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Structural diversity underpins carbon storage in Australian temperate forests

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1 **Title:**

2 Structural diversity underpins carbon storage in Australian temperate forests

3

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40

41 **Biosketch**

42 The author team is broadly interested in understanding forest dynamics and the impacts of fire,
43 climate and management on forest values now and into the future.

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45 **Data Accessibility**

46

47 Data available from Figshare

48 <https://doi-org.ezp.lib.unimelb.edu.au/10.26188/5b760d977ed75>

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Title: Structural diversity underpins carbon storage in Australian temperate forests

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Abstract

Aim: Forest carbon storage is the result of a multitude of interactions among biotic and abiotic factors. Our aim was to use an integrative approach to elucidate mechanistic relationships of carbon storage with biotic and abiotic factors in the natural forests of temperate Australia, a region that has been overlooked in global analyses of carbon-biodiversity relations.

Location: South-eastern Australia

Time period: 2010 – 2015

Major taxa studied: Forest trees in 732 plots

Methods: We used the most comprehensive forest inventory database available for south-eastern Australia and structural equation models to assess carbon-storage relationships with biotic factors (species or functional diversity, community-weighted mean (CWM) trait values, structural diversity) and abiotic factors (climate, soil, fire history). To assess the consistency of relationships at different environmental scales, our analyses involved three levels of data aggregation: six forest types, two forest groups (representing different growth environments), and all forests combined.

Results: Structural diversity was consistently the strongest independent predictor of carbon storage at all levels of data aggregation, whereas relationships with species- and functional-diversity indices were comparatively weak. CWMs of maximum height and wood density were also significant independent predictors of carbon storage in most cases. In comparison, climate, soil, and fire history had only minor and mainly indirect effects via biotic factors on carbon storage.

33 **Main conclusions:** Our results indicate that carbon storage in our temperate forests was
34 underpinned by tree structural diversity (representing efficient utilisation of space) and by
35 CWM trait values (representing selection effects) more so than by tree species richness or
36 functional diversity. Abiotic effects were comparatively weak and mostly indirect via biotic
37 factors irrespective of the environmental range. Our study highlights the importance of
38 managing forests for functionally important species and to maintain and enhance their
39 structural complexity in order to support carbon storage.

40 **Keywords:** forest carbon, fire, functional diversity, functional identity, mass-ratio, niche-
41 complementarity, structural diversity, structural equation model, temperate forests.

43 1. INTRODUCTION

44 Forests are a critical component of the global carbon cycle as they support 70-90% of
45 terrestrial aboveground and belowground biomass (Houghton, Hall, Goetz, 2009) and are a
46 major carbon sink (Pan et al., 2011). Carbon stored in forest biomass is often estimated as a
47 cumulative function of net primary productivity (Pan, Birdsey, Phillips, Jackson, 2013), which
48 has been positively linked with plant diversity (species, phylogenetic, and/or functional) in a
49 range of forest types (Liang et al., 2016; Paquette, Messier, 2011; Poorter et al., 2017).
50 Similarly, positive relationships have been documented between plant diversity and other
51 forest-ecosystem functions relating to nutrient cycling, regeneration, and resistance to
52 disturbance (Ratcliffe et al., 2017). Nonetheless, much remains unknown about the
53 mechanisms underpinning positive associations between biodiversity and functions like
54 productivity, particularly in natural ecosystems (Tilman, Isbell, Cowles, 2014). In addition,
55 relationships between biodiversity and carbon stocks ('carbon storage'), which are driven not
56 only by productivity but also by mortality (Pan et al., 2013), remain under-examined for
57 many forest types.

58 Two main non-mutually exclusive mechanisms underpin positive biodiversity-
59 ecosystem functioning (BEF) relationships: the niche complementarity effect, where niche
60 partitioning and facilitation among species allow diverse communities to exploit available
61 resources more efficiently than less diverse communities; and the selection effect, where
62 diverse communities are more likely than species-poor communities to contain highly
63 functional species that contribute strongly to ecosystem productivity and carbon storage
64 (Loreau, Hector, 2001; Tilman et al., 2014). The importance of niche complementarity in

65 forests worldwide has been indicated by multiple examples of greater carbon storage with
66 increasing diversity of plant species (Huang et al., 2018; Poorter et al., 2015; Ratcliffe et al.,
67 2017), and/or functional traits ('functional diversity'; (Ruiz- Benito et al., 2014).
68 Nonetheless, selection effects on forest carbon storage have also been indicated in part
69 through support for the 'mass-ratio' hypothesis (Ruiz- Benito et al., 2014), which suggests
70 that carbon storage will be mainly determined by the functional traits of the dominant species
71 (Mokany, Ash, Roxburgh, 2008). That is, support for the mass-ratio hypothesis has been
72 indicated by close associations of forest biomass or carbon stocks with community-weighted
73 mean (CWM) trait values for a range of forest types (Adair, Hooper, Paquette, Hungate, 2018;
74 Finegan et al., 2015; Fotis et al., 2018). Indeed, the relative importance of complementarity
75 and selection mechanisms can vary between forest types (Ruiz- Benito et al., 2014),
76 highlighting the need for further BEF studies that encompass an extended range of forest
77 conditions.

78 In addition to plant species/functional diversity and CWM trait values, the structural
79 arrangement of forests provides insights into the mechanisms underpinning relationships
80 between forest carbon storage and biotic factors. In particular, tree 'structural diversity' –
81 represented by measures of tree-size variability (Brassard, Chen, Wang, Duinker, 2008) – has
82 been highlighted in some studies as having a positive association with forest carbon storage
83 (Wang, Lei, Ma, Kneeshaw, Peng, 2011), since high structural complexity of trees can
84 enhance efficient use of resources for growth (Zhang, Chen, 2015). Structural diversity can be
85 related to species or functional diversity since increasing species/functional diversity could
86 lead to the occupation of more spatial niches (Brassard et al., 2008; Zhang, Chen, 2015).
87 However, structural and functional diversity are not always highly correlated since
88 monospecific and species-poor stands can still be structurally diverse through vertical and
89 horizontal differentiation of a limited number of species (Brassard et al., 2008). Similarly,
90 while old-growth forests can be structurally complex (Franklin, 1988), structural diversity
91 might not simply increase with time since disturbance. For example, successional pathways
92 may lead to similar or greater complexity at early- (Donato, Campbell, Franklin, 2012) or
93 mid-seral stages (Brassard et al., 2008). Also, disturbances like non-stand replacing fire may
94 lead to mixed-aged structures comprised of post-fire regeneration and older resprouting
95 cohorts (Bennett et al., 2017).

96 Abiotic factors influence forest carbon storage both directly through effects on
97 processes like growth and decomposition, and indirectly through influences on biotic factors
98 (Adair et al., 2018). Climate, for example, is closely associated with forest net primary

99 productivity worldwide (Luysaert et al., 2007), although this is at least partly due to indirect
100 effects of climate on vegetation age (as influenced by time since last disturbance) and
101 biomass (driven by maximum plant size; (Michaletz, Cheng, Kerkhoff, Enquist, 2014).
102 Relationships between climate and forest productivity vary with the environmental range
103 considered (Luysaert et al., 2007), and climate also influences the relative importance of
104 diversity effects on productivity. For example, tree productivity has been more closely
105 associated with niche complementarity in harsher climates, and with selection effects in more
106 benign climates (Mori, 2018; Paquette, Messier, 2011). However, complementarity effects on
107 forest productivity are not always stronger in more stressful climates (Ruiz- Benito et al.,
108 2014), and selection for particular traits can be important for tree growth in harsh climates
109 (Ratcliffe et al., 2016), although the latter was at least partially attributed to successional
110 shifts in trait variation (see also (Craven, Hall, Berlyn, Ashton, van Breugel, 2018). In terms
111 of forest carbon storage, which is only partly dependent on productivity (Pan et al., 2013),
112 forest biomass (a principal carbon stock) can be closely related to climate variables within
113 geographically-restricted forest types but poorly related at broader continental scales (Stegen
114 et al., 2011). This inconsistency in climate-biomass trends reflects spatially variable
115 relationships among biomass, productivity, and mortality, which are also influenced by the
116 spatial distribution of non-climatic factors including soil, disturbance, and species
117 interactions (Pan et al., 2013).

