests, but the difference was never statistically significant. This pattern held for the following variables:
243 $GPP\$$, NPP , $ANPP$, $ANPP_{stem}$, $ANPP_{branch}$, $ANPP_{foliage}$, $BNPP$, R_{eco} , R_{root} , R_{soil} , and $R_{het-soil}$.
244 For two of the variables without significant differences among biomes ($ANPP_{litterfall}$ and $BNPP_{fine}$; Figs.
245 S8 and S11, respectively), the same general trends applied but were not statistically significant. Another
246 exception was for $BNPP_{root-coarse}$, where all records came from high-biomass forests in the US Pacific
247 Northwest, resulting in marginally higher values for the temperate conifer biome (Table 1, Fig. S10;
248 differences significant in mixed effects model but not in post-hoc pairwise comparison).

249 The most notable exception to the pattern of decreasing flux from tropical to boreal biomes was NEP , with
250 no significant differences across biomes but with the largest average in temperate broadleaf forests, followed
251 by tropical, boreal, and temperate conifer forests (Figs. 5,S1).

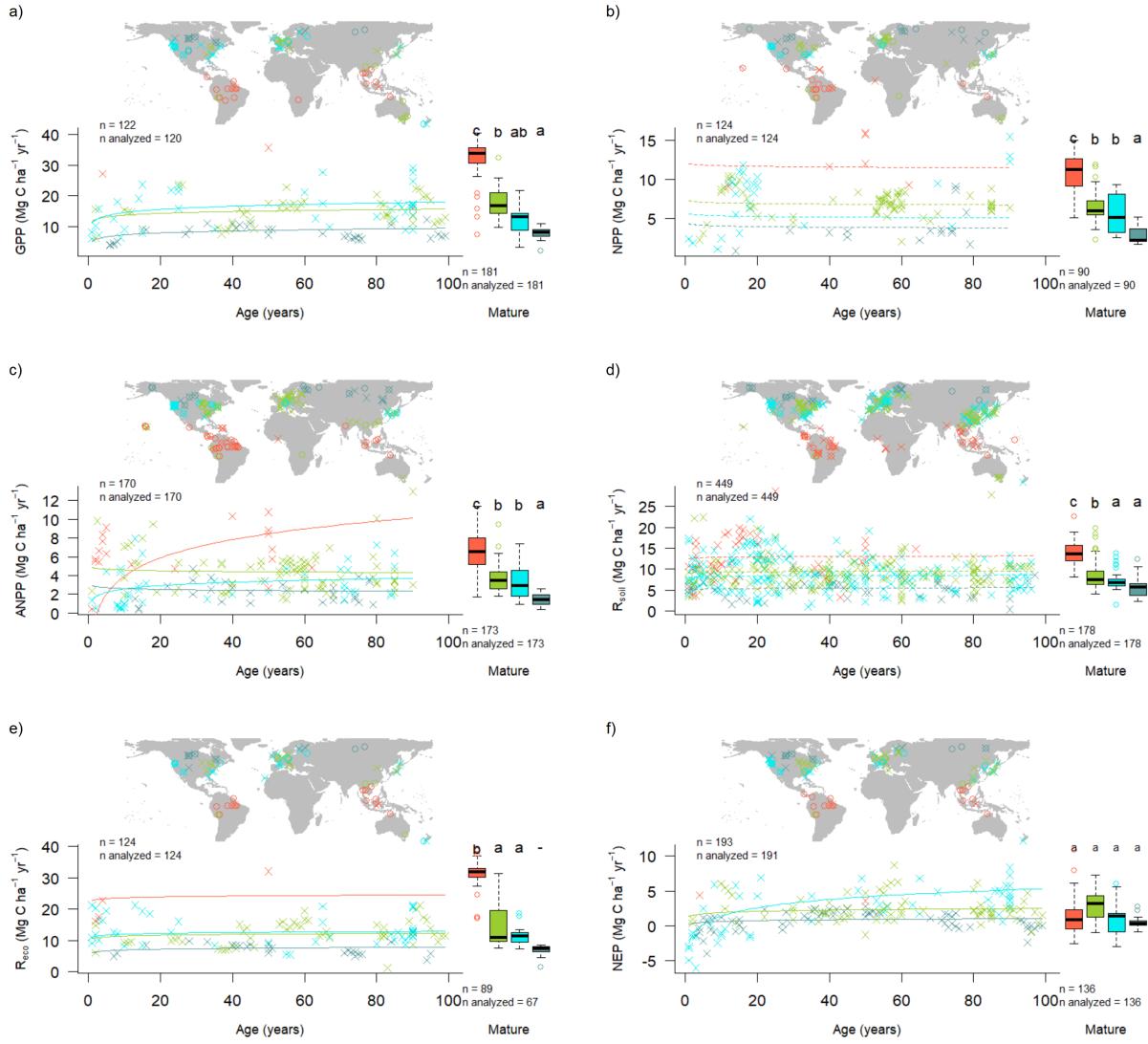


Figure 6 | Age trends and biome differences in some of the major C fluxes: (a) GPP , (b) NPP , (c) $ANPP$, (d) R_{soil} , (e) R_{eco} , and (f) NEP . Map shows data sources (x and o indicate young and mature stands, respectively). In each panel, the left scatterplot shows age trends in forests up to 100 years old, as characterized by a linear mixed effects model with fixed effects of age and biome. The fitted line indicates the effect of age on flux (solid lines: significant at $p < 0.05$, dashed lines: non-significant), and non-parallel lines indicate a significant age \times biome interaction. The boxplot illustrates distribution across mature forests, with different letters indicating significant differences between biomes. Data from biomes that did not meet the sample size criteria (see Methods) are plotted, but lack regression lines (young forests) or test of differences across biomes (mature forests). Individual figures for each flux with sufficient data are given in the Supplement (Figs. S1-S15).

