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3

4 **Title:** Carbon fractions in the world's dead wood

5

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18

19 **Keywords:** Carbon accounting, coarse woody debris, forest, greenhouse gas inventory,
20 tree, wood carbon, wood trait, wood chemistry.

21 **Alarming increases in tree mortality due to environmental change suggest that**
22 **contributions of dead wood to global carbon (C) cycles are rapidly increasing**¹⁻³,
23 **with dead wood C flux estimates already approximating total annual anthropogenic**
24 **C emissions**⁴. **Quantifying C in dead wood critically depends on accurate estimates**
25 **of dead wood C fractions (CFs) to convert dead woody biomass into C. Most C**
26 **accounting protocols, including those recently revised by the IPCC**⁵, **utilize a**
27 **default dead wood CF of 50%, but live tree studies suggest this assumption results**
28 **in substantial bias in forest C estimates**⁶. **Here we compile and analyze a global**
29 **database of dead wood CFs in trees, showing that dead wood CFs average 48.5%**
30 **across forests worldwide, deviating significantly from 50%, with systematic**
31 **variation among biomes, plant phyla, tissue types, and decay classes. Accounting for**
32 **data-driven dead wood CFs corrects systematic overestimates in global dead wood C**
33 **stock estimates of ~1.6 Pg C, an estimate approaching annual C flux estimates from**
34 **land-use change globally**⁷. **Our analysis provides, for the first time, robust**
35 **empirical CFs for dead wood globally to inform global terrestrial C accounting**
36 **protocols, and revise estimates of forest C stocks and fluxes.**

37

38 Forests are a large and dynamic part of the global carbon (C) cycle with estimates
39 indicating an annual average net global forest C sink of 1.1-1.4 Pg C y⁻¹ in recent decades
40^{7,8}. Global forest C sinks owe to high net uptake in regenerating forests of ~1.3 Pg C year⁻¹;
41 intact forests contribute an additional sink of 0.85-2.4 Pg C year⁻¹^{7,8}, though with
42 evidence of a declining trend in the tropics¹. These sinks are offset by losses of C due to
43 deforestation and forest degradation, particularly in tropical regions where forest loss
44 accounts for ~0.43-1.3 Pg C year⁻¹ on average^{7,9}.

45 Estimates of C stocks and fluxes in woody debris – i.e., fallen and standing dead
46 trees, branches, and other woody tissues – are a critical component of forest C dynamics.
47 Dead wood accounts for ~8% (or 73 Pg) of total C pool in forests globally⁷, and global
48 fluxes of C due to woody decomposition range from 2-11 Pg C y⁻¹, e.g.¹⁰; the upper
49 estimates of this range approximate the 2008-17 decadal average of total anthropogenic C
50 emissions (~9.4 Pg C year⁻¹⁴). There is also wide biogeographic variability in dead wood
51 C stocks and fluxes. For instance, dead wood C stocks represent ~3-25% of total forest C

52 storage depending on biome, with this variability attributable to differences in primary
53 production, tree mortality, and decomposition rates that are linked with climate and
54 species' wood traits¹⁰⁻¹². Dead wood C dynamics are also sensitive to fine-scale
55 disturbances such as harvesting, windstorm impacts, and pest or pathogen outbreaks e.g.
56 ^{13,14}.

57 Given its importance in the global C cycle, robust methods for quantifying C in
58 woody debris are critical for estimating forest C stocks and fluxes at multiple scales. One
59 important consideration in estimating dead wood C fluxes that has received limited
60 attention, is the proportion of C in dead wood, as is used to convert dead wood biomass
61 into C stocks¹⁵. Assessments of dead wood C have most often utilized a single
62 generalized C fraction (CF) – that wood is comprised of 50% C on a mass/mass basis –
63 when converting woody debris mass to C¹⁶⁻²⁰. Recent studies have made clear that 50%
64 is a poor approximation of CFs in live trees: the best available live wood CF average is
65 ~47.6%, and this estimate ranges from 28-65% across biomes, species, and tissue types
66 ^{6,21}. In live trees, accounting for variability in wood CF corrects major systematic errors
67 in forest C stocks^{6,21,22}. For example, accounting for live wood CF refines existing over-
68 estimates of up to 20.1 Pg C in tropical forests⁶. Nevertheless, generalized dead wood
69 CFs have not been obtained for the purposes of global forest C estimation. Instead dead
70 wood CF estimates remain scattered throughout multiple individual studies e.g. ²³,
71 making calculations of robust dead wood CFs, and their integration into forest C
72 accounting protocols, highly challenging.