118 In this study, we examine the relative importance of biotic factors (species and
119 functional diversity, CWM trait values, and structural diversity) and abiotic factors to forest
120 carbon storage in temperate south-eastern Australia, a region that has been overlooked in
121 global analyses of carbon-diversity relations (Duffy, Godwin, Cardinale, 2017). Landscapes
122 of south-eastern Australia encompass considerable biotic and abiotic heterogeneity (Kasel,
123 Bennett, Aponte, Fedrigo, Nitschke, 2017), supporting a range of broadleaf evergreen forests
124 of varying productivity, including some considered to be the most carbon-dense forests in the
125 world (Keith, Mackey, Lindenmayer, 2009). These landscapes are frequently disturbed by
126 fire, which has increased in frequency and extent in recent decades (Fairman,
127 Nitschke, Bennett, 2016) raising concerns about the ongoing productivity and carbon stability
128 of even the most fire-tolerant forests (Bennett et al., 2017). Our data include 14,933 trees and
129 134 species from 732 plots, which we aggregate into six forest types, and two forest groups
130 representing productive and less-productive growth environments. We use structural equation
131 modelling (SEM) as a powerful integrative approach (Grace et al., 2016) to examine the
132 independent effects of multiple biotic factors (species and functional diversity, CWM trait

133 values, structural diversity) on carbon storage, while controlling for relationships among
134 those biotic factors and for both the direct and indirect effects of abiotic factors (climate, soil,
135 fire history). Our hypotheses were: 1. Forest carbon storage increases with species and
136 functional diversity, even when accounting for abiotic factors; 2. CWM trait values and
137 structural diversity have comparable or greater independent effects than species/functional
138 diversity on carbon storage; and 3. That the relative importance of biotic effects on carbon
139 storage varies between growth environments, and, in particular, that species, functional and
140 structural diversity (representing complementarity effects) are more important for carbon
141 storage in the less-productive than productive forest group.

142 **2. METHODS**

143 **2.1 Study area and forest plot data**

144 We used data collected from c. 730 forest plots across Victoria, in south-eastern Australia
145 (Figure 1), which we selected to encompass as wide a geographic range as possible, and to
146 meet two key criteria: that they included only forest (i.e. not shrubland or grassland); and that
147 all trees had been assessed in sufficient detail to calculate carbon stocks and biotic-factor
148 variables (as below). Our plots spanned about 750 km east-west (35.95S to 39.11S), 360 km
149 north-south (141.35E to 149.64E), and 1500 m in altitude (45–1600 m a.s.l.). Mean annual
150 temperature ranged from 6.4 to 14.6 °C, and annual precipitation from 540 to 1960 mm
151 predominantly falling in winter (~30%) and spring (~30%). Forest plots encompassed 22
152 ecological vegetation classes based on classifications by the Victorian State Government
153 Department of Environment, Water, Land and Planning. We grouped those classes into six
154 broad forest types ('Mist', 'Rainforest', 'Damp', 'Montane woodland', 'Foothill', 'Lowland')
155 based on the dominant tree species (mostly Eucalyptus spp.), mapped distributions, and stand
156 structure (Supplementary Table S1), and used climate conditions (precipitation, mean annual
157 temperature) to aggregate these six types into 'Wet' (four types) or 'Dry' (two types) forests,
158 where Wet forests generally represented a more productive environment than our Dry forests.

159 Plots were sampled in five different field campaigns from 2010 to 2015
160 (Supplementary Table S2) and involved a range of plot types from fixed-area plots of 0.1 ha,
161 0.04 ha to variable radius plots (Basal area factor = 4); Supplementary Table S2). At least
162 two plot types were used in each forest type, with the exception of fixed-area plots only in
163 Montane woodland.

164 **2.2 Estimation of above-ground carbon storage**

165 Carbon storage was estimated as carbon stored in the above-ground biomass of all live trees,
166 which represent the principal carbon stocks in these forests and have the greatest carbon
167 sequestration potential (Bennett, Aponte, Baker, Tolhurst, 2014 ; Bennett et al., 2017). Within
168 each plot, live trees were assessed for species, diameter at breast height (DBH, 1.3 m height)
169 and height (Supplementary Table S2; Online extended methods). We calculated above-
170 ground biomass using DBH-based allometric equations that were specific for most eucalypts
171 or generic for less common eucalypts and non-eucalypt species (Supplementary Table S3).
172 We then multiplied tree biomass by average biomass carbon content (50%, (Aponte,
173 Tolhurst, Bennett, 2014), scaled-up to a hectare and summed across all trees at plot level to
174 estimate above-ground carbon storage (Mg ha^{-1}).

175 **2.3 Predictor variables**

176 We initially characterised each plot using 54 potential predictor variables that described
177 biotic factors (species or functional diversity, CWM trait values, structural diversity) and
178 abiotic factors (climate, soil, fire history; Supplementary Table S4). Potential species-
179 diversity indices were based on the number of tree species (species richness, rarefied species
180 richness) and their relative abundance (Shannon and Simpson species diversity indices;
181 (Magurran, 2013). Functional diversity (FD) indices (dispersion, richness, evenness,
182 divergence; (Laliberté, Legendre, 2010; Villéger, Mason, Mouillot, 2008) and community-
183 weighted mean (CWM) trait values were calculated using five functional traits of tree
184 species: maximum height, maximum DBH, wood density, seed mass, and specific leaf area
185 (SLA). CWM trait values (based on relative species abundance as proportional basal area)
186 were calculated for each individual trait, whereas FD indices (based on presence/ absence
187 data) were calculated for all traits together to capture the multidimensional nature of plant
188 functional space (Villéger et al., 2008). Our trait selection was based on the potential to
189 influence tree reproduction, survival, and growth (Reich, 2014), and on evidence from forest
190 BEF studies of trait importance to forest resource partitioning, productivity, and/or carbon
191 storage; examples include: SLA (Craven et al., 2018), maximum DBH (Craven et al., 2018),
192 and combinations of seed mass, maximum height, and wood density (Adair et al., 2018; Fotis
193 et al., 2018; Ruiz- Benito et al., 2014). While linked through allometry, we included both
194 maximum DBH and maximum height in FD indices as representations of potentially different
195 growth forms and horizontal-vertical spatial niches, and on the basis that any (non-trivial)

196 correlation among traits can be considered ‘a relevant aspect of species distribution in
197 functional trait space’ (Villéger et al., 2008). Trait data were compiled from field measures,
198 databases or published sources (as listed for CHM variables; Supplementary Table S4), and,
199 depending on the trait, covered 60–100% of species, which together contributed >96% of the
200 total basal area; missing trait values were filled using values from the nearest-related species
201 of the same genus. Structural diversity indices were based on variability and evenness of tree
202 height and DBH (Supplementary Table S4). Calculations of species and structural diversity
203 were made using the ‘vegan’ R package (Oksanen et al., 2014), calculations of FD and
204 CWM were made using the ‘FD’ R package (Laliberté, Legendre, Shipley, Laliberté, 2014).

205 Potential climate, soil, and fire-history variables (Supplementary Table S4) were
206 collated based on the field-recorded location of each plot centre. Climate data of $\sim 1\text{-km}^2$
207 resolution were obtained from Worldclim (Hijmans, Cameron, Parra, Jones, Jarvis, 2005) and
208 CGIAR (Zomer, Trabucco, Bossio, Verchot, 2008); soil data ($\sim 90\text{-m}^2$ resolution) were
209 obtained from CSIRO Data Collection (Viscarra Rossel et al., 2014); and fire-history data
210 were obtained from DELWP (DELWP, 2014).

211 An initial assessment of predictor variables based on correlation analyses and
212 principal component analysis (PCA) among variables in the same biotic or abiotic group was
213 used to identify variables that were redundant (correlated with other predictors in the same
214 group, $r \geq |0.7|$) and/or not significantly related to the response variable, carbon storage.
215 These variables were excluded from subsequent analyses (see Supplementary Table S4). To
216 reduce the number and collinearity of soil variables, the first PCA axis, rather than individual
217 soil variables, was retained for further analysis because it explained 58% of soil data
218 variability (collectively representing a gradient of increasing soil nutrient availability, clay
219 content, and water retention capacity), and was more strongly correlated with carbon storage
220 than any single soil variable. The final selected predictors of carbon storage included: Species
221 richness (S), Functional dispersion (F_{dis}), CWM of maximum height (CWM_{MAXH}), CWM of
222 specific leaf area (CWM_{SLA}), CWM of wood density (CWM_{WD}), Shannon structural diversity
223 index (H'), Mean annual temperature (MAT, °C), Soil PCA (SOIL_{PCA}), and Time-since-last
224 wildfire (TSLWF, years).

