

Fungal succession in decomposing woody debris across a tropical forest disturbance gradient: A field experiment

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Keywords: Bulong nature reserve, carbon cycle, coarse woody debris, decomposition, fungi, landscape, Mengsong, wood density

Posted Date: March 13th, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-17149/v1>

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1 **Title of the manuscript:**
2 Fungal succession in decomposing woody debris across a tropical forest disturbance gradient: A
3 field experiment.

4

5 **Running title:** Tropical fungal diversity community dynamic in wood decay

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32 **Conflict of Interest**

33 None

34

35 **Competing Interests**

36 The authors declare no competing financial interests

37

38 **Abstract**

39

40 **Background**

41 Fungi are essential agents in decomposing woody debris (WD), an important carbon pool in forests.
42 However, the ecology and dynamics of these fungal communities are poorly understood, especially
43 in tropical forests. A better understanding of anthropogenic impacts, such as forest disturbances, on
44 WD decomposition is also needed to appreciate their consequences on ecosystem functioning. Here,
45 we examined the impacts of forest degradation and roles of fungal diversity and composition on
46 WD decomposition rates across a disturbance gradient in a tropical montane rain forest in
47 Xishuangbanna, SW China over three years. We measured wood specific gravity (WSG) loss from
48 280 logs from *Litsea cubeba* (low-WSG) and *Castanopsis mekongensis* (high-WSG). We
49 concomitantly monitored fungal communities from 418 samples using next-generation sequencing
50 after 0, 18 and 36 months field exposure.

51 **Results**

52 Incubation time, habitat and termite presence were key drivers of fungal community composition.
53 Fungal community succession showed a priority effect of precedent communities. *C. mekongensis*
54 WD consistently harbored ~1.4 times less fungal species than *L. cubeba*, but had ~1.4 times more
55 unique operational taxonomic unit (OTU) at 18 mo. Shared OTUs between wood species increased
56 with time up to ~63 % at 36 mo. Regardless of wood species, fungal diversity and both saprotrophs
57 and white-rot abundances peaked at 18 months. However, fungal diversity was not a significant
58 predictor of WSG loss. WSG loss did not vary among habitats. This may result from compensatory
59 changes in dominant functional traits, such as decay mechanisms (e.g., proportion of white rot-fungi,
60 soft-rot fungi). For example white- rot fungal proportions were double in open land compared to
61 mature forest. Likewise, more saprotrophs colonized high-WSG wood. Finally, ascomycetes

62 (mainly Sordariomycetes and Dothideomycetes) and basidiomycetes (mostly Agaricomycetes)
63 were dominant fungal groups. Open land was dominated by *Trichoderma*, regenerating forest by
64 Herpothrichiellaceae and mature forest by *Penicillium*.

65 **Conclusions**

66 White- and soft-rot fungi co-dominated decomposition, with the later increasing through time. A
67 succession of different fungal functional groups yielded similar decomposition rates across the
68 disturbance gradient. Incorporating dominant fungal functional trait dynamics into biogeochemical
69 models may improve predictions of carbon dynamics.

70

71

72 **Key words:** Bulong nature reserve, carbon cycle, coarse woody debris, decomposition, fungi,
73 landscape, Mengsong, wood density.

74 **Background**

75 Organic matter decomposition represents an ecological process that redistributes nutrients
76 produced by plants during their lifetime back into the atmosphere and soil. Woody debris (WD)
77 comprises an important carbon pool [73 petagrams, [1]] with a relatively long residence time [2].
78 Moreover, WD is an important habitat for many microorganisms, animals and plants [3,4].

79 The abundance of WD and its relatively long residence time means that WD
80 decomposition exerts a strong control on carbon cycling [5]. Factors affecting wood
81 decomposition are diverse and generally classified into abiotic (e.g., temperature, moisture, soil
82 parameters, etc.) and biotic factors (e.g., wood substrate quality, arthropods, microbial diversity,
83 etc.) [6], although others suggested considering a third category of anthropogenic factors (e.g.,
84 prescribed fire, forest harvesting practices) [7]. Previous studies have largely dealt with abiotic
85 factors and have found that wood biophysical traits along with climatic variables can only
86 explain up to 56 % of the variation in WD decomposition at global scales [8]. Moreover, to
87 obtain a more mechanistic understanding of the process of WD decomposition, it is vital to
88 combine our understanding of the effects of abiotic factors with those of biotic factors. Such
89 knowledge would greatly improve accuracy in predictive models of wood decomposition and
90 therefore carbon cycling [9].