73 Identifying the factors explaining differences in woody debris CFs has also
74 remained elusive in the absence of data consolidation. Arguably the most important factor
75 driving dead wood CF variability is the decay process, commonly discretized as wood
76 decay class (DC). There is disagreement in the literature as to the magnitude and
77 direction of changes in CF through decomposition. For instance, studies from temperate
78 and tropical forests have detected little to no change in CFs through decomposition²⁴⁻²⁶,
79 others have found increases in CFs^{27,28}, while others report both decreasing and
80 increasing trends depending on phyla (i.e., conifers vs. angiosperms) and tissue type^{23,29-}
81 ³³. In the absence of a global data compilation and analysis, these contrasting patterns
82 pose a challenge for estimating “generic” changes in CFs through wood decay.

83 Data on CF from live trees also suggests tissue-specific variability in dead wood
84 CF will be pronounced. Specifically, there is likely to be especially high CFs in bark vs.
85 other tissues, due to their high concentrations of C-rich and recalcitrant compounds such
86 as lignin, suberin, and tannins³⁴⁻³⁶. Finally, the position of dead wood – i.e., standing vs.
87 downed – may also influence CFs¹⁵, but hypotheses and findings related to this are
88 mixed with some research suggesting that standing dead wood has higher CFs vs.
89 downed wood²³, while other lines of evidence suggest the opposite³⁷. Whether or not
90 these differences are systematic and/or independent of other factors such as biome,
91 species identity, and DC, is unclear, as is the relative importance of these factors.

92 Here we develop, for the first time, a novel global dataset of 973 dead wood CF
93 observations from 112 species and all forested biomes, to inform forest C estimation and
94 to identify the primary factors determining dead wood CFs in trees. We specifically
95 evaluate: 1) Do dead wood CFs differ from (a) the generalized 50% CF value commonly
96 employed in forest C accounting, and (b) live wood CFs? As a corollary we also assess:
97 2) if live wood CFs predict dead wood CFs within species, 3) is there systematic and
98 generalizable variability in dead wood CFs across biomes, species, position, and decay
99 classes, and 4) how do dead wood CFs change through decomposition?

100

101 **Dead wood carbon fractions compared to IPCC protocols and live wood**

102 Dead wood CFs ranged widely from 29.4-60.2% across the compiled dataset, with
103 an average CF estimate of $48.5 \pm 0.8\%$ (s.e.). Dead wood CFs are significantly lower than
104 the widely assumed 50% CF estimate by 1.5% on average (two-sided $z = -6.2$, $p < 0.001$).
105 Average estimated dead wood CFs are also significantly larger than live wood CF which
106 average $47.2 \pm 0.8\%$ ($F_{1, 3392.7} = 67.7$, $p < 0.001$; Fig. 1). Across 63 species with both dead
107 and live wood CFs, average live wood CFs were significantly and strongly related to
108 average dead wood CFs ($r^2 = 0.462$, $p < 0.001$, Fig. S1). This relationship differed
109 significantly from a 1:1 relationship across the entire species pool (model slope = 0.7 ± 0.1
110 (s.e.), linear hypothesis test $p = 0.011$). The intercept of the live-dead wood CF
111 relationship, but not the slope, differed significantly across groups ($p < 0.001$; Fig. S2,
112 Tables S5, S6, S7). Including phyla-specific intercepts in the linear model (i.e., for
113 angiosperms and conifers individually) explained an additional ~15% of the variation in

114 dead wood CFs (i.e., model r^2 when including plant phyla-specific intercept
115 terms=0.601).

116

117 **Factors explaining variation in dead wood carbon fractions**

118 Dead wood CFs varied significantly across biomes, phyla (i.e., conifers and
119 angiosperms), tissue types, and DC (ANOVA $p<0.001$; Table S1). ANOVA revealed
120 significant interactions between biome and phylum, tissue type, and DC, as well as
121 between position and tissue type (Table S1). Variance partitioning indicated that the
122 largest proportion of variability in dead wood CFs was associated with biome (23.1% of
123 variance explained), with systematic and significant differences across all of the biomes
124 represented (Fig. 2, Tables 1, S2, S3). Accounting for all other factors, dead wood CFs in
125 temperate and boreal biomes ($49.3\pm 0.8\%$ and $48.8\pm 0.8\%$, respectively) were ~ 1.7 - 3.1%
126 greater than those observed in subtropical/Mediterranean and tropical biomes (46.2 ± 0.8
127 and 47.2 ± 0.8 , respectively; Fig. 2, Table 1). Tissue type was also a significant factor
128 explaining 18.9% of variability in dead wood CFs (Fig. 2, Tables 1, S2). Bark, fine tissue,
129 and stem wood showed the largest average dead wood CFs (48.1-48.8%), roots being
130 intermediate (47.8%), and branches showing the lowest average dead wood CF estimates
131 (45.7%; Fig. 2, Tables 1, S2).