225 2.4 Statistical analyses

226 We examined relationships of carbon storage (as above-ground carbon stocks in live trees per
227 plot) with plot-level estimates of the nine selected predictor variables using bivariate

228 relationships with each predictor, and structural equation models (SEMs) that integrated
229 multiple predictors. To examine consistency of relationships across growth environments and
230 environmental ranges, we implemented all statistical analyses at three levels of plot
231 aggregation: forest type (n=6), Wet and Dry forests, and Temperate forest (all data pooled).
232 To adhere to assumptions of data normality and homoscedasticity, both carbon storage and S
233 were square-root transformed, and TSLWF was $\log_{10}+1$ transformed, prior to statistical
234 analyses. All non-transformed and transformed predictor variables were standardised (by
235 subtracting the variable's mean and dividing by the standard deviation) prior to bivariate
236 analyses and SEM development.

237 We examined bivariate linear and non-linear (quadratic) relationships of carbon
238 storage with predictors to elucidate the form of these relationships, and to ensure that they
239 were adequately captured in the SEMs (below). Bivariate relationships were run as mixed
240 models using the 'nmlme' R package (Pinheiro, Bates, DebRoy, Sarkar, R-core Team, 2019),
241 with plot type (i.e. large plot, 0.1 ha; small plot, 0.04 ha; and variable radius plot BAF4) as a
242 random effect. The relative strength of a predictor's relationship with carbon storage was
243 assessed using the standardized coefficients (β , the higher the value the stronger the
244 relationship), and the change in the Akaike Information Criteria (ΔAIC). Heterogeneity in
245 plot size can influence estimates of diversity and carbon storage (Rosenzweig, 1995). We
246 found no significant relationships between plot type and diversity metrics and carbon storage.
247 Plot type was included in the mixed models, but it had not influence on the strength of
248 predictor relationships with carbon storage. A separate analysis (data not shown) using
249 boosted tree regression showed negligible influence of plot type on our results ($< 1\%$ relative
250 to other predictors) (Zhang, Chen, 2015).

251 We used SEMs as an integrative approach (Grace et al., 2016) to examine the
252 independent effects of each biotic factor on carbon storage. Our SEM schematic (Figure 2)
253 reflects our main hypotheses; for example, that species or functional diversity would have a
254 significant independent effect on carbon storage even when accounting for the direct and
255 indirect effects of abiotic factors and the direct effects of other biotic factors. Note that while
256 correlations among biotic factors included in SEMs were weak ($r \leq 0.4$, Supplementary Table
257 5) and their covariance was accounted for in the SEMs they are not considered further
258 because our focus was on comparing the independent effect of each biotic factor on carbon
259 storage (after (Adair et al., 2018; Poorter et al., 2017)). We built on a previous conceptual
260 SEM for biomass stocks in neotropical forests (Poorter et al., 2017) by including H', as a test
261 of the independent effects of structural diversity, rather than basal area, which might have

262 been trivially related to tree-biomass carbon since both were derived from DBH. A separate
263 analysis on the relationships between H' , basal area and tree-biomass carbon showed that the
264 three variables tended to covariate ($r \sim 0.5$) but confirmed the independent effect of structural
265 diversity on tree carbon when accounting for basal area (Online extended methods). At each
266 level of data aggregation, we considered six possible SEMs, which were the result of
267 combining each of two variables representing species or functional diversity (S or F_{dis}), with
268 each of three CWM trait values (CWM_{SLA} or CWM_{MAXH} or CWM_{WD}), and a fixed set of
269 variables to represent structural diversity (H'), and abiotic factors (MAT , $SOIL_{PCA}$, $TSLWF$).
270 MAT was included as a composite variable (“ $MAT+MAT^2$ ”) to account for its unimodal
271 relationship with carbon storage (as indicated by the above bivariate analyses). All SEMs
272 were developed using the lavaan R package (Rosseel, 2012), with models compared using
273 ΔAIC , AIC weights (normalized model relative likelihoods, which can be directly interpreted
274 as conditional probabilities for each model), and the comparative fit index (CFI), which
275 provides an indication of the relative improvement in fit of a given SEM over an
276 (implausible) baseline model, which assumes all variables are non-correlated ($CFI > \sim 0.9$
277 indicating good fit; (Rosseel, 2012)).

278 3. RESULTS

279 3.1 Carbon stocks and forest environment

280 Mean carbon storage was greater in Wet (178 Mg C ha^{-1}) than Dry (109 Mg C ha^{-1}) forests
281 (Supplementary Table S6), with trends in carbon stores by forest type reflecting those in
282 basal area and tree density (Figure 3). Dry forests were on average 30% drier and two degrees
283 warmer than Wet forests, with Lowland forest being the driest ($MAP = 943 \text{ mm}$) and
284 Montane woodland being the coldest ($MAT = 8.1 \text{ }^\circ\text{C}$; Figure 3). Species diversity (S) was on
285 average lower in Dry than Wet forests, although mean S was low (2 to 5) irrespective of
286 forest type (overall range 1 to 14; Supplementary Table S6). The two broad forest groups
287 encompassed similar ranges in most other biotic variables (Figure 3; Supplementary Table
288 S6).

289 3.2 Bivariate relationships

290 Carbon storage was most strongly related to structural diversity (H') in all cases (as evidenced
291 by greater β and ΔAIC ; Table 1; Figure 4). Carbon storage was also consistently related to
292 CWM trait values, although the strength and direction of the CWM relationships varied

293 across forest types and levels of data aggregation. Carbon storage increased with CWM_{MAXH}
294 and decreased with CWM_{WD} for all forest types (except Montane woodland) and all levels of
295 aggregation. However, while carbon storage was positively related to CWM_{SLA} in Wet forests
296 and most component forest types, it was not in Dry forests. In contrast to biotic variables,
297 relationships of carbon storage with abiotic variables (climate, soil, fire history) at the forest-
298 type level were inconsistent and relatively weak, particularly for those forest types with fewer
299 than 50 plots (Rainforest, Montane Woodland; Table 1). Abiotic relationships with carbon
300 storage were stronger at the higher levels of data aggregation (Temperate forests, Wet and
301 Dry forest), but their predictive capacity (as indicated by ΔAIC) was always lower than the
302 best biotic predictors (H' , CWM_{MAXH} ; Table 1).

303 **3.3 Structural equation models: direct and indirect effects on carbon storage**

304 All models had a better fit than the baseline model ($CFI \geq 0.9$) and explained variation in
305 carbon storage that ranged from $R^2_{carbon} = 0.20$ in the Foothill forest to $R^2_{carbon} = 0.50$ in
306 Montane woodland (Supplementary Table S7). The best models explained close to 40% of
307 the variance in carbon storage in Temperate forests (i.e. all data pooled) and Wet forests, and
308 22% in Dry forests (Supplementary Table S7).

309 Forest carbon storage increased with either species or functional diversity in SEMs at
310 the highest level of data aggregation (Temperate Forest, Wet or Dry forests) and for most
311 forest types with the exception of Foothill forest, and the two forests that had fewer than 50
312 plots (Rainforest, Montane woodland; Figures 5 and 6; Supplementary Table S8). Overall,
313 the strength of species and functional diversity effects on carbon storage in Wet and Dry
314 forests was comparable, if less consistent in Dry forests (no effect of F_{dis}). Among the biotic
315 factors, structural diversity (H') had consistently the greatest independent effect on carbon
316 storage, comparatively stronger than that of species or functional diversity, CWM trait
317 values, and both the direct and indirect effects of abiotic factors (Figures 5 and 6;
318 Supplementary Table S8, S9). CWM_{MAXH} and CWM_{WD} (but not CWM_{SLA}) were also
319 significant predictors of carbon storage at the highest levels of data aggregation and across
320 most forest types (particularly Rainforest), although the CWM-trait effects were mostly
321 weaker (lower β coefficients) than those of structural diversity (Supplementary Table S8, S9).