252 **check this with final data (based on Table 1):** There were sufficient data to assess mature forest
 253 biome differences for **9** stock variables, and significant differences among biomes were detected for **6** variables
 254 (B_{tot} , B_{ag} , $B_{ag-wood}$, $B_{foliage}$, $B_{root-coarse}$, DW_{tot} ; Table 1). C stocks had less consistent patterns across
 255 biomes (Figs. 7, S16-S26). In **four of the six** cases (B_{tot} , $B_{ag-wood}$, $B_{root-coarse}$, DW_{tot}), temperate
 256 conifer forests had significantly higher stocks than the other biomes, and boreal forests in the lowest, with
 257 tropical and temperate broadleaf forests in between. For B_{ag} , which had by far the highest sample size,
 258 tropical forests exceeded temperate conifer forests (but not significantly). For $B_{foliage}$, temperate broadleaf
 259 forests were lowest (again, not significantly). The high values for the temperate conifer biome were driven by

260 the very high-biomass forests of the US Pacific Northwest, which are disproportionately represented in the
 261 current version of ForC. Thus, biome differences should be interpreted more as driven more by geographic
 262 distribution of sampling than by true differences.

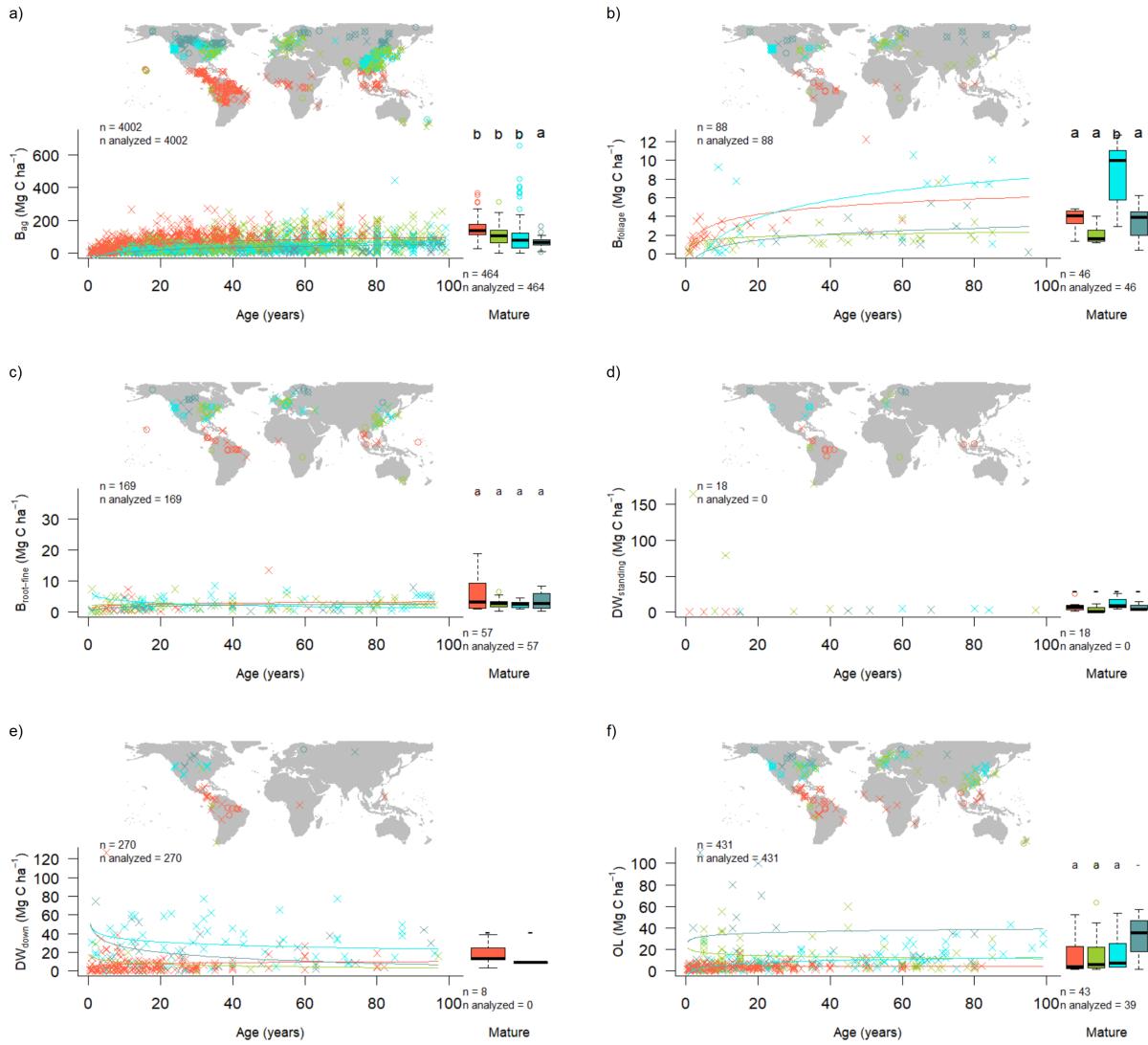


Figure 7 | Age trends and biome differences in some of the major forest C stocks: (a) aboveground biomass, (b) foliage, (c) fine roots, (d) dead wood. Map shows data sources (x and o indicate young and mature stands, respectively). In each panel, the left scatterplot shows age trends in forests up to 100 years old, as characterized by a linear mixed effects model with fixed effects of age and biome. The fitted line indicates the effect of age on flux (solid lines: significant at $p < 0.05$, dashed lines: non-significant), and non-parallel lines indicate a significant age x biome interaction. The boxplot illustrates distribution across mature forests, with different letters indicating significant differences between biomes. Data from biomes that did not meet the sample size criteria (see Methods) are plotted, but lack regression lines (young forests) or test of differences across biomes (mature forests). Individual figures for each stock with sufficient data are given in the Supplement (Figs. S16-S26).