132 Phylum also explained a significant proportion (7.6%) of the variability in dead
133 wood CFs ($p<0.001$; Tables S2, S3), with gymnosperms dead wood CFs being 2.0%
134 higher on average compared to angiosperms (Fig. 2, Table 1). Decay class explained
135 8.8% of the variation ($p<0.001$, Tables S2, S3), with systematic increases in dead wood
136 CFs occurring across DCs 1-3 (average dead wood CF 47.5-48.0%), to DCs 4 and 5
137 (average dead wood CFs 48.7% and 48.6, respectively; Fig. 2, Table 1). There were only
138 slight differences in the CFs of standing vs. downed wood ($p=0.05$; Fig. 2, Table 1). In
139 total, the factors considered here accounted for 58.6% of the variance in dead wood CFs
140 (Table S2).

141 In the subset of data ($n=431$) for which coarse wood debris (CWD) size was
142 available, dead wood CFs did vary widely across size categories with diameter
143 accounting for 7.4% of the variability (Table S2). When CWD diameter was included in
144 the variance partitioning model, biome, tissue type, and DC class accounted for the

145 largest proportion of explained variation (31.8%, 14.4%, and 14.7%, respectively), and
146 variance explained by the model increased to 68.3% (Table S2).

147

148 **Dead wood carbon fractions across decay classes**

149 Based on a large subset of data (i.e., species with dead wood CFs from at least
150 four DCs; where $n=728$ observations across $n=56$ species; Table S4) patterns of change
151 in dead wood CFs with increases in DC varied widely. The majority of species (41 of 56)
152 showed increases in dead wood CF with increasing DC, with species-specific slopes
153 ranging from 0.03-1.64; these changes were statistically significant (i.e., slope $p \leq 0.05$) in
154 only 5 species (Fig. 3, Table S5). In these 41 species, across DCs 1-5 dead wood CF was
155 predicted to increase on average from 0.15-8.2% (Fig. 3). The remaining 15 species
156 showed trends of declining dead wood CF with increasing DC (slope $p \leq 0.05$ in six
157 instances), with slopes ranging from -0.04 to -4.14% (Fig. 3). The five species with the
158 strongest negative trends (slope $p \leq 0.002$ in all cases) were all subtropical/ Mediterranean
159 angiosperm species (Fig. 3, Table S5).

160

161 **Dead wood carbon fractions and forest C accounting**

162 Prominent forest C protocols, namely those of the IPCC⁵, are a critical tool in
163 compiling forest C budget data globally, and support the implementation and monitoring
164 of critical climate change policies and programs. Reducing uncertainty in forest C
165 estimates is therefore a key priority, with the most recent updates to the IPCC protocols
166 updating key C accounting variables such as tree biomass stocks and growth rates (e.g.,
167 Tables 4.4 and 4.7 in⁵). However, the 2019 Refinement to the 2006 IPCC Guidelines for
168 National Greenhouse Gas Inventories⁵ included no updates to dead wood CFs – or wood
169 CFs in general, despite considerable research on this topic⁶ – and instead only
170 recommend a 50% CF as the default value for dead wood in temperate forests; there is no
171 IPCC-recommended CF estimate suggested for dead wood in tropical or subtropical
172 forests.

173 While deviations in dead wood CFs from the widely used 50% assumption appear
174 small (i.e., 1.5% on average; Fig. 2, Table 1), our findings suggest that existing estimates
175 of dead wood (and hence forest) C stocks are significantly overestimated. For example,

176 global forest C inventories that assumed a 50% dead wood CF, reported a global dead
177 wood C stock of 72.9 Pg C in 2007 ⁷. However, in employing our average dead wood CF
178 of 48.5%, we would estimate this number at 70.7 Pg C. This difference of ~2.2 Pg C is
179 equivalent to 2/3 of the total dead wood C stock in the entire temperate forest biome,
180 which was estimated for the year 2007 as 3.3 Pg C by Pan et al. ⁷. This overestimate of
181 2.2 Pg C also falls well within estimated error bounds for total C fluxes from land-use
182 change annually ⁴.

183 When compared to other sources of uncertainty in forest C assessments, dead
184 wood CFs can be a minor consideration ³⁸. Yet these biases are systematic and easily
185 corrected. Our findings of systematic variation in dead wood CFs across biomes, tissue
186 types, and DCs (and to lesser extent taxonomic groups and size classes; Table S2),
187 support the calculation and promulgation of generalized dead wood CFs for the purposes
188 of forest C accounting (Table 1). The dead wood CF data compiled here, along with CFs
189 from live wood ⁶, provide a basis for better supported approximations of CFs in trees and
190 wood globally as compared to current IPCC protocols ⁵.