322 Direct effects of abiotic variables relating to climate (MAT), soil ($SOIL_{PCA}$) and fire
323 history (TSLWF) were weak compared with biotic factors, and were all non-significant in
324 Wet-forests SEMs (Figures 5 and 6). Interestingly, the indirect effects of abiotic variables

325 were more pronounced than direct effects in most SEMs irrespective of the level of data
326 aggregation, although the strength of indirect effects varied markedly among forest types
327 (Figure 6). The indirect effects of SOIL_{PCA} were comparatively stronger (β coefficients >0.3)
328 than MAT or TSLWF effects for the full Temperate forest data (strongest effects on S, F_{dis},
329 H', and all CWM trait values), and for Dry forests (strongest effects on H', and all CWM trait
330 values), whereas the indirect effects of MAT on all types of biotic variables were similar if
331 not stronger than those of SOIL_{PCA} for Wet forests (Figure 5 and 6, Supplementary Table S8).
332 Indirect effects of TSLWF were comparatively weak or non-significant, and the majority of
333 abiotic effects on biotic variables were positive (with notable exceptions being negative MAT
334 effects on H' and CWM_{MAXH} in Dry forests; Supplementary Table S8).

335 4. DISCUSSION

336 4.1 Carbon storage more strongly associated with structural diversity than species or 337 functional diversity

338 Consistent with forest studies elsewhere (Huang et al., 2018; Ruiz- Benito et al., 2014), we
339 found some support for our first hypothesis that forest carbon storage increased with tree-
340 species diversity and functional diversity. However, while our species- and functional-
341 diversity relationships with forest carbon storage were of comparable strength to those in
342 other SEM-based analyses (β coefficients ~ 0.2 ; (Poorter et al., 2015; Poorter et al., 2017)),
343 they were relatively weak at all levels of data aggregation compared to those with our other
344 biotic variables (H', CWM_{MAXH}, CWM_{WD}). We anticipated strong diversity effects on carbon
345 storage in our forests given generally low tree-species numbers (range 1 to 14), since the
346 largest changes in forest carbon storage can occur at low levels of functional diversity
347 (Ruiz- Benito et al., 2014) where each additional species can still influence niche
348 complementarity effects (Poorter et al., 2015). However, diversity effects on carbon storage
349 can be weak in species-poor forests where strong environmental filtering leads to a small
350 number of species (van der Sande et al., 2018), which is consistent with indications in our
351 data of stronger associations of species- and functional-diversity indices with abiotic factors
352 (as indirect effects) than with carbon storage itself.

353 Between the diversity indices, structural diversity consistently had the strongest
354 relationships with carbon storage irrespective of the level of data aggregation. This is
355 consistent with results for boreal forests (Zhang, Chen, 2015) where a measure of structural
356 diversity, the coefficient of variation of tree DBH, had greater effects on above-ground

357 biomass than species diversity. Structural diversity as measured in our study (H') accounts for
358 the number and evenness of canopy layers and DBH size classes (Staudhammer, LeMay,
359 2001) and was moderately correlated ($r=0.5$) with basal area. Greater structural diversity
360 implies a complex canopy structure that optimises canopy packing and aboveground light
361 capture within a site (Parker et al., 2004) thereby increasing the potential for productivity and
362 carbon storage (Wang et al., 2011; Yachi, Loreau, 2007; Zhang, Chen, 2015). This suggests
363 that carbon storage in our temperate forests was underpinned by efficient utilisation of space
364 by a limited number of tree species more so than by diversity in species or species functional
365 traits. That is, while at least part of the structural-diversity effect on carbon storage in our
366 study could be associated with tree-species diversity – since more efficient space occupation
367 of mixed than mono-specific forests can contribute to greater productivity (Pretzsch et al.,
368 2015) – the strong independent effect of H' , as well as relatively weak overall correlations of
369 H' with species diversity (r 0.4) and functional dispersion (r 0.3), indicate that structural
370 diversity in its own right was a principal biotic mechanism of carbon storage. Indeed, that H'
371 effects on carbon storage were relatively strong irrespective of forest type or growth
372 environment suggests that structural diversity would be a robust indicator of carbon storage
373 in the temperate forests of southern Australia.

374 **4.2 Carbon storage also associated with CWM trait values**

375 CWM trait values were also relatively strong predictors of carbon storage in many of our
376 forest types and in both growth environments, suggesting that the identity of the community
377 and the species within (i.e. their trait values and therefore functional strategy) are important
378 determinants of forest carbon stores (Prado- Junior et al., 2016). This finding provides
379 support for the ‘mass-ratio hypothesis’, where the ecosystem processes underpinning above-
380 ground carbon stores are determined by the functional traits of the dominant species.
381 Consistent with other studies across a range of forest types (Adair et al., 2018; Finegan et al.,
382 2015; Ruiz- Benito et al., 2014), the stronger associations of CWM trait values than species-
383 or functional-diversity indices with carbon storage also provides evidence of a stronger role
384 for selection effects than niche complementarity effects in our forests.

385 We included three functional identity traits that relate to species acquisition strategies
386 in our analyses: a whole-plant trait (maximum height), a foliar trait (SLA), and a stem trait
387 (wood density). CWMs of maximum height and wood density were more strongly related to
388 carbon storage than CWM_{SLA} , which was a non-significant predictor in all SEMs. Species

389 maximum height is often positively related to species productivity and of greatest importance
390 at the extremes of the productivity gradient (Ratcliffe et al., 2016). Similarly, species with
391 lower wood density are also considered fast-growing acquisitive species as they generally
392 have higher stem hydraulic conductivity and photosynthetic carbon gain and lower
393 construction cost per wood volume (Chave et al., 2009). Consistent with the mass-ratio
394 hypothesis, forests dominated by highly productive species have the potential to support the
395 greatest amount of carbon, although this is not a limitless possibility because fast-growing
396 trees with lower wood density might also have higher turnover through mortality (Pan et al.,
397 2013). We might expect CWM_{MAXH} and structural diversity to be related, as higher canopies
398 would allow for a greater number of canopy layers. However, the two variables were only
399 weakly correlated (r 0.3) and both emerged as significant predictors, indicating that their
400 effects on forest carbon storage were somewhat independent.

401 Bivariate analyses showed some significant relationships between CWM_{SLA} and
402 carbon storage (for Temperate forests and Mist forest) but we found no significant
403 relationships in the multivariate SEM analyses. This suggests that CWM_{SLA} bivariate
404 relationships with carbon storage reflected covariation with other predictor variables, but that
405 the independent effects of SLA on carbon storage were weak. This contrasts with results from
406 cold deciduous to xeric evergreen forests in Spain, where CWM_{SLA} was a better predictor of
407 tree productivity and carbon stores than CWMs of maximum height, wood density, seed
408 mass, and leaf nitrogen content (Ruiz- Benito et al., 2014). Our study included a
409 comparatively small range in CWM_{SLA} values, which was probably due to the dominance of
410 all forest types (except Rainforest) by eucalypt species.

411 **4.3 Abiotic factors indirectly influence above-ground carbon storage**

412 With few exceptions, our SEM analyses indicated that the indirect effects of abiotic factors
413 on carbon storage via biotic factors were greater than their direct effects at all levels of data
414 aggregation. Moreover, while bivariate relationships of carbon storage with abiotic variables
415 were strongest at the broadest environmental range (i.e. all data combined), these
416 relationships were weak compared to those with most biotic factors. Thus, the principal
417 importance of climate and soils to above-ground carbon stocks in other broad-scale forest
418 studies (Adair et al., 2018; Poorter et al., 2015; van der Sande et al., 2018) were not clearly
419 evident in our temperate forests. Similarly, carbon storage in our forests was not clearly
420 related to fire history, despite its prominence as a disturbance in the fire-prone landscapes of

421 south-eastern Australia. This could in part be due to the crudeness of available fire-history
422 variables like time-since-last-wildfire (Kasel et al., 2017), particularly given the diverse range
423 of potential fire effects on tree recovery in eucalypt-dominated forests from full stand
424 replacement to variable mixtures of post-fire seedlings with resprouting established trees
425 (Fairman et al., 2016).