91 Fungi are commonly recognized as key biotic agents driving wood decomposition [9,10].
92 However, critical aspects of the role of fungal community ecology in the decay of WD remain to
93 be explored [11]. For example, our understanding of the link between fungal richness and wood
94 physio-chemical parameters is limited [12,13]. The roles of both the taxonomic and functional
95 composition of the fungal community in determining wood decomposition rates is also not well
96 understood [14]. Although it is generally accepted that white rot and brown rot basidiomycete

97 fungi play key roles in decay of lignocellulose [4,15,16], the role of “soft-rot” ascomycete fungi
98 and the relative importance of each of these groups in tropical *versus* temperate forest
99 ecosystems has not been well characterized. Moreover, studies that examined fungal community
100 composition in temperate and boreal biomes have suggested that wood host species identity has
101 the strongest effect on the composition of fruiting fungal species, followed by microclimatic
102 factors (e.g., canopy openness) [17], as well as bark coverage [18].

103 Both negative and positive diversity-function relationships have been reported for wood
104 decomposer fungal diversity and decomposition rates in microcosm experiments under
105 controlled laboratory conditions [19–22], as well as in several field studies [9,12,13,17,23–25].
106 Recently, Maynard *et al.* suggested that the direction of the diversity-function relationship
107 depends on the nature of the competitive network within fungal communities [21]. Maynard and
108 colleagues also found that the importance of functional outcomes resulting from fungal species
109 interactions and fungal community structure surpasses that of differences in environment
110 conditions (i.e., abiotic factors).

111 Understanding how forest disturbance impacts WD decomposition is of critical importance
112 [26–28], especially in tropical ecosystems. Tropical biomes are heavily affected by
113 anthropogenic activities, such as deforestation and degradation, and have far higher woody plant
114 and fungal diversity, as well as biomass. Moreover, there is a strong debate concerning whether
115 tropical forests are carbon sinks or sources, and how this may be altered by climate change. Yet,
116 across the globe, there is a marked geographical imbalance in studies on the role of microbes in
117 wood decomposition, with far more studies in temperate and boreal biomes [7,9,29] than in the
118 tropical biome [9,12,30]. Additionally, there is a paucity of studies characterizing the succession
119 of fungal communities and decay type in WD over time. The few studies of WD decomposition

120 in the tropics have suggested that white rot dominates the early stages of decay [30], but how
121 fungal communities change in later stages of decay beyond two years and in response to
122 microclimatic variation or forest disturbance are poorly characterized [31,32].

123 In this study, our overarching goal was to investigate the role of abiotic and biotic factors
124 shaping the diversity and composition of fungal decomposers in decomposing logs and how
125 these change through time in a tropical montane rain forest in SW China across a disturbance
126 gradient from open land to mature forest. We aimed to address the following questions: (i) What
127 is the effect of wood species identity on the diversity and community structure of fungi? (ii) How
128 does the degree of forest disturbance affect fungal diversity and community structure? (iii) How
129 does fungal diversity and composition in woody debris change through time? And (iv) how do
130 these factors interact to influence the decomposition rate of WD?

131

132 **Results**

133 **Dynamics of WSG loss**

134 We previously examined the abiotic factors affecting wood decomposition in this landscape
135 (Dossa *et al.*, submitted). After 36 months of incubation, the WSG loss varied from 29.47 to
136 48.46 % (Fig. 1). The effect of habitat on WSG loss was not significant (Table S3), nor was the
137 main effect of tree species identity (Table S2). However, wood species identity interacted with
138 incubation time (Table S3), indicating a different temporal pattern of WSG loss in the two
139 species (Dossa *et al.* submitted).