191

192 **Factors explaining systematic variation in dead wood carbon fractions**

193 Our study uncovers the following general patterns in CFs across dead wood
194 globally: A) lower dead wood CFs in tropical vs. other forest biomes, B) lower dead
195 wood CFs in angiosperms vs. gymnosperms, and C) higher dead wood CFs in bark vs.
196 other tissues (Table 1). These results are consistent with studies on live wood CF
197 variability ^{6,34,35,39}, and perhaps are not surprising given the strong relationship between
198 dead and live wood CFs observed in a subset of tree species evaluated here (Fig. S2).
199 Based on similarities in how dead and live wood CFs vary across and within species, our
200 study indicates that live wood chemical traits (along with their environmental and
201 evolutionary drivers) also play a deterministic “afterlife” role *sensu* ⁴⁰ in driving dead
202 wood C dynamics.

203 There is considerable variability in patterns of dead wood CF change through
204 decay (Fig. 3), suggesting that multiple mechanisms operate across different species and
205 forest regions. Cellulose and hemicellulose generally decompose more rapidly than lignin
206 ^{23,41}, and lignin has a considerably higher C concentration (~60-70% C mass mass⁻¹) than

207 cellulose/ hemicellulose ($\sim 40\text{-}44\%$ C mass mass⁻¹)⁴²; thus CFs would be expected to
208 increase through decomposition as a function of increasing lignin concentrations. Our
209 data on generalized CFs across DCs qualitatively correspond to this expectation (Fig. 1).
210 Quantitatively, in assuming an average C concentration of 62.5% for lignin and 41.2%
211 for cellulose, then our observed changes in dead wood CFs from DC 1 (47.5%) to DC 5
212 (48.6%) correspond to an increase in lignin concentrations through decomposition from
213 $\sim 27\%$ to 33% (mass mass⁻¹). These approximate changes in lignin concentrations match
214 patterns observed in wood decomposition experiments^{41,43,44}, and support the findings of
215 increases in CFs with decomposition in the majority of tree species (Fig. 3).

216 However, certain species deviate from this pattern and instead show non-
217 significant changes or significant declines in CFs through decomposition (Fig. 3). That
218 these species are disproportionately observed in certain biomes, suggests there are
219 mechanisms other than the degradation of cellulose and lignin that drive chemical
220 changes in decomposition globally. One possible mechanism is the import of soil
221 particles and soluble nutrients into dead wood by soil macrofauna – in particular termites
222⁴⁵ – which would reduce dead wood CFs through the decomposition process primarily in
223 tropical and subtropical forests.

224 Similarly, there is an expectation that the import of soluble nutrients and particles
225 from soils into woody debris should decrease dead wood CFs in downed wood, as
226 compared to standing necromass²³. Support for this expectation has been observed in
227 temperate and boreal forests, where standing dead trees express significantly greater CFs
228 vs. downed wood (i.e., on the order of $\sim 1.6\text{-}2.0\%$) at later stages of decay (i.e., DC 4)²³.
229 This is consistent with our findings of dead wood CFs being higher in standing vs.
230 downed wood, though the magnitude of the average differences in our pooled analysis is
231 lower ($\sim 0.4\%$; Fig. 1). Disentangling how these and other mechanisms drive variability in
232 CFs through decomposition will likely require detailed experimental studies that evaluate
233 long-term decay patterns⁴⁶, account for species differences in wood functional traits³⁶,
234 incorporate emerging environmental analytical techniques e.g.⁴⁷, and test for biochemical
235 changes in wood such as the accumulation of anaerobic metabolic products⁴⁸.

236 At global scales, accurate estimates of CF in dead wood are critical for refining
237 global C budgets, quantifying potential changes in dead wood fluxes under global change

238 scenarios, mechanistically understanding the drivers of decomposition and predicting
239 how they change in the future. Recent troubling observations of increased tree mortality
240 in multiple forest biomes^{2,3} suggest that a synthetic understanding of dead wood
241 chemistry dynamics is especially critical for all of these avenues of forest ecological and
242 global change science.

243

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252

253 **Author Contributions**

254 A.R.M conceived the study, lead data compilation and analysis, and wrote the
255 manuscript; G.M.D. helped write and edit the manuscript; M.D. contributed to data
256 compilation and helped write and edit the manuscript; S.C.T. contributed to data
257 compilation and analysis, and helped write and edit the manuscript.

258

259 **Author Contributions**

260 The authors declare no competing interests.

261

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389 **Tables**

390

391 **Table 1.** Generalized mean dead wood carbon fractions (CF) across five different factors.