426 Our study suggests that structural diversity and, to a lesser degree, CWM trait values
427 were relevant to carbon storage in all of our forests irrespective of their growth environments.
428 That is, the consistent relative influences of biotic factors (strongest for H' and CWM trait
429 values, minimal for species and functional diversity) on carbon storage across our Wet and
430 Dry forests provided little support for our third hypothesis that biotic-factor effects would
431 vary between growth environments. Indeed, indirect effects of climate on biotic factors were
432 strongest in our more benign growth environment (Wet forests), which seems at odds with
433 general understanding of increasing modulation of biotic effects on forest functioning with
434 increasing climatic harshness (Ratcliffe et al., 2017). Nonetheless, environmental filtering
435 was still suggested for our Dry forests both in significant (albeit weaker) effects of MAT and
436 often stronger effects of Soil_{PCA} on multiple biotic variables particularly H' and CWM trait
437 values. In the absence of clear bivariate relationships, our study highlights the importance of
438 using an integrative approach like structural equation modelling (Grace et al., 2016) to
439 disentangle the many ways that abiotic and biotic factors can influence carbon storage in
440 forests.

441 5. CONCLUSIONS

442 Our study highlights complex relationships of above-ground carbon storage with biotic and
443 abiotic factors in Australia's temperate forests. Consistent with our first hypothesis, carbon
444 storage increased with species and functional diversity, even when accounting for abiotic
445 factors. Nonetheless, in relation to our second hypothesis, diversity effects on carbon storage
446 were weaker than those of structural diversity (in particular) and CWM trait values for all
447 forest types and at all levels of data aggregation. In addition, contrary to our third hypothesis,
448 biotic-factor effects were relatively consistent among forest types and levels of data
449 aggregation and were not more important for carbon storage in the less-productive than
450 productive growth environment. Direct relationships of carbon storage with abiotic factors
451 were comparatively weaker than biotic factors, but stronger indirect effects indicated
452 influence of climate and soil on carbon storage via effects on multiple biotic variables.

453 Our study had various limitations that might have influenced the strength of our
454 carbon-storage relationships including fewer plots (<50) in two forest types, and imprecise
455 climate, soil, and fire variables. Nonetheless, it is the first study to comprehensively assess
456 BEF relationships across a range of forest types in temperate Australia. Our study's relevance
457 extends beyond the testing of ecological theory to implications for forest management. Our
458 results indicate that maintaining and increasing structural diversity as well as maintaining
459 functionally important species would enhance forest above-ground carbon storage. They also
460 highlight indirect effects of abiotic factors on carbon storage via biotic pathways, raising the
461 importance of understanding biotic-abiotic interactions in temperate forests under changing
462 climate and disturbance regimes (Millar,Stephenson, 2015). Fostering the natural structural
463 complexity and composition of these forests would maintain and enhance their carbon storage
464 capacity.

465

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- 619

Tables

Table 1. Bivariate relationships of above-ground carbon storage with selected abiotic and biotic predictor variables at three levels of plot aggregation (plot numbers indicated in brackets). Relationships were modeled using linear or quadratic mixed models with plot size included as a random variable. Variables were centered and scaled prior to analysis. Values are standardized coefficients (β) and AIC differences to the null model (Δ AIC). Standardized coefficients can directly be compared; the higher the value, the stronger the relationship (strongest relationships in bold). Greater Δ AIC indicates greater predictive capacity. Significance level refers to β coefficients (as indicated by mixed models): *** P <0.001, ** P <0.01, * P <0.05, • P <0.1. For the MAT quadratic model (indicated by Q), maximum p-value between linear and quadratic coefficient is presented. Acronyms as per Figure 3 caption.

Predictor	Temperate forests (732)		Wet forests (280)		Dry forests (452)		Wet forest types						Dry forest types					
	β	Δ AIC	β	Δ AIC	β	Δ AIC	Mist forest (102)		Rainforest (40)		Damp forest (90)		Montane woodland (48)		Foothill forest (228)		Lowland forest (224)	
							β	Δ AIC	β	Δ AIC	β	Δ AIC	β	Δ AIC	β	Δ AIC	β	Δ AIC
Abiotic																		
MAT (Q)	-0.9 ***	90	-1.3 ***	54	0.2	25	-0.9 **	8	0.1	-3	-1.4 ***	8	-0.7	9	-0	-1	0.3	11
MAP	1.2 ***	82	0.7	3	0.5 **	3	-0.1	-1	0.2	1	1.3 **	6	-1.5	4	-0.4 •	0	1.2 ***	12
SOIL _{PCA}	-1.3 ***	97	-0.9 **	7	-0.7 ***	11	-0.3	-1	-2.4	3	1.4 **	7	-2.1 **	9	-0.1	-3	1.2 ***	13
TSLWF	0.4 ***	7	1.3 ***	18	0.4 ***	9	1.1	4	1.1	2	0.4	-1	1.4 •	3	0.7 ***	27	0.1	-3
Biotic																		
S	1.4 ***	129	1.4 ***	49	0.6 ***	15	1.7 ***	21	0.1	-1	0.4	-1	2.7 ***	19	0.3 •	0	0.8 ***	9
F _{dis}	1.4 ***	120	1.6 ***	46	0.4 **	5	1.2 **	6	-1.4 •	2	1.4 ***	12	1.7 **	7	0.1	-3	0.6	3
CWM _{MAXH}	1.7 ***	165	1.6 ***	56	1.1 ***	48	1.5 ***	18	1.8 ***	14	1.7 ***	19	1.4	5	0.9 ***	8	1.2 ***	24
CWM _{SLA}	1.3 ***	76	1.2 ***	32	0.3 •	-1	0.7 **	0	-0.1	-3	0.8 *	3	1.6 *	4	0.2	-3	0.1	-3

CWM _{WD}	-1.1 ***	-67	-0.9 ***	12	-0.8 ***	23	-1.5 ***	18	-0.5 ***	11	-0.9 *	3	2.1 **	6	-0.7 *	1	-0.6 ***	9
H'	2.1 ***	281	2.5 ***	132	1.2 ***	79	2.4 ***	49	2.4 ***	8	1.7 ***	24	2.8 ***	32	0.9 ***	26	1.4 ***	41

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Figure legends

Figure 1. Location of forest plots in the state of Victoria, south-eastern Australia.

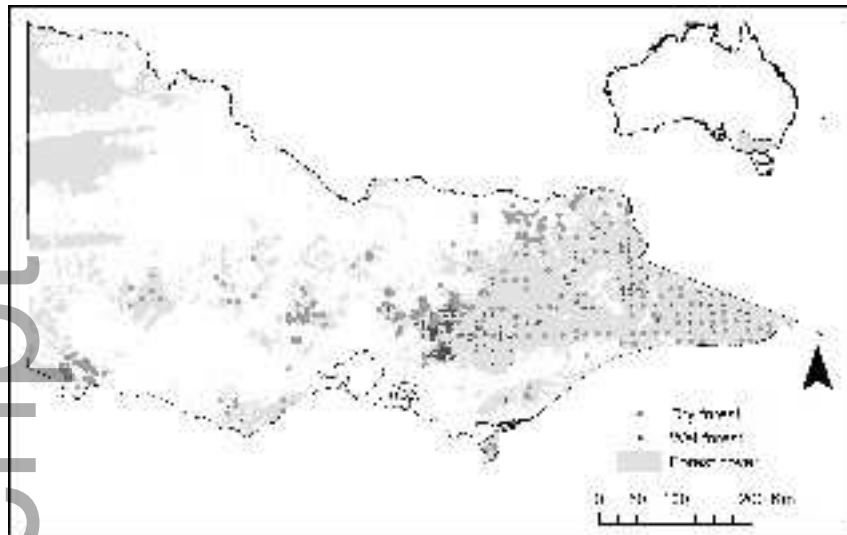
Figure 2. Conceptual diagram of hypothesised relationships of above-ground carbon storage with biotic factors (species or functional diversity, CWM traits, structural diversity), and abiotic factors (climate, soil, fire history). Black lines indicate direct effects whereas dotted lines indicate indirect effect of abiotic factors on carbon storage via influence on biotic factors.