140

141 **Taxonomic and functional classification of fungal community**

142 In total, after quality control steps, we obtained 9073 operational taxonomic units (OTUs).
143 Ascomycota was the dominant phylum followed by Basidiomycota throughout all sampling time
144 points (Fig. 2, S3). Sordariomycetes, Agaricomycetes, and Dothideomycetes were the most
145 abundant classes regardless of wood species, forest types and incubation time. Other moderately
146 abundant (>5% of total reads) classes included Leotiomycetes, Eurotiomycetes,
147 Saccharomycetes, and Tremellomycetes (Fig. S4).

148 Based on orders, Helotiales had the highest relative abundance regardless of wood
149 species except at 18 mo in open land and in mature forest. The relative abundance of other orders
150 varied with species, habitat and incubation time (Fig. S4). Those with greater than 5% relative
151 abundance included two basidiomycete orders, Agaricales and Polyporales, and various
152 ascomycete orders dominated by Xylariales, Hypocreales, Pleosporales, Chaetothyriales,
153 Coniochaetales, and Capnodiales (Fig. S4).

154 At the family level, the Xylarialeceae (Xylariales) and Sclerotiniaceae (Helotiales), which
155 was dominated by the genus *Botrytis*, were most abundant in the initial (0 mo) fungal community
156 in *L. cubeba* in all forest types, while Sclerotiniaceae and Cordycipitaceae (Hypocreales) were
157 most abundant at 0 mo in *C. mekongensis*. Across habitat types, Hypocreaceae (Hypocreales),
158 comprising primarily of fungi in the genus *Trichoderma*, was detected at >7% relative abundance
159 exclusively in open land at 18 mo for both tree species, while Herpotrichiellaceae
160 (Chaetothyriales) was abundant at 18 mo only in regenerating and mature forests. Genera
161 with >5% relative abundance included the ascomycetes *Penicillium* (Hepotrichiellaceae),
162 *Trichoderma* (Nectriaceae), *Beauveria* (Cordycipitaceae), *Hyaloscypha* and *Mollisia*
163 (Dermataceae; Helotiales), *Scytalidium* (family incertae sedis; Helotiales), and *Candida*

164 (Saccharomycetales), as well as the basidiomycete genus *Phlebia* (Meruliaceae; Polyporales)
165 (Fig. S4).

166 At 18 mo the average proportions of pathotrophs, saprotrophs, and symbiotrophs across
167 all habitat types and species were 11.5 %, 80.0 % and 8.5 %, respectively (Fig. 2 and S4).

168 Regardless of habitat type or wood species, saprotroph abundance peaked at 18 mo. Pathotrophs
169 also peaked at 18 mo, except for *L. cubeba* in mature forest. Within the saprotrophs, we were
170 able to assign a small proportion ~30% to rot types (Fig. 2 B, C and Fig. S3). *C. mekongensis*
171 harbored no brown rot initially, whereas *L. cubeba* had a relatively small proportion (< 1 %). As
172 decomposition proceeded, the abundance of white rot fungi peaked at 18 mo, except for *L.*
173 *cubeba* in mature forest (Fig. 2, Table S4) where there was a continuous increase in white rot
174 fungi up to 36 mo. The proportion of all rot types out of the total fungal community increased
175 from mature forest to open land. There was also a larger total abundance of fungi from all rot
176 types in *C. mekongensis* than in *L. cubeba*, except in mature forest where the total proportion of
177 rot types did not differ much between species.

178

179 **Fungal alpha diversity in decomposing logs**

180 *L. cubeba* harbored more fungal OTUs than *C. mekongensis* (Fig. 3, Table S5). In both species,
181 fungal diversity peaked at 18 mo incubation. The best model for alpha diversity explained 23.3 %
182 of the total variance including both fixed and random factors, while fixed factors explained 12.0 %
183 of the variance. Incubation time and species identity had a significant effect on fungal diversity
184 (Table S6), whereas habitat had no significant effect. However, fungal diversity explained only
185 ~1 % of the variation in WSG loss, although this was still marginally significant. The presence of
186 termites also significantly enhanced WSG loss (Table S5).