263 C cycling in young forests

264 Average C cycles for forests <100 years old are presented in Figures 8-11.
 265 Both C stocks and fluxes commonly increased significantly with stand age (Tables 1, S2, Figs. 6-11, S1-S26;
 266 detailed below).

267 *ForC* contained 14 flux variables with sufficient data for cross-biome analyses of age trends in regrowth
268 forests (see Methods) (Fig. 6-7 and **S#- SI figures including plots for all variables**). Of these, 9
269 increased significantly with age: *GPP*, *NPP*, *ANPP*, *ANPP_{foliage}*, *ANPP_{woody}*, *ANPP_{woody-stem}*,
270 *BNPP*, *BNPP_{root-fine}*, *R_{eco}*, and net C sequestration (*NEP*). The remaining five—*ANPP_{woody-branch}*,
271 *BNPP_{root-coarse}*, *R_{soil-het}*, and *R_{soil-het}*—displayed no significant relationship to stand age, although all
272 displayed a positive trend.

273 Differences in C fluxes across biomes typically paralleled those observed for mature forests, with C cycling
274 generally most rapid in the tropics and slowest in boreal forests.

275 The single exception was *ANPP_{stem}*, for which temperate broadleaf forests and temperate conifer forests of
276 age >~30 had slightly higher flux rates than tropical forests (*represented by a single chronosequence*).

277 Notably, the trend of tropical > temperate > boreal held for *NEP* in regrowth forests, in contrast to the
278 lack of biome differences in *NEP* for mature forests (Fig. 6).

279 There were only ## flux variables with sufficient data to test for biome x age interactions: *ANPP*,
280 *ANPP_{woody}*, *ANPP_{stem}*, *ANPP_{litterfall}*, and *BNPP* (Table S2). (**more could be added if age trends
281 become significant after outliers are resolved**) For three of these (*ANPP*, *ANPP_{litterfall}*, *BNPP*),
282 the increase in C flux with age was steepest increase in tropical forests, followed by temperate and then
283 boreal forests (Figs S#). Similarly, *ANPP_{woody}* displayed a steeper increase with age in temperate than
284 boreal forests (no tropical data for this variable). In contrast, for *ANPP_{stem}*, tropical and temperate
285 broadleaf forests had the highest flux rates at young ages, but were surpassed by temperate conifer forests
286 between ages 20 and 50 (Fig. S6).

287 (**this needs to be updated with latest data**) In terms of C stocks, 10 variables had sufficient data to
288 test for age trends. Six of these—*total biomass*, *aboveground biomass*, *aboveground woody biomass*, *foliage
289 biomass*, *root biomass*, and *coarse root biomass*—increased significantly with $\log_{10}[\text{stand.age}]$. The
290 remaining four displayed non-significant positive trends: *fine root biomass*, *total dead wood*, *standing dead
291 wood*, and *organic layer*. (*discuss rates of increase*)