Figure 3. Notched boxplots of key attributes of the study's six forest types. Medians are significantly different where notches (95% CI of the median) do not overlap. Acronyms: MAT: Mean annual temperature, MAP: Mean annual precipitation, TSLWF: time since last wildfire, S: species richness, H': structural diversity, F_{dis} : functional dispersion, CWM_{MAXH} : community weighted mean of maximum height, CWM_{SLA} : community weighted mean of specific leaf area, CWM_{WD} : community weighted mean of wood density. Light shading represents Dry forest types and darker shading represents Wet forest types.

Figure 4. Relationships of above-ground carbon storage with abiotic and biotic predictor variables for Dry forests (light grey circles, dotted line) and Wet forests (dark grey triangles, dashed line). Acronyms as per Figure 3. The relative strength of the relationships is summarised in Table 1.

Figure 5. Example SEMs for Temperate forest (all pooled data), Wet forests and Dry forests. Numbers indicate standardized β coefficients. Line width is proportional to the coefficient. Solid lines indicate direct effects whereas dotted lines indicate indirect effects of abiotic variables ($MAT^2 + MAT$, $Soil_{PCA}$, TSLWF) on carbon storage via influence on biotic variables (F_{dis} , H', CWM_{MAXH}). Grey lines indicate coefficients that were not significant (ns). Acronyms as per Figure 3.

Figure 6. Direct (dark grey) and indirect (light grey) effects of predictor variables on above-ground carbon storage in the SEM. Variables were scaled and centred prior to analysis. Direct effects are model standardized coefficients (i.e. are directly comparable, the higher the value the stronger the effect). Indirect effects are calculated by multiplying the standardized coefficients of all paths on one route between the variable and carbon storage. Bars show model-weighted averaged (using AICw) standardized coefficients with error bars showing standard errors. Only significant coefficients ($P < 0.05$) are shown. Acronyms as per Fig. 3.



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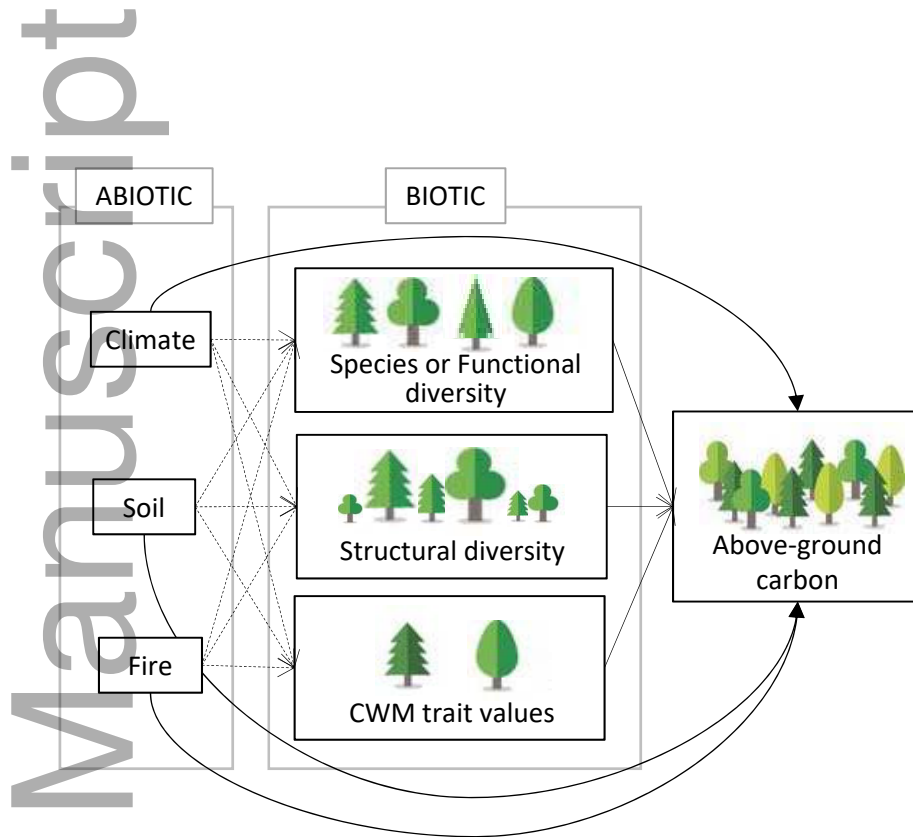


Figure 2. Conceptual diagram of hypothesised relationships of above-ground carbon storage with biotic factors (species or functional diversity, structural diversity, CWM trait values), and abiotic factors (climate, soil, fire history). Black lines indicate direct effects whereas dotted lines indicate indirect effect of abiotic factors on carbon storage via influence on biotic factors.

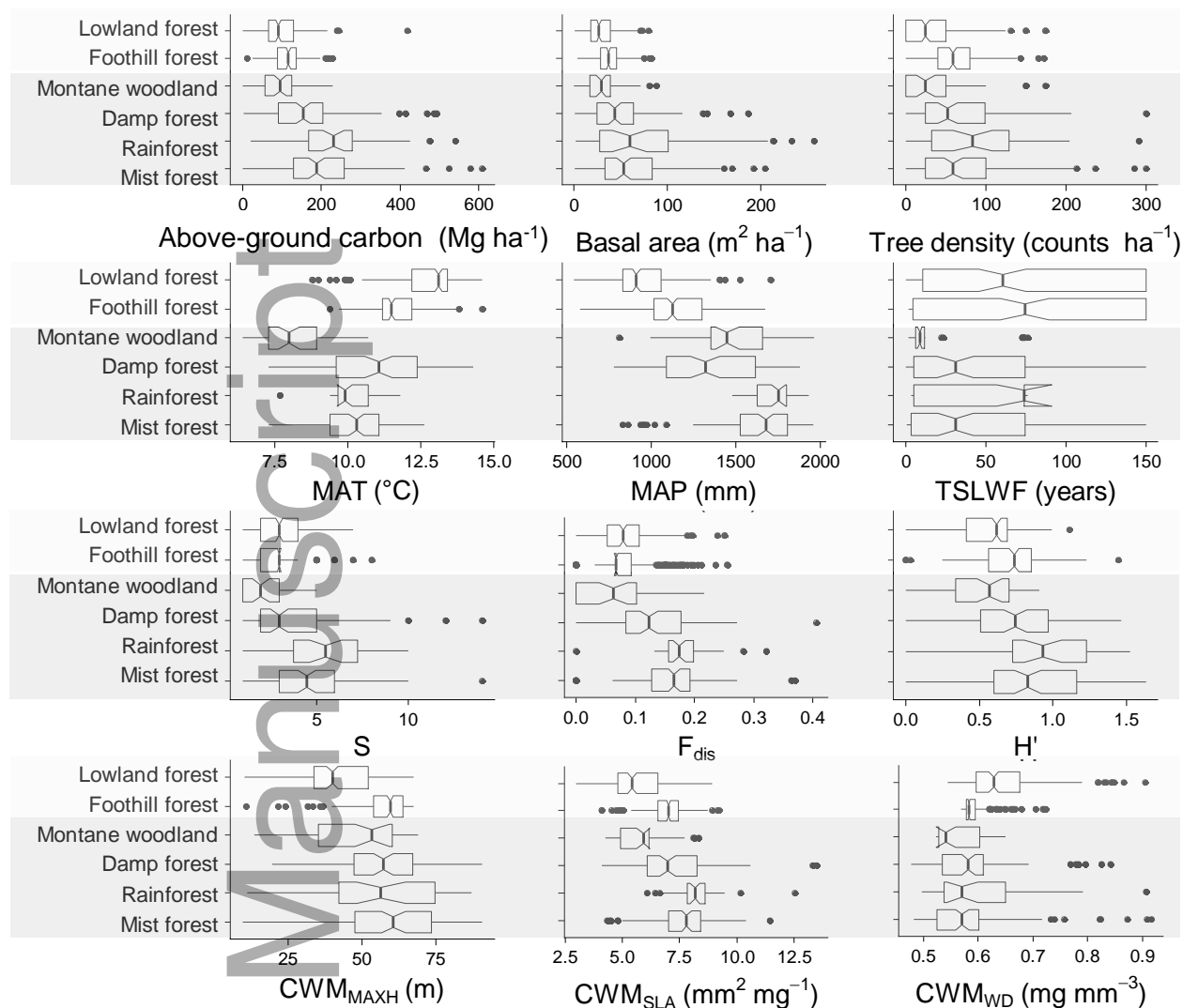


Figure 3. Notched boxplots of key attributes of the study's six forest types. Medians are significantly different where notches (95% CI of the median) do not overlap. Acronyms: MAT: Mean annual temperature, MAP: Mean annual precipitation, TSLWF: time since last wildfire, S: species richness, H' : structural diversity, F_{dis} : functional dispersion, CWM_{MAXH} : community weighted mean of maximum height, CWM_{SLA} : community weighted mean of specific leaf area, CWM_{WD} : community weighted mean of wood density. Light shading represents dry forest types and darker shading represents wet forest types.