187

188 **Fungal community structure**

189 NMDS plots of fungal communities showed substantial overlap among species, but variation
190 among samples increased through time ($F_{1,382} = 6.694$, $P = 0.01$, Fig. 4), and varied among
191 habitat type ($F_{2,381} = 6.775$, $P = 0.001$, Fig. 4 and S6). Nevertheless, a multivariate analysis of
192 factors influencing differences in fungal communities using *adonis* [33] found that time, habitat
193 type and the interaction between time and presence of termites, but not species identity, had
194 significant effects on community composition (Table 1). However, the model explained only ~ 3 %
195 of the variance in fungal composition. Procrustes analysis showed a relationship between the
196 position of the points in the first ordination (0 mo) and second ordination (18 mo) (For time 0 mo
197 to 18 mo, Procrustes Sum of Squares (m12 squared) = 0.882, correlation in a symmetric
198 procrustes rotation = 0.344, significance, $P = 0.001$, Figure S5A) and also between 18 mo and 36
199 mo (Procrustes Sum of Squares (m12 squared) = 0.884, correlation in a symmetric procrustes
200 rotation = 0.340, significance, $P = 0.001$, Fig. S4B), indicating a priority effect of the initial
201 community on the succession of fungal communities that developed at the early decay stage (0
202 mo to 18 mo) and in the transition from early to late decay stage (18 mo to 36 mo). A Venn
203 diagram depicting number of unique or shared OTUs over time showed that regardless of wood
204 species, there was a peak in number of unique OTUs at 18 mo, which declined afterwards. The
205 percentage of unique OTUs at 18 mo was 1.44 times higher for *C. mekongensis* than for *L.*
206 *cubeba* (Fig. 5), but the absolute number of unique OTUs was higher in *L. cubeba*. The shared
207 OTUs between the two woody species increased through time and reached 63% after 36 mo of
208 incubation (Fig. 5), at which time there were no unique OTUs in *C. mekongensis*.

209

210 **Structural equation modeling**

211 Our SEM revealed a best model that included all the direct effects and a few of our hypothesized
212 indirect effects (Fig. 6). The final results showed a good fit (Chi square = 4.17, P-value = 0.53,
213 degrees of freedom (DF) = 5, Comparative Fit Index (CFI) = 1, Fig. 6). Within this best model,
214 the strongest path was from time with a standardized path coefficient = 0.97 (P < 0.001). The
215 second strongest path was habitat with a path coefficient = -0.12 (P < 0.001). While the SEM
216 showed that the effect of open land did not differ from that of mature forest, regenerating forest
217 significantly reduced WSG loss compared to mature forest (Fig. 6, Table S7). Woody species
218 identity and abundance of white rot fungi were also significant predictors of WSG loss. In
219 addition, there was an indirect time effect mediated *via* white rot fungi abundance. Meanwhile
220 woody species identity had a strong effect on fungal alpha diversity (Fig. 6, Table S7).

221

222 **Discussion**

223 Our current understanding of wood decomposition and fungal ecology relies heavily on patterns
224 found in temperate and boreal ecosystems. Our study aimed to investigate successional changes
225 in fungal diversity and composition in decomposing logs of two tree species across a disturbance
226 gradient in a tropical forest, and their effects on WSG loss. We found that fungal diversity
227 consistently peaked at 18 mo regardless of wood species and habitat. Fungal diversity was also
228 significantly influenced by wood species identity, while fungal composition at the OTU level
229 varied significantly with time, habitat type and the interaction between time and termite
230 colonization. The peak of fungal species diversity at 18 mo coincided with a peak in both the
231 relative abundance of saprotrophs and the number of unique OTUs. Within the saprotrophs,
232 fungi assigned to the white rot type peaked at 18 mo, with the exception of *L. cubeba* in mature

233 forest which peaked at 36 mo. The abundance of soft rot fungi also peaked at 18 mo, except for
234 *Castanopsis mekongensis* in open land and *L. cubeba* in mature forest, which both peaked at 36
235 mo. Overall, fungal diversity was not a significant factor determining WSG loss, but the
236 abundance of white rot fungi explained a small but significant amount of the variation in WSG
237 loss.