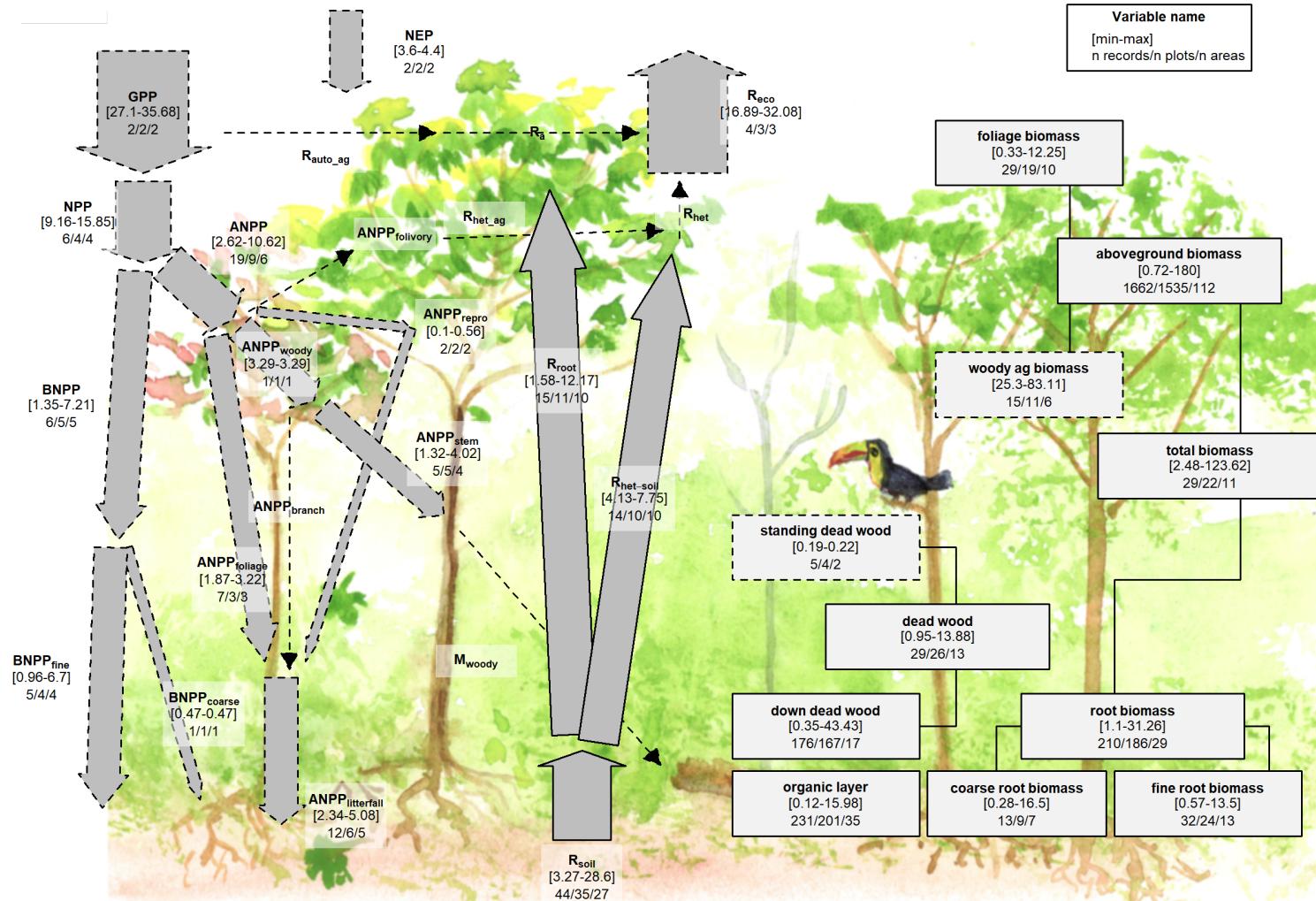


Figure 8 | C cycle diagram for young tropical broadleaf forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are observed ranges, where geographically distinct areas are treated as the unit of replication. All units are $\text{Mg C ha}^{-1} \text{ yr}^{-1}$ (fluxes) or Mg C ha^{-1} (stocks). Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux.

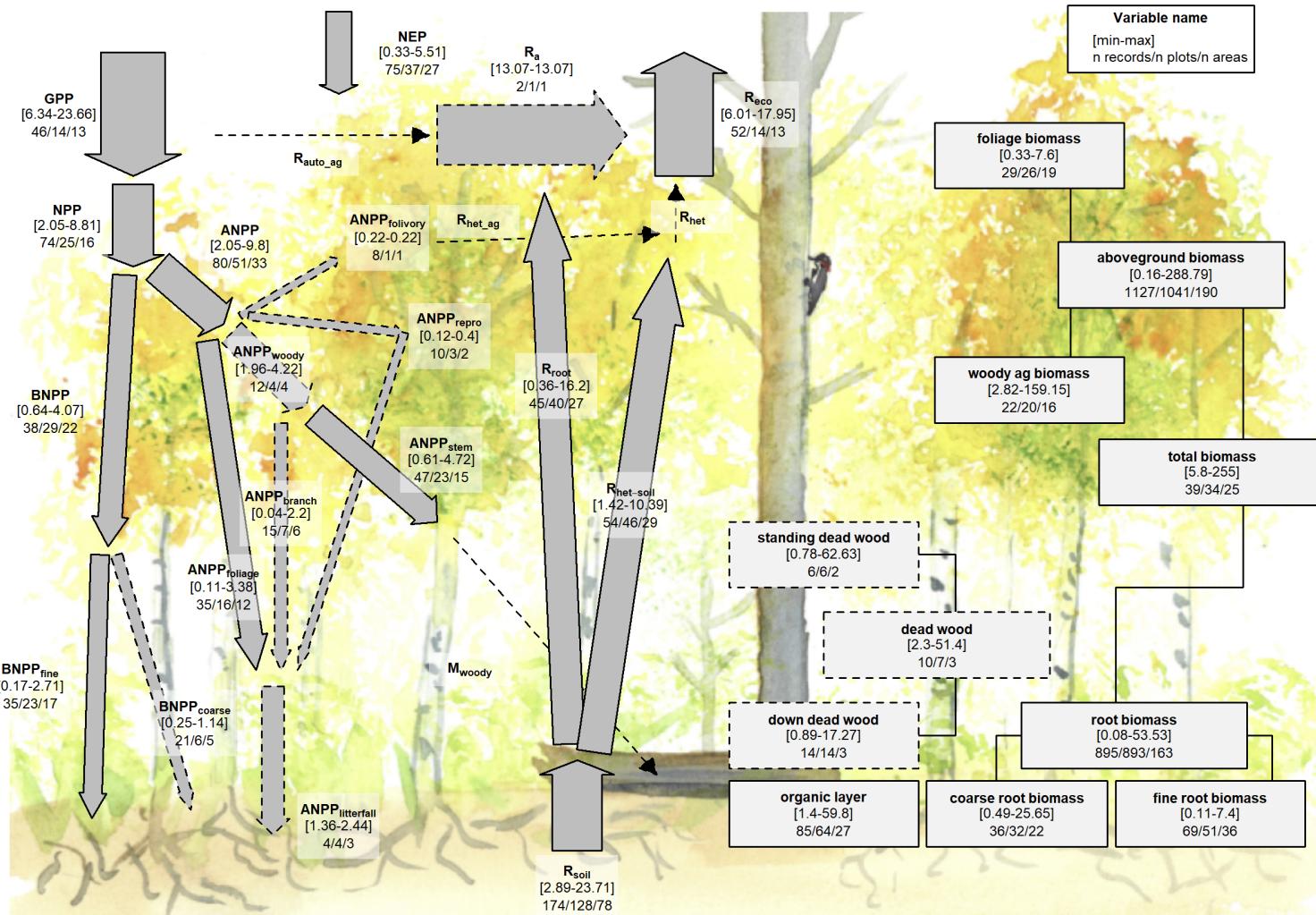


Figure 9 | C cycle diagram for young temperate broadleaf forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are observed ranges, where geographically distinct areas are treated as the unit of replication. All units are $\text{Mg C ha}^{-1} \text{ yr}^{-1}$ (fluxes) or Mg C ha^{-1} (stocks). Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux.