392 Mean values here were calculated as least squares means, derived from five different

393 linear-mixed effects models (all fit as modified versions of Equation 1). Values here

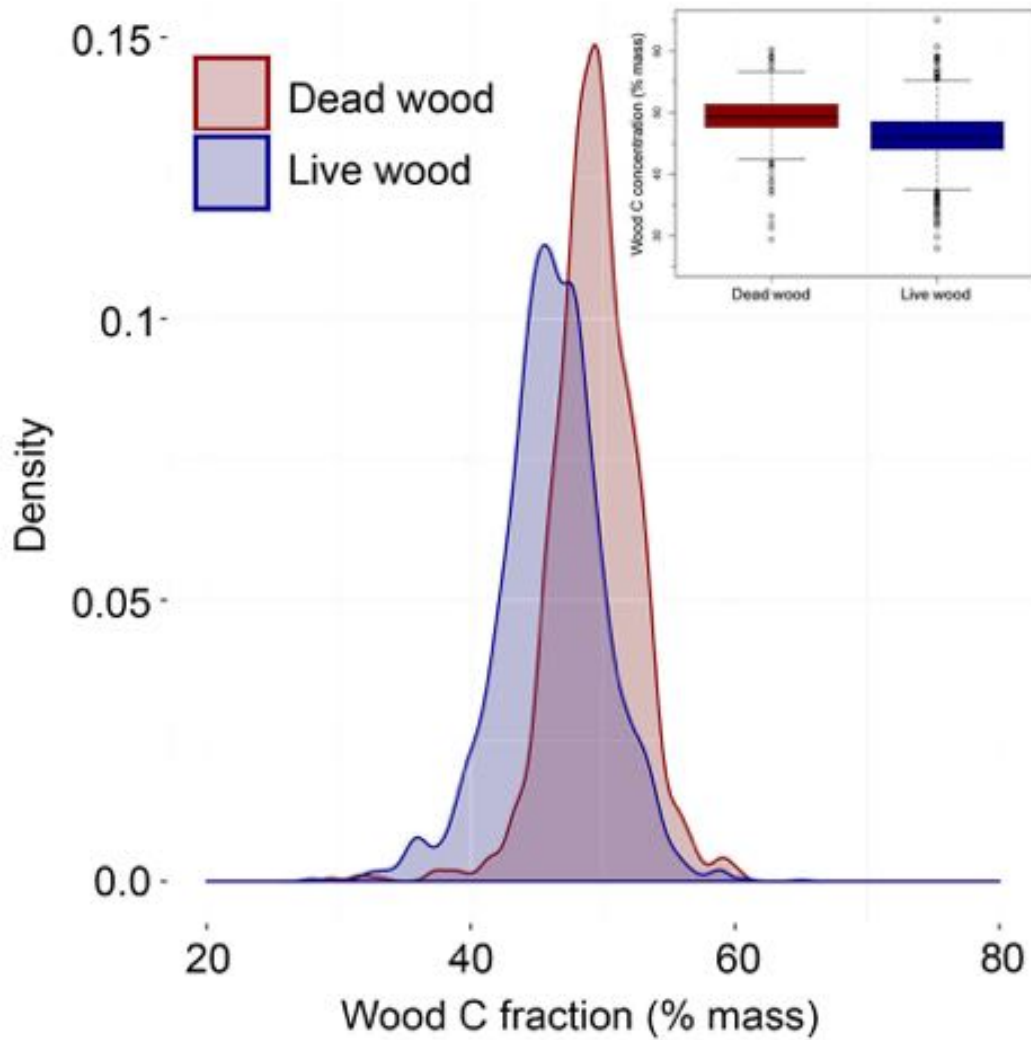
394 correspond to data presented in Fig. 2, while linear mixed effects model diagnostics are

395 presented in Table S3.

396

Factors	Value	Mean CF	S.E.	Lower C.I.	Upper C.I.
Biomes	Boreal	48.84	0.76	40.69	56.98
	Subtropical/ Medit.	46.24	0.83	37.38	55.09
	Temperate	49.29	0.74	41.29	57.28
	Tropical	47.16	0.79	38.66	55.66
Phyla	Angiosperm	47.18	0.79	44.59	49.77
	Gymnosperm	49.19	0.79	46.58	51.79
Tissues	Branch	45.67	1.14	42.13	49.21
	Root	47.79	1.14	44.25	51.33
	Stem	48.07	1.07	44.75	51.4
	Bark	48.73	1.08	45.38	52.09
	Fine tissue	48.8	1.23	44.97	52.63
Position	Downed	47.81	1.05	44.32	51.31
	Standing	48.22	1.06	44.7	51.74
Decay class	1	47.53	1.03	44.16	50.9
	2	47.55	1.03	44.18	50.93
	3	47.98	1.03	44.61	51.36
	4	48.68	1.04	45.28	52.08
	5	48.61	1.05	45.17	52.04

397



399

400 **Fig. 1. Carbon fractions (CF) in dead vs. live wood in a global wood CF database.**