238

239 **Initial wood quality and WSG loss**

240 Given the differences in the tree species wood quality and density, we expected pronounced
241 differences in the decomposition rates. Surprisingly, only the interactive effect between wood
242 species identity with incubation time was significant. *C. mekongensis* logs had much higher
243 initial WSG, slightly slower initial loss of WSG and consistently lower fungal diversity. The
244 bark of *L. cubeba* had more labile carbon in the form of sugars that are easily accessible to
245 microorganisms, which may explain the more rapid initial WSG loss and higher fungal alpha-
246 diversity in this species [34]. Whether this is a general effect of bark chemistry on fungal
247 diversity will require investigation over a more diverse selection of species. The lack of any
248 significant effect of habitat on WSG loss was surprising. Rates of fungal decomposition were
249 expected to be higher in forest habitats, where ambient moisture is higher. However, structural
250 equation modelling showed a small but significant negative effect of regenerating forest on
251 decomposition rates (Fig. 6).

252

253 **Taxonomic and functional classification of fungal community**

254 We found Ascomycota and Basidiomycota were the dominant phyla throughout the
255 decomposition process regardless of woody species and forest type, with Ascomycetes being

more abundant than Basidiomycetes. These findings are in line with previous studies [27] and recent findings from researchers who monitored the decomposition of three tropical woody species and found Ascomycota and Basidiomycota to be the dominant phyla in all species at 3 and 11 mo after incubation [25]. This is not surprising given the fact that Basidiomycota contain the majority of white rot fungi, which are able to degrade both lignin and cellulose, and brown rot fungi, which modify lignin and degrade primarily cellulose [35,36]. Ascomycota, including many soft-rot fungi, have also been shown to play an underappreciated role in the early decay process, feeding on a diet of sugars to lignocellulose compounds [37–39]

The proportion of saprotrophs was greatest at 18 mo, which coincided with the peak in fungal diversity, and was ~2 times higher in *C. mekongensis* than in *L. cubeba*. This difference may explain why there was not more of a wood species effect on WSG loss. Although *C. mekongensis* had much higher initial wood density and lignin content, the higher proportion of saprotrophic fungi may have compensated to equalize decay rates over time. The higher initial rates of WSG loss in *L. cubeba* may be partially explained by a greater availability of sugars and hemicelluloses leading to a quick growth of decomposer fungi able to use these carbon sources (Figure 1). Notably, the proportion of saprotrophs in *L. cubeba* did not peak until 36 mo. In contrast, WSG loss in *C. mekongensis* was slow initially, presumably because of the relatively low proportion of easily digestible substrates and higher lignin content, but increased over time. Both this study and a previous study investigating aboveground decay of this species found the highest proportion of saprotrophs in *C. mekongensis* at 18 mo [40].

Our results also agree with previous studies [27,30,41] showing that white rot fungi dominate the early stage of decay in tropical forests. However, our study followed wood decay for a longer time period of 36 mo and found that after an initial peak of white rot fungi at 18 mo,

279 in some habitats, the proportion of brown and soft-rot fungi increased, especially in *C.*
280 *mekongensis*. This increase in brown rot and soft rot fungi in *C. mekongensis* in later stages of
281 decay, presumably after the early degradation of lignin by white rot fungi has freed cellulose and
282 sugars bound in lignin for degradation by these other decay mechanisms, may also partially
283 explain the lack of difference in final WSG loss of the two tree species. Both brown and soft rot
284 types can lead to substantial strength loss as quantified here by WSG loss [42]. In addition, there
285 is also a ~2 fold difference between the proportion of white rot in open versus mature forest,
286 which could also explain the lack of differences observed in WSG loss among habitats.