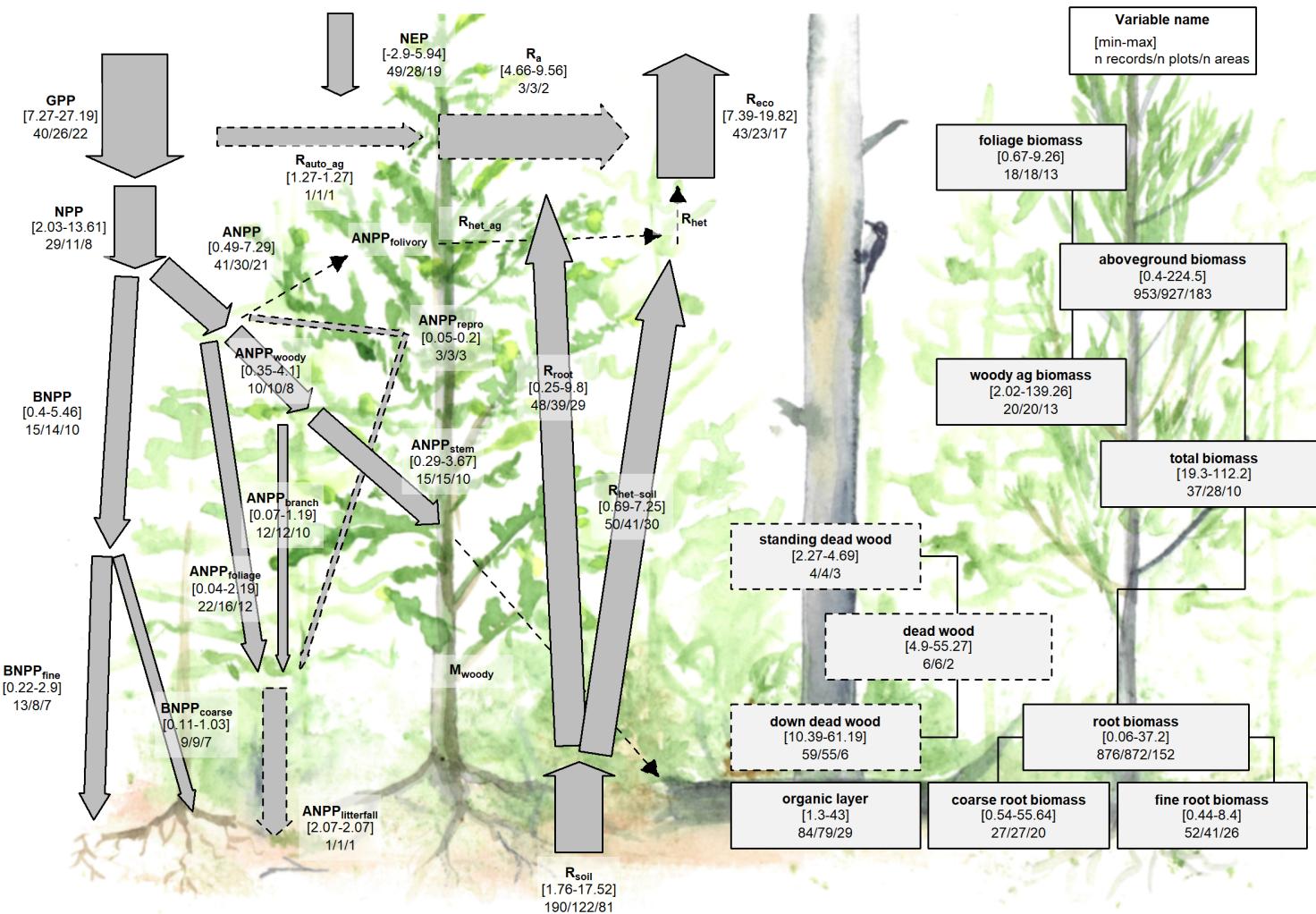


Figure 10 | C cycle diagram for young temperate conifer forests. Arrows indicate fluxes ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$); boxes indicate stocks (Mg C ha^{-1}), with variables as defined in Table 1. Presented are observed ranges, where geographically distinct areas are treated as the unit of replication. All units are $\text{Mg C ha}^{-1} \text{ yr}^{-1}$ (fluxes) or Mg C ha^{-1} (stocks). Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux.