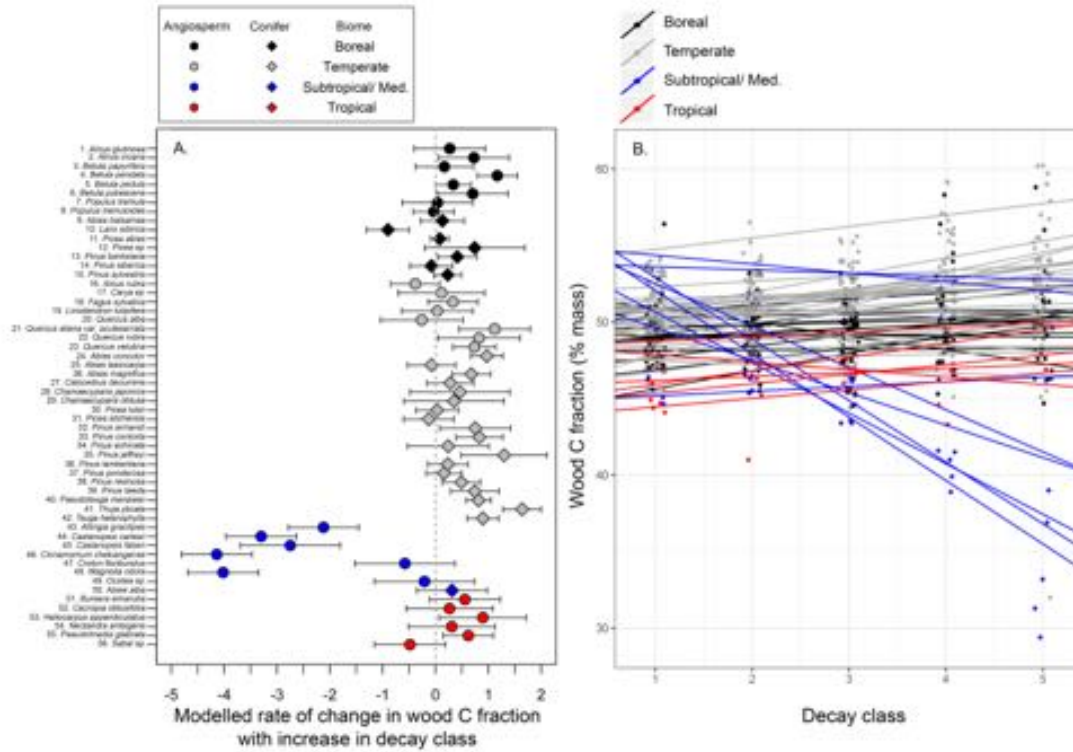
401 Histograms correspond to kernel density estimates fit for CF values from dead ($n=973$)

402 and live wood ($n=2,437$) separately, with corresponding boxplots (showing medians, 25-

403 75th percentiles, outliers, and range excluding outliers) inset.



405 **Fig. 2. Sample sizes, distributions and mean dead wood carbon fraction (CF) values**
406 **across biomes, phyla, tissue type, dead wood position, and decay class.** Middle panels
407 (B) represent kernel density estimates fit to subsets of dataset (based on the sample sizes
408 presented in pie charts). Right panels (C) represent least square mean values (\pm s.e.)
409 estimated from a linear mixed effects model fit to the entire dead wood dataset ($n=973$).
410 Within a given data subset, different letters above mean values denotes statistically
411 significant differences (at $p<0.05$) in mean dead wood C values.



412

413 **Fig. 3. Changes in dead wood carbon fractions (CF) as a function of wood**
 414 **decomposition stage.** Panel A presents modeled rates of change in dead wood CFs as a
 415 function of decay class, which are the slope estimates derived from a mixed effect model.
 416 Panel B presents the species-specific models predicting dead wood CFs as a function of
 417 decay class.

418 **Methods**

419 *Literature review*

420 We built on our existing wood C database⁴⁹, which consists of $n=2,228$
421 observations of CFs in live wood only, as the basis for dead wood CF consolidation. We
422 first reviewed all peer-reviewed papers that were cited by our previous work i.e.,^{49,50,51}
423 for records of dead wood CFs. Then we searched three peer-reviewed literature databases
424 (Web of Science, Scopus, and Google Scholar) for papers with dead wood CF records,
425 using the primary search terms “coarse wood debris”, “dead wood”, and “carbon”, and
426 “wood nutrient.” Articles identified by these terms or combinations thereof, as well as
427 papers that cited these publications, were searched for dead wood CF data. Data
428 compilation was halted at the end of 2019.

429 Criteria for inclusion broadly followed that of Martin et al.⁴⁹, such that only dead
430 wood CF data associated with species identities and tissue type identities were included
431 in our database. This was done to maximize our sample size, while allowing analysis that
432 was specific enough to inform forest C estimation. For each paper with species- and
433 tissue-specific data, dead wood CF observations were then extracted from text, tables and
434 figures, with figure-based data extracted using the Web-Plot Digitizer software⁵².