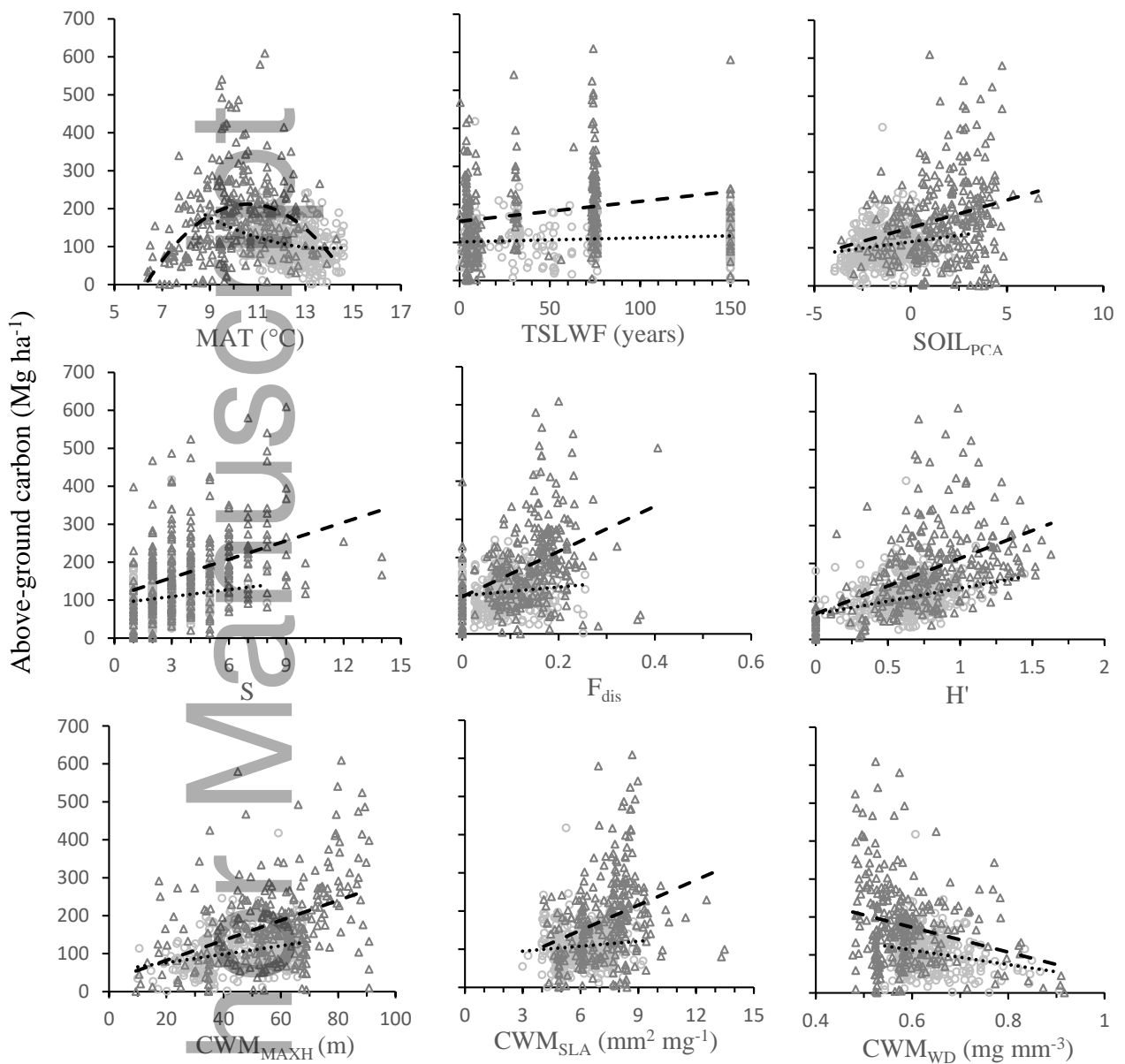
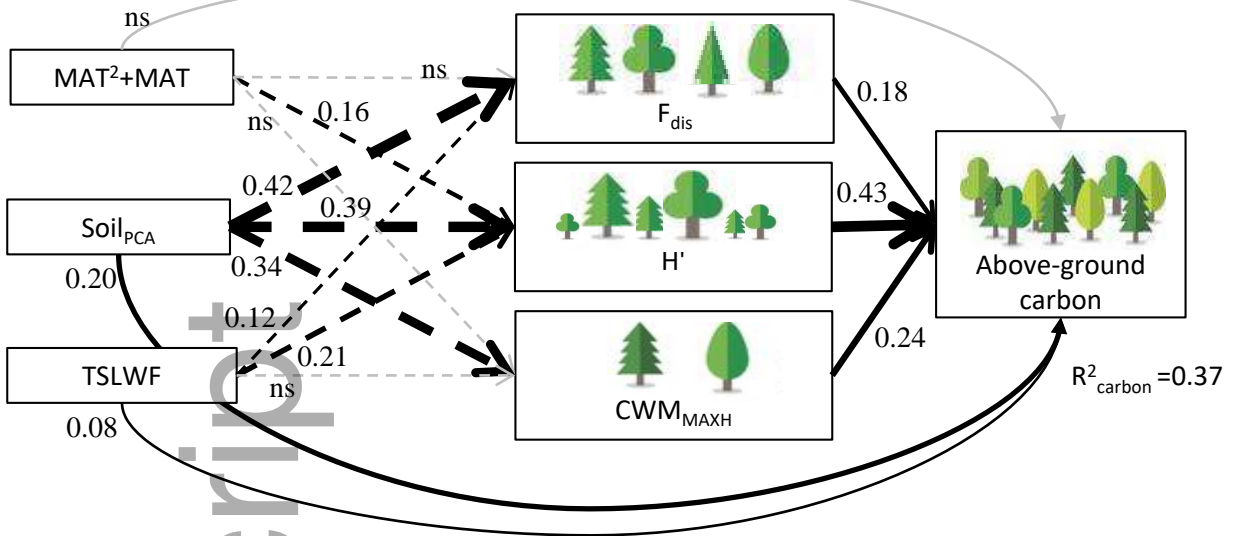
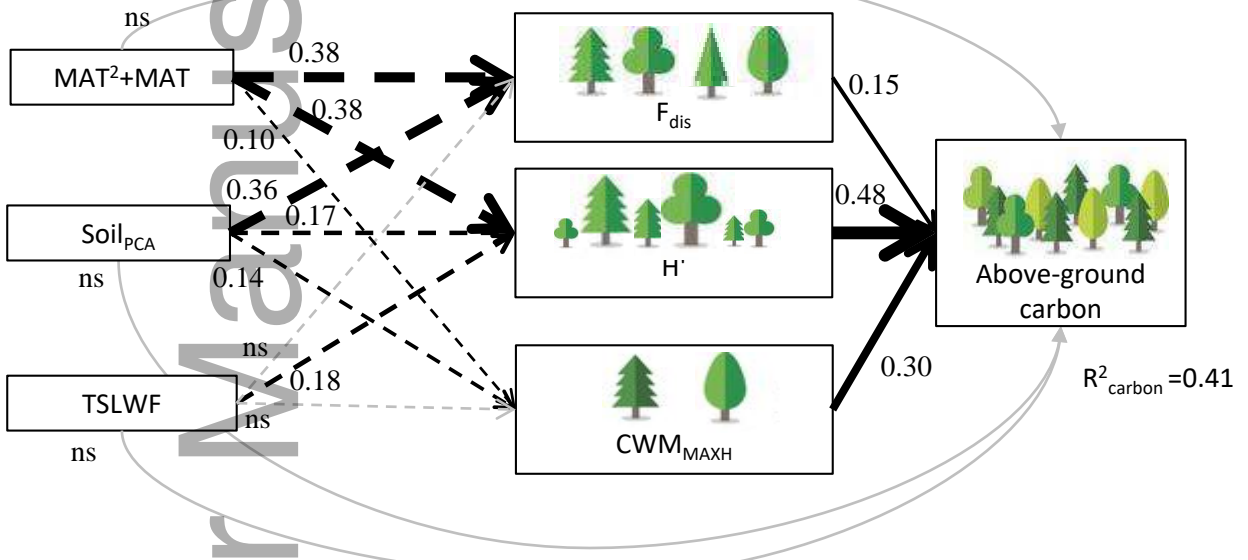


Figure 4. Relationships between above-ground carbon storage and environmental, diversity and identity predictor variables for Dry forests (light grey circles, dotted line) and Wet forests (dark grey triangles, dashed line). Acronyms as per Figure 3.