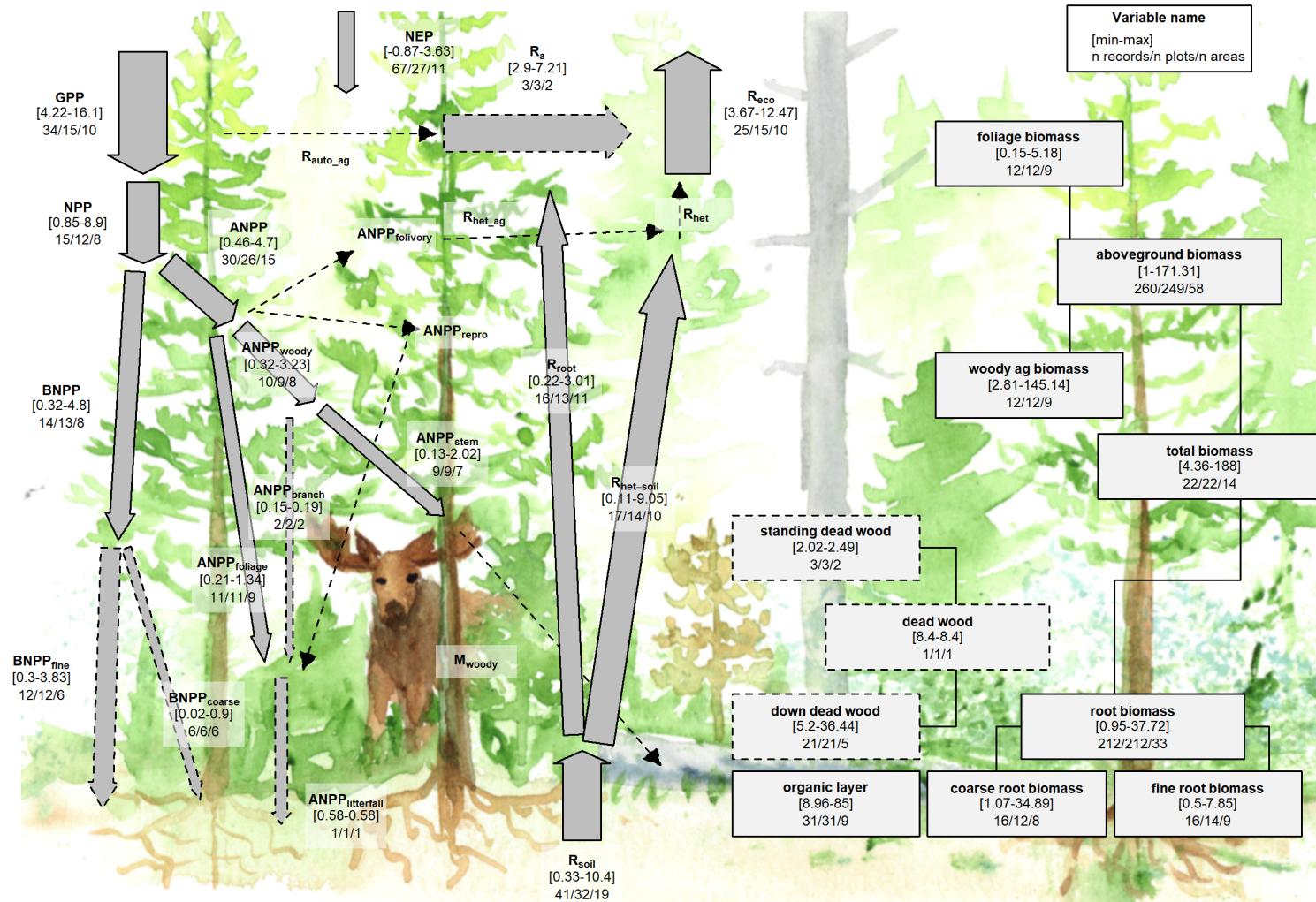


Figure 11 | C cycle diagram for young boreal conifer forests. Arrows indicate fluxes ($Mg\ C\ ha^{-1}\ yr^{-1}$); boxes indicate stocks ($Mg\ C\ ha^{-1}$), with variables as defined in Table 1. Presented are observed ranges, where geographically distinct areas are treated as the unit of replication. All units are $Mg\ C\ ha^{-1}\ yr^{-1}$ (fluxes) or $Mg\ C\ ha^{-1}$ (stocks). Dashed shape outlines indicate variables with records from <7 distinct geographic areas, and dashed arrows indicate fluxes with no data. To illustrate the magnitude of different fluxes, arrow size is proportional to the square root of corresponding flux.

292 **Discussion**

293 *ForC* v3.0 provided unprecedented coverage of most major variables, yielding an internally consistent picture
294 of C cycling in the world's major forest biomes. Carbon cycling rates generally increased from boreal to
295 tropical regions and with stand age. Specifically, the major C fluxes were highest in tropical forests,
296 intermediate in temperate (broadleaf or conifer) forests, and lowest in boreal forests – a pattern that generally
297 held for regrowth as well as mature forests (Figs. 6-7). In contrast to C fluxes, there was little directional
298 variation in mature forest C stocks across biomes (Figs. 2-5, 7). The majority of flux variables, together with
299 most live biomass pools, increased significantly with stand age (Figs. 6-11). Together, these results indicate
300 that, moving from cold to tropical climates and from young to old stands, there is a general acceleration of C
301 cycling, whereas C stocks and *NEP* of mature forests are correlated with a different set of factors.

302 **C variable coverage and budget closure**

303 The large number of C cycle variables covered by *ForC*, and the general consistency between them, provide
304 confidence that our overall reported means provide accurate and useful baselines for analysis (with the
305 caveats that they are unlikely to be accurate representations of C cycling for any particular forest, and that
306 these sample means almost certainly do not represent true biome means).

307 There are of course notable holes in the *ForC* variable coverage, as discussed by Anderson-Teixeira et
308 al. (xxxx), that limit the scope of our inferences here. Notably, *ForC* lacks coverage of fluxes to herbivores
309 and higher consumers, along with the woody mortality and dead wood stocks. Geographically, all variables
310 are poorly covered in Africa and Siberia, a common problem in the carbon-cycle community (Xu and Shang
311 2016 10.1016/j.jplph.2016.08.007, Schimel et al. 2015 10.1073/pnas.1407302112). *ForC* does not include soil
312 carbon, which is covered by other efforts (e.g. Köchy et al. 2015 10.5194/soil-1-351-2015). *ForC* is not
313 intended to replace databases that are specialized for particular parts of the C cycle analyses, e.g.,
314 aboveground biomass (REFS), land-atmosphere fluxes (Baldocchi et al. 2001
315 10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2), soil respiration (Jian et al. 2020
316 10.5194/essd-2020-136), or the human footprint in global forests (Magnani et al. 2007 10.1038/nature05847).

317 In this analysis, the C cycle budgets for mature forests (Figs. 2-5) generally “close”—that is, the sums of
318 component variables do not differ from the larger fluxes by more than one standard deviation. On the one
319 hand, this reflects the general fact that ecosystem-scale measurements tend to close the C budget more easily
320 and consistently than, for example, for energy balance (Stoy et al. 2013 10.1016/j.agrformet.2012.11.004). On
321 the other, however, as noted above *ForC* derives data from multiple heterogeneous sources, often with large
322 errors (standard deviations); as a result, the standard for C closure is relatively loose (cf Houghton 2020
323 10.1111/gcb.15050). Nonetheless, the lack of closure, in the few instances where it occurs, is probably more
324 reflective of differences in the representation of forest types (e.g., disproportionate representation of US
325 Pacific NW for aboveground woody biomass relative to AGB; Fig. 4) than of methodological accuracy. The
326 overall high degree of closure implies that *ForC* gives a consistent picture of C cycling within biomes. This is
327 an important and useful test, because it allows for consistency checks within the C cycle, for example
328 leveraging separate and independently-measured fluxes to constrain errors in another (Phillips et al. 2017
329 10.1007/s11104-016-3084-x, Williams et al. 2014 10.1016/j.rse.2013.10.034, Harmon et al. 2011
330 10.1029/2010JG001495), or producing internally consistent global data products (Wang et al. 2018
331 10.5194/gmd-11-3903-2018).