435 For each observation, we recorded species-specific taxonomy as presented in
436 original publications, which was then adjusted according to the Taxonomic Name
437 Resolution Service v.4.0⁵³. Each dead wood CF observation was then classified as
438 belonging to one of four major forested biomes including A) boreal, B) temperate, C)
439 subtropical/ Mediterranean, and D) tropical. Tissue type was recorded as one of the
440 following: A) bark, B) stem (inclusive of heartwood and sapwood, which were largely
441 undifferentiated in dead wood CF studies), C) branch (inclusive of three observations
442 reported as small “twigs”), D) roots (large and small, which were by-in-large
443 undifferentiated in dead wood CF publications), and E) unspecified fine tissue. Two
444 papers reported sampled material as belonging to “stems and branches”, which were
445 classified as “stems” for analysis here assuming stems contributed the larger proportion
446 of biomass to these analyses.

447 Each dead wood CF observation was then categorized according to three primary
448 factors associated with wood decomposition and related chemical change: A) decay class

449 (DC), B) position, C) size (diameter and length). In the majority of publications dead
450 wood DC was reported along a conventional 1-5 scale, and was therefore included in our
451 database as published while noting the decay class scale employed. In cases where DC
452 for was reported as a two-category range (e.g. DC 1-2) the higher DC was used for
453 analysis, while in cases where a multi-category DC was presented (e.g. DC 1-5) the middle
454 DC value was used. In the few instances DC was reported along a 0-5 point scale (where
455 DC 0 is clearly defined in the publication as dead and not live wood), dead wood reported
456 with a DC of 0 was classified as DC 1. Lastly, in a subset of papers the number of years
457 since tree death (instead of DC) was reported. In these cases, years since death were
458 converted to DC based on published decay class transition matrices^{e.g. 54}.

459 Position was recorded as one of A) “standing” referring to snags, or B) “downed”
460 referring to anything sampled from the forest floor. Values for “suspended” woody debris
461 were combined with those for snags. A few publications did not differentiate dead wood
462 as being standing vs. downed in the original publication, and instead classified dead wood
463 as “standing/ downed.” These few cases were classified as “downed” for analysis here,
464 since there were very few observations in this group (particularly across multiple DCs).

465 Diameter measurements were available for less than 50% of dead wood CF
466 observations, and papers presented a combination of quantitative and categorical
467 measurements. Therefore diameter values were recorded following the original
468 publication, and then categorized into one of seven groups that were chosen to maintain
469 maximum resolution while balancing sample sizes. These diameter groups employed here
470 were: 1) 0.1-1.0 cm, 2) 1.1-2.5 cm, 3) 2.51-5.0 cm, 4) 5.1-10.0 cm, 5) 10.1-20 cm, 6)
471 20.1-30 cm, and 7) ≥ 30.1 cm. There are two caveats to these classifications. First, in
472 instances where publications reported size ranges that overlapped two or more of our
473 groups (e.g., one paper reported dead wood as 7-12 cm in diameter), the mid-point of the
474 size range was used to allocate observations into final diameter classes. Second, in cases
475 where dead wood was reported as belonging to undefined categories (e.g. one paper
476 reporting diameter values of ≥ 2.5 cm), all observations from that publication were placed
477 in the next highest diameter group. Length measurements were available only for a small
478 subset of observations, and were recorded as in the original publication and categorized
479 as either 1) 1-100 cm, or 2) ≥ 100 cm.

480 Our literature-based search was augmented with a structured trait query from the
481 TRY Functional Trait Database⁵⁵. Specifically, we requested records for coarse woody
482 debris C concentration (TRY Database trait number 868). However, all of the $n=42$
483 records for this trait were not associated with a species, and were therefore not included
484 in our final dataset.

485

486 *Data analysis – dead wood CFs vs. live wood CFs and a generalized 50% CF*

487 All analyses were performed using R v.3.2.1 (R Foundations for Statistical
488 Computing). First, we utilized a two-tailed z-test to evaluate if dead wood CFs across our
489 entire dataset ($n=973$ observations total) differed significantly from a 50% CF
490 assumption. Then, two approaches were then taken to compare live vs. dead wood CFs.
491 First, we fit a linear mixed effects model using the ‘*lmer*’ function in the ‘*lme4*’ R
492 package⁵⁶ to our entire wood CF dataset ($n=3,410$ observations total from both dead and
493 live wood). In this model, wood CF values were predicted as a function of an observation
494 being “dead or live” (as a fixed effect), while accounting for biome and phylum as
495 random effects. These random effects were incorporated in this model in efforts to better
496 isolate “dead vs. live” differences since 1) the dead and live CF datasets differ in the
497 number and proportion of observations per biome and phyla, and 2) wood CFs vary
498 systematically as a function of biome and phylum; therefore failing to account for these
499 factors statistically may have biased dead vs. live comparisons. (Note: we also sought to
500 include tissue type as a random effect in this model, though since tissue types are
501 reported more specifically in live wood ($n=8$ types) than in dead wood ($n=5$ types), it was
502 not possible to parameterize the model with this random effect). Based on this model we
503 then calculated and statistically compared least square mean CF values for both groups
504 using the ‘*lsmeans*’ and ‘*difflsmeans*’ functions in the ‘*lsmeans*’ R package⁵⁷.
505 Distributions for dead and live wood CF data were presented visually using kernel
506 density estimates calculated in ‘*ggplot2*’⁵⁸.