Temperate forests



Wet forests



Dry forests

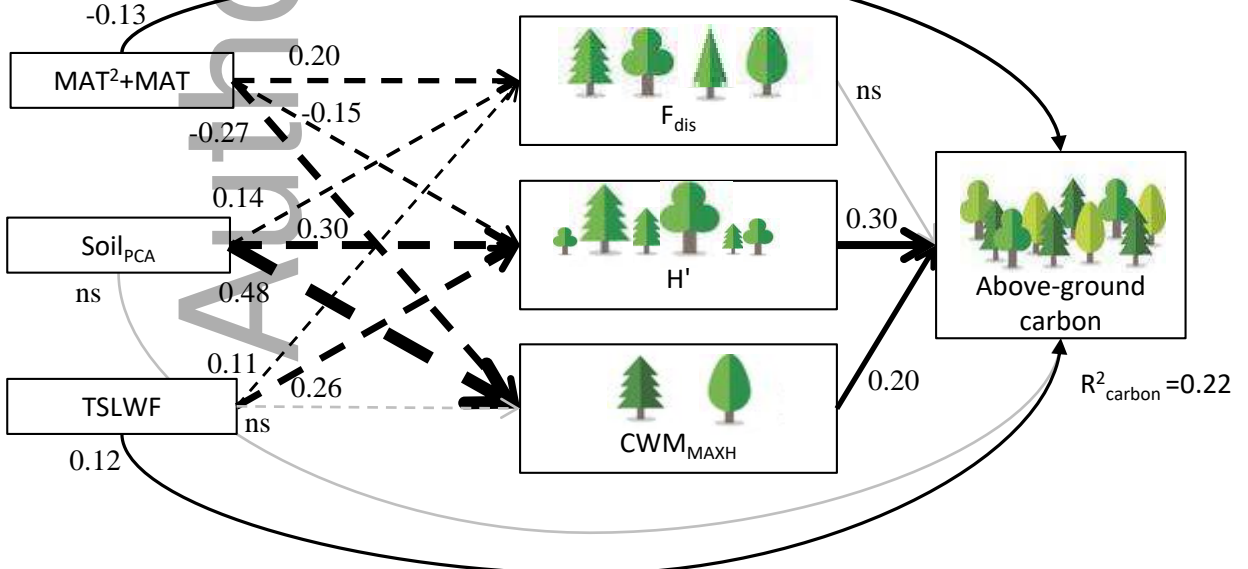


Figure 5. Results of a subset of the SEM for Temperate forest (all pooled data), Wet forest and Dry forest. Numbers indicate standardized path coefficients. Line width is proportional to the coefficient. Solid lines indicate direct effects whereas dotted lines indicate indirect effects of environmental variables on aboveground carbon storage via influence on diversity and identity. Acronyms as per Figure 3.

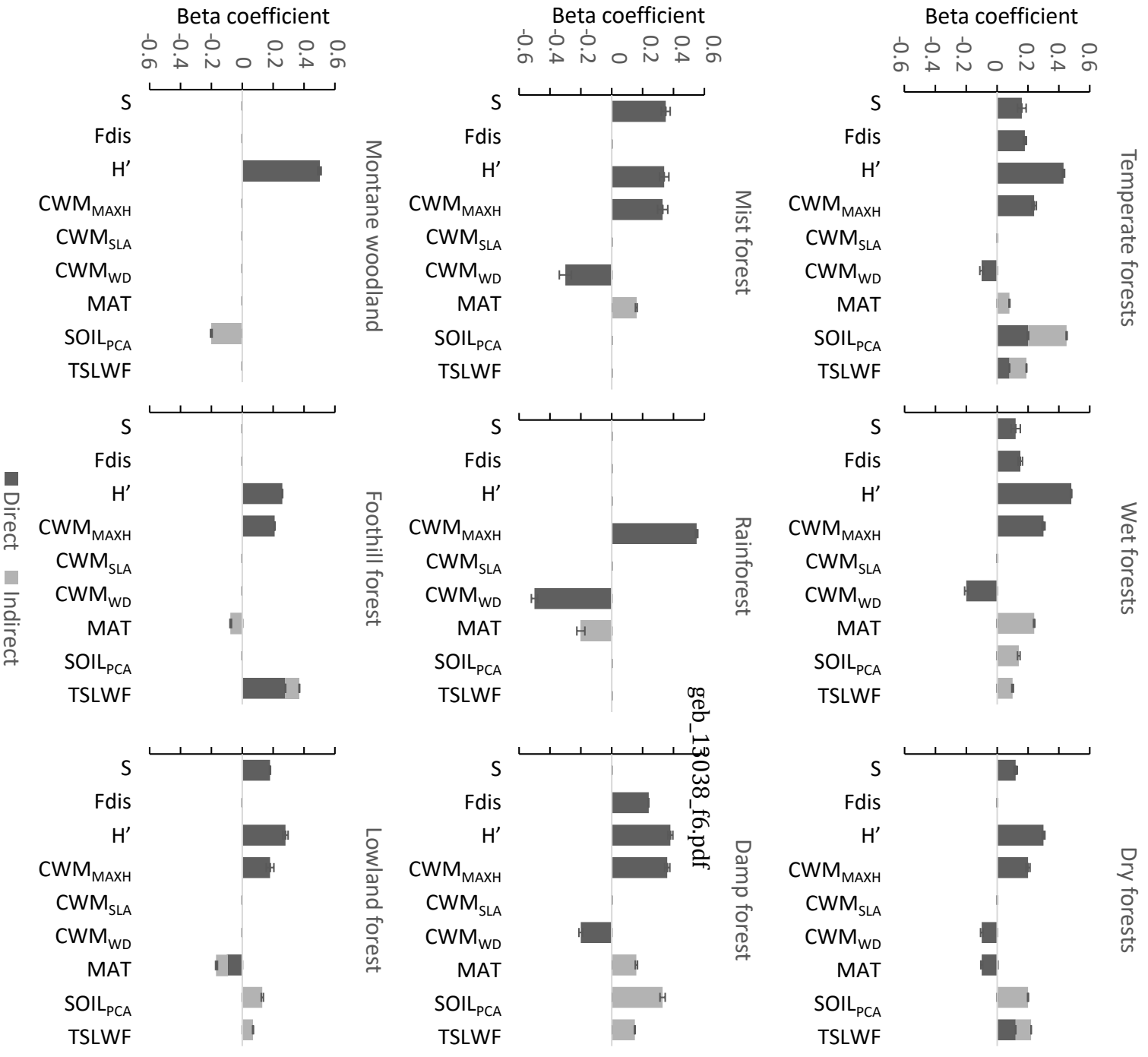


Figure 6. Direct (dark grey) and indirect (light grey) effects of predictor variables on above-ground carbon storage in the SEM. Variables were scaled and centred prior to analysis. Direct effects are model standardized coefficients. Indirect effects are calculated by multiplying the standardized coefficients of all paths on one route between the variable and carbon storage. Bars show model-weighted averaged (using AICw) standardized coefficients with error bars showing standard errors. Only significant coefficients ($P < 0.05$) are shown. Acronyms as per Fig. 3.