332 **C cycling across biomes**

333 Our analysis reveals a general deceleration of carbon cycling from the tropics to boreal regions. For mature
334 forests, this is consistent with a large body of previous work demonstrating that C fluxes generally decline
335 with latitude (or increase with temperature) on a global scale (e.g., ???, ???, Li and Xiao 2019, Banbury
336 Morgan *et al* n.d.). The consistency with which this occurs across numerous fluxes is not surprising, but has
337 never been simultaneously assessed across such a large number of variables (but see Banbury Morgan *et al*
338 n.d. for nine autotrophic fluxes). Thus, our analysis reveals that carbon cycling is most rapid in the tropics
339 and slowest in boreal regions, including C fluxes into (*GPP*), within (e.g., *NPP* and its components), and
340 out of (e.g., R_{soil} , R_{eco}) the ecosystem.

341 The notable exception to the pattern of fluxes decreasing from tropical to boreal regions is *NEP* (Fig. 6f),
342 which showed no significant differences across biomes. Unlike the other C flux variables, *NEP* does not
343 represent the rapidity with which C cycles through the ecosystem, but is the balance between C
344 sequestration (*GPP*) and respiratory losses (R_{eco}) and represents net CO₂ sequestration (or release) by the
345 ecosystem. *NEP* tends to be relatively small in mature forest stands [(???), **MORE REFS?**; discussed
346 further below], which accumulate carbon slowly relative to younger stands [(???)**; REFS**], if at all (**REFS**).
347 It is therefore unsurprising that there are no pronounced differences across biomes, suggesting that variation
348 in *NEP* of mature forests is controlled less by climate and more by other factors including moderate
349 disturbances (**REFS**) or disequilibrium of R_{soil} relative to C inputs [e.g., in peatlands where anoxic
350 conditions inhibit decomposition; **REFS**].

351 In contrast to the patterns observed for *NEP* in mature stands, *NEP* of stands between 20 and 100 years of
352 age varied across biomes, being lowest in boreal forests, intermediate in temperate broadleaf forests, and
353 highest in temperate conifer forests (with insufficient data to assess tropical forests; Figs. 6f, S1). This is
354 consistent with findings that live biomass accumulation rates (e.g., ΔB_{ag} or ΔB_{tot}) during early secondary
355 succession decrease with latitude [Anderson *et al* (2006); Cook-Patton *et al* (2020); Figs. 7a, S16-S22]. Note,
356 though, that *NEP* includes not only ΔB_{tot} , but also changes in DW_{tot} , *OL*, and soil carbon, and biome
357 differences in the accumulation rates of these variables have not been detected, in part because these variables
358 do not consistently increase with stand age [Cook-Patton *et al* (2020); Figs. 7, S23-S26; see discussion below].

359 For regrowth forests, little is known about cross-biome differences in carbon fluxes, and we are not aware of
360 any previous large-scale comparisons of C fluxes that have been limited to regrowth forests [although they're
361 commonly mixed in with mature forests; e.g., **REFS**]. Thus, this analysis was the first to examine flux
362 trends in regrowth forests across biomes. The observed tendency for young forest fluxes to decrease from
363 tropical to boreal regions paralleled patterns in mature forests (Figs. 6, S1-S15), suggesting that regrowth
364 forests follow latitudinal trends in carbon cycling similar to those of mature forests (e.g., Banbury Morgan *et*
365 *al* n.d.). Yet, *data remain sparse, and further work will be required to explore age x climate*
366 *interactions. Nevertheless, our broad-brush overview indicates that C cycling of regrowth forests is not only*
367 *higher in the tropics, parallel to fluxes in mature forests (Banbury Morgan et al n.d.), but also that it*
368 *accelerates more rapidly with stand age in the tropics, consistent with more rapid biomass accumulation.*

369 In contrast to C fluxes and biomass accumulation rates in regrowth forests, stocks showed less systematic
370 variation across biomes. For aboveground biomass, this Patterns are consistent with others studies showing
371 that variation in forest biomass across broad climatic gradients is modest and constrained more by moisture
372 than temperature (???). (???), using spaceborne lidar, showed a decline in aboveground biomass (all forests,

373 including secondary) with latitude in the N hemisphere, but values exceeding tropical forests in coastal
374 climates of both the southern and northern hemisphere. Highest biomass forests are found in temperate
375 oceanic climates (REF- , something in GEB, some global forest C map) (???). Lack of synthesis comparing
376 deadwood and organic layer across biomes, but see Cook-Patton *et al* (2020) for age trends.

377 Thus, biome differences should be interpreted more as driven more by geographic distribution of sampling
378 than by true differences.

379 Age trends in C cycling

380 (*Just some rough notes at this point*)

381 A relative dearth of data on C cycling in secondary forests, particularly in the tropics (Anderson-Teixeira et
382 al 2016), is problematic in that almost 2/3 of the world's forests were secondary as of 2010 (FAO 2010),
383 implying an under-filled need to characterize age-related trends in forest C cycling.

384 Moreover, as disturbances increase (???, McDowell *et al* 2020), understanding the carbon dynamics of
385 regrowth forests will be increasingly important.

386 It's also important to understand secondary forest C sequestration to reduce uncertainty regarding the
387 potential for carbon uptake by regrowth forests (???, Cook-Patton *et al* 2020).