507 Next, we tested if live wood CFs can be used to predict dead wood CFs. Using the
508 subset that included only species with values of both, we calculated species-specific mean
509 live wood and dead wood CFs values, and fit a linear regression to predict dead wood CF
510 from live wood CFs. This linear model was then statistically compared to a 1:1

511 relationship using the ‘*linearHypothesis*’ function in the ‘*car*’ R package ⁵⁹. We then
512 included both phylum and phylum-by-live wood CF interaction terms in this model to
513 evaluate if intercepts and slopes of live-dead wood CF relationship differed among
514 species groups (i.e., conifers vs. angiosperms).

515

516 *Data analysis – factors explaining dead wood CFs*

517 We first used an analysis of variance (ANOVA) to evaluate if dead wood CFs
518 vary as a function of biome, phylum, tissue type, position, and DC, as well as all two-way
519 interaction terms. We then complemented this ANOVA with a variance partitioning
520 analysis to quantify the proportion of variability in dead wood CFs explained by biome,
521 phylum, tissue type, position, and DC (where $n=973$ dead wood observations). This
522 analysis followed the methods developed and employed by multiple studies evaluating
523 functional trait variability in plants e.g. ^{60,61}, including our own earlier work on live wood
524 CF variability in trees ⁴⁹.

525 Specifically, the variance partitioning analysis entailed fitting a linear mixed
526 effects model with the ‘*lme*’ function in the ‘*nlme*’ R package ⁶² where all nested levels –
527 namely DC, within position (i.e., standing, dead), within tissue, within phylum (i.e.,
528 conifer, angiosperm), within biome) – are entered as sequential random effects, and the
529 overall intercept (or overall mean dead wood CF value) is the only estimated fixed effect
530 ⁶⁰. We then used the ‘*varcomp*’ function in the ‘*ape*’ R package ⁶³ to quantify and
531 partition variation in dead wood CFs across these nested levels. (Note: the variance
532 partitioning analysis was also performed while including size as a factor, but since this
533 necessarily reduced our sample size by over half (to $n=413$ observations), these results
534 are discussed only briefly).

535 We then estimated and compared generalized dead wood CF across DCs,
536 positions, tissues, phyla, and biomes. Specifically, we fit five linear mixed effects models
537 wherein one of the five variables (i.e., DC, position, tissue, phylum, biome) was included
538 as a fixed effect, and the other four variables were included as nested random effects.
539 Based on these five models, we then used the ‘*lsmeans*’ function to calculate least square
540 mean dead wood CFs individually for each DC, position, tissue type, phylum, and biome,
541 and compared them using the ‘*diffsmeans*’ function. (Note: this analysis did not include

542 interaction terms since with few exceptions these were largely non-significant predictors
543 of dead wood CFs (Table S1)).

544

545 *Data analysis – changes in dead wood CFs through decomposition*

546 We evaluated how dead wood CFs changes with DC in more specific detail, using
547 a subset of data that included only species with wood C values from at least four DCs.
548 For this subset of $n=56$ species, we then used a linear mixed effects model to evaluate
549 how wood C changes across DC, and if/how the rate of change differs across species
550 (subset species highlighted in Table S4). This analysis entailed using the ‘*lme*’ function to
551 fit species-specific models predicting dead wood CFs as a function of DC. Specifically,
552 dead wood CFs were predicted as a function of species identity (representing a species-
553 specific intercept) and a species-by-DC interaction term (representing a species-specific
554 slope parameter) as fixed effects, while accounting for biome, phylum, tissue type, and
555 position) as random effect.

556

557 *Data availability*

558 The compiled data set used in our analyses is available through the TRY
559 Functional Trait Database (data set ID number to be determined upon article publication),
560 and is available from the corresponding author upon request.

561

562 *Code availability*

563 The code used to perform all analyses and generate figures is available upon
564 request to the corresponding author.

565

566 **Methods References**

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599 **Supplementary Information** is available for this paper.

600 Correspondence and requests for materials should be addressed to Adam R. Martin.

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