287 In terms of specific fungal taxa that may play roles in WD decay, the fungal communities
288 were dominated by Sordariomycetes and Dothideomycetes, both large and diverse classes of
289 ascomycetes found in many different habitats, as well as the basidiomycete class
290 Agaricomycetes, which contains a majority of both white rot and the brown rot fungi that
291 preferentially degrade lignin and cellulose, respectively [43]. In a previous study of early
292 decomposition (11 months) in five tropical species in Panama, researchers found an increase in
293 the abundance of Agariomycetes with time, which was not observed in our study, and the same
294 researcher also observed a decrease in Sordariomycetes over time [25]. In our study,
295 Sordariomycetes, including orders Xylariales and Hypocreales, were most abundant at the initial
296 sampling point and decreased slightly over time (Fig. S4). Some Xylariales are endophytes of
297 woody plants, including tropical trees [44], and many cause white rot [4]. The Sordariomycetes
298 genus *Beauveria* (Hypocreales), which was abundant at the initial sampling time point in *C.*
299 *mekongensis*, is also an endophyte of diverse grasses, angiosperms, and some woody plants
300 [45,46]. Surprisingly, Leotiomycetes, especially members of the family Sclerotiniaceae
301 (Helotiales), were also highly abundant at the initial time point in *L. cubeba*, comprising nearly

302 30% of all taxa at 0 mo, and also decreased over time. These patterns suggest the hypothesis that
303 these Sordariomycetes and Leotiomycetes taxa may be endophytes that are highly abundant
304 initially, but do not always persist in later fungal communities in WD. This is in contrast to other
305 studies that have shown a strong priority effect for endophytic taxa or initial hyphal inoculum in
306 dead wood in microcosm studies [47,48]. It is possible that competitive interactions among later
307 colonizers in natural environments may lead to a decrease in initially abundant taxa during the
308 succession of wood decay communities (Maynard et al. 2017). Nevertheless, we did observe
309 large overlap between fungal community structure at different time points and evidence for
310 priority effects in significant Procrustes results between initial (0 mo) and early decay (18 mo)
311 and between early decay (18 mo) and later decay (36 mo). It is possible that endophytic taxa
312 initially present in low abundance may increase in abundance in deadwood and contribute
313 substantially to the decay processes over time [47]. In *C. mekongensis*, for example,
314 Leotiomycetes as a whole showed an increase over time. While the family Sclerotiniaceae
315 (Helotiales) was the most abundant at the initial sampling time point but decreased over time,
316 other members of Helotiales (Dermateaceae and an unclassified family Incertae_sedis) increased
317 at 18 or 36 mo. Similarly, the Eurotiomycete family Herpotrichiellaceae (Chaetothyriales)
318 increased in abundance up to 18 mo for *C. mekongensis* in all habitats and for *L. cubeba* in
319 regenerating and mature forest. Recent studies have shown that abundance of fungi within the
320 ascomycete family Coniochaetaceae (Coniochatales), which were found in high abundance in the
321 decaying wood of 13 temperate European tree species and were also detected in our study,
322 correlated with abundance of laccases and different (hemi)cellulolytic enzymes, supporting a role
323 in wood decay. The ecological and functional traits of these orders of ascomycete fungi have not

324 been well characterized, but our study and others suggests they warrant further attention for their
325 role in wood decay in tropical systems.

326 Across habitats, the genus *Trichoderma*, which includes fungi known to degrade
327 cellulose [50], was more abundant in open land, while Herpothrichiellaceae (Chaetothyriales)
328 was more abundant in regenerating forest and mature forest. The higher abundance of
329 *Penicillium* in logs in mature forest than in open land might reflect colonization from soil, as an
330 earlier study at the same site found *Penicillium* was abundant in mature forest soils and declined
331 in abundance in open land soils [51]. Many fungi involved in WD may colonise the substrate *via*
332 the soil. Indeed, previous research suggests a dynamic interaction among soil and wood
333 decomposing fungi in a temperate forest [52], as well as a homogenization of fungi involved in
334 fungal necromass decomposition in both soil and wood media [53].

335

336 **Fungal alpha diversity**

337 We found that wood species identity and time were the main determinants of fungal alpha
338 diversity during wood decomposition. This result corroborates recent findings in a subtropical
339 forest in China, where Kahl and colleagues monitored the decomposition of *Pinus* sp. and
340 *Schima* sp. over 2 years, and found species identity determined the composition of colonizing
341 fungi. They also found that *Pinus* sp., which had higher C:N ratio and lower N content, harbored
342 higher fungal diversity than *Schima* sp. [12,23]. In our study, *L. cubeba* had higher wood C:N
343 ratio and lower N content and consistently higher fungal diversity through time.