388 (discuss NEP well, including) NEP increases with log(age) to 100 -> strongest C sinks are established
389 secondary forests. (But presumably this exact number is an artifact; don't over-emphasize.)

390 Our findings are largely consistent with, but built from a far larger dataset than, those of Pregitzer and
391 Euskirchen (2004 <http://dx.doi.org/10.1111/j.1365-2486.2004.00866.x>), who found that NPP and NEP to be
392 higher in intermediate-aged forests than older forests, and emphasize the importance of forest age at the
393 biome scale. Quickly-changing and age-dependent fluxes were also found in a number of previous syntheses
394 (Amiro *et al*. 2010 10.1029/2010JG001390, Magnani *et al*. 2007 10.1038/nature05847).

395 In contrast to most fluxes, *NEP* is highest at intermediate ages

396 Relevance for climate change prediction and mitigation

397 The future of forest C cycling (???) will shape trends in atmospheric CO₂ and the course of climate change.
398 For a human society seeking to understand and mitigate climate change, the data contained in *ForC* and
399 summarized here can help to meet two major challenges.

400 First, improved representation of forest C cycling in models is essential to improving predictions of the future
401 course of climate change. To ensure that models are giving the right answers for the right reasons, it is
402 important to benchmark against multiple components of the C cycle that are internally consistent with each
403 other. By making tens of thousands of records readily available in standardized format, *ForC* makes it
404 feasible for the modeling community to draw upon these data to benchmark models. Integration of *ForC*
405 with models is a goal (Fer *et al.*, in revision).

406 Second, *ForC* can serve as a pipeline through which forest science can inform forest-based climate change
407 mitigation efforts. Such efforts will be most effective when informed by the best available data, yet it is not
408 feasible for the individuals and organizations designing such efforts to sort through literature, often behind
409 paywalls, with data reported in varying units, terminology, etc. One goal for *ForC* is to serve as a pipeline

410 through which information can flow efficiently from forest researchers to decision-makers working to
411 implement forest conservation strategies at global, national, or landscape scales. This is already happening!
412 *ForC* has already contributed to updating the IPCC guidelines for carbon accounting in forests [IPCC 2019;
413 Requena Suarez *et al* (2019); Rozendaal *et al* in prep], mapping C accumulation potential from natural forest
414 regrowth globally (Cook-Patton *et al* 2020), and informing ecosystem conservation priorities (Goldstein *et al*
415 2020).

416 **ForC can complement remote sensing to provide a comprehensive picture of global forest C**
417 **cycling.** (*here, discuss what is well-covered by remote sensing, where ForC is useful for calibrating remote*
418 *sensing, and what ForC can get that remote sensing can't.*) AGB is the largest stock, and most of the
419 emphasis is on this variable. Remote sensing, with calibration based on high-quality ground-based data
420 (Schepaschenko *et al* 2019, Chave *et al* 2019), is the best approach for mapping forest carbon (REFS).
421 However, it is limited in that it is not associated with stand age and disturbance history, except in recent
422 decades when satellite data can be used to detect forest loss, gain, and some of their dominant drivers
423 (Hansen *et al* 2013, Song *et al* 2018, Curtis *et al* 2018). *ForC* is therefore valuable in defining age-based
424 trajectories in biomass, as in Cook-Patton *et al* (2020).

425 *Remote sensing measurements are increasingly useful for global- or regional-scale estimates of forest GPP*
426 *(???, Li and Xiao 2019), aboveground biomass (B_{ag}) (REFS), woody mortality (i.e., B_{ag} losses to mortality*
427 *M_{woody}) (Clark *et al* 2004, Leitold *et al* 2018), and to some extent net ecosystem exchange (NEP) (REFS).*
428 Other variables, in particular respiration fluxes, cannot be remotely sensed ((??)), and efforts such as the
429 Global Carbon Project (**le quere REF**) and NASA CMS (**citation:**

430 https://carbon.nasa.gov/pdfs/CMS_Phase-1_Report_Final_optimized.pdf but maybe
431 better to cite open literature, one of the papers listed at
432 <https://cmsflux.jpl.nasa.gov/get-data/publication-data-sets>) typically compute them as residuals
433 only. (**Ben, it woudl be particularly helpful if you could flesh this out some more.**)

434 In terms of C stocks, there is a paucity of data on dead wood and organic layer (Pan *et al.* ?). These can be
435 significant. (**Note that we've given a lot of emphasis to dead wood (work by Abby), and as a**
436 **result this work really advances knowledge of dead wood. We'll want to highlight that here.**)
437 (*give some stats/ cite figures*).

438 **Move to data availability statement, or methods?:** We recommend that use of *ForC* data go to the
439 original database, as opposed to using “off-the-shelf” values from this publication. This is because (1) *ForC*
440 is constantly being updated, (2) analyses should be designed to match the application, (3) age equations
441 presented here all fit a single functional form that is not necessarily the best possible for all the variables.

442 As climate change accelerates, understanding and managing the carbon dynamics of forests will be critical to
443 forecasting, mitigation, and adaptation. The C data in *ForC*, as summarized here, will be valuable to these
444 efforts.

445 Acknowledgements

446 Thanks to all researchers whose data are included in *ForC* and this analysis, to Jennifer McGarvey and Ian
447 McGregor for help with the database, and to Norbert Kunert for helpful discussion. Funding sources
448 included a Smithsonian Scholarly Studies grant to KAT and HML and a Smithsonian Working Land and
449 Seascapes grant to KAT.

450 **Data availability statement**

451 Materials required to fully reproduce these analyses, including data, R scripts, and image files, are archived
452 in Zenodo (DOI: TBD]. Data, scripts, and results presented here are also available through the open-access
453 *ForC* GitHub repository (<https://github.com/forc-db/ForC>), where many will be updated as the database
454 develops.

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456 Kristina J. Anderson-Teixeira: <https://orcid.org/0000-0001-8461-9713>

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