344 Previous studies have reported both negative [12] and positive relationships [9,20,22,52]
345 between fungal alpha diversity and incubation time but focused primarily on the early stages of
346 decay during the first two years. A comparison of the results from these studies to ours should

347 also take into account the speed of decomposition in temperate *vs.* tropic environments. With this
348 in mind, we could say for early stage decomposition (18 mo in the tropical ecosystem and up to
349 36 mo elsewhere), we observed an increase in fungal diversity. However, after 18 mo, we
350 observed a decrease in diversity, with a continuous increase in WSG loss, suggesting a shift from
351 a positive to negative biodiversity – function relationship in later stage decomposition. These
352 results instead suggest a dynamic shift in the diversity and composition and the nature of
353 interactions among fungi that decompose wood through time, which may depend on various
354 factors, including wood properties. The first phase may reflect colonisation, when the log is still
355 relatively rich in easily decomposable components, and weak competitive interactions [9]. In
356 contrast, the next phase may reflect the exhaustion of easily decomposable components and
357 increasingly competitive interactions. Indeed, the sharp increase in the number of unique species
358 (Fig. 5) up to 18 mo may be explained by colonization of a newly available resource.
359 Increasingly strong competition through time for remaining resources may have led to a decline
360 of fungal richness thereafter. Moreover, the increase in white rot fungi up to 18 mo could have
361 enabled digestion of recalcitrant lignin, thereby exposing cellulose and hemicellulose, which are
362 then easily digestible by brown and soft rot fungi [30]. In most habitats in our study, the
363 proportion of brown and soft rot fungi increased from 18 mo to 36 mo. The magnitude of
364 increase was higher for *C. mekongensis*, which contained a higher initial lignin content (Table 1;
365 Fig. S2).

366

367 **Fungal community structure**

368 Fungal community composition at 0, 18 and 36 mo overlapped considerably, suggesting priority
369 effects were important [47,54]. However, both incubation time and habitat significantly affected

370 the fungal community composition as has been observed in other studies [55]. It is expected that
371 fungal composition changes through time as the nature of the carbon substrates available are
372 altered during the decay process, and similar results are reported from studies in temperate
373 environments [9]. The microclimate within different habitats may not only affect which species
374 of fungi colonize a log, but also may dictate the outcome of fungal interactions in decomposing
375 logs. Hence, a significant effect of habitat on fungal composition is expected. However, our
376 model only explained 3% of the variance in fungal composition. A large proportion of the
377 variance in composition may arise from stochastic processes, such as dispersal-colonisation,
378 which is supported by the fact that the variance in composition increased through time (Fig. 4).
379 Termites also were found to alter indirectly wood decomposition through changes in the fungal
380 composition [56], which is in line with our finding of a significant interactions between time and
381 presence of termites. Termites may aid in dispersal-colonization for fungi by introducing fungal
382 spores in holes or entry-points they created.

383 **Caveats**

384 Although, molecular methods are becoming popular and hold high potential of detecting species
385 that would not otherwise being detected under traditional culture methods [11], these methods
386 heavily rely on existing species sequences with taxonomic representation in public databases
387 libraries. Moreover, the functional traits of many fungi have not been investigated thoroughly.
388 The best available database to assign fungal sequences to trophic modes is the FunGuild database,
389 yet a large proportion (70%) of OTUs could not be assigned to a rot type (see supplementary
390 materials Fig. S3). This reflects both the lack of fungal DNA sequences for tropical fungi and the
391 lack of knowledge of trophic modes and functions of many fungal taxa.

393 **Conclusion**

394 The effects of biotic factors on woody debris decomposition, including microbial diversity and
395 functional composition, have been understudied in tropical ecosystems. In the present study, we
396 employed next generation sequencing to investigate the succession of fungal communities in WD
397 over time and their role in wood decomposition rates in a tropical mountainous forest subjected
398 to anthropogenic disturbance. Over three years, habitat did not have a significant effect on WSG
399 while the effect of wood species on fungal diversity and composition varied through time. The
400 logs of the wood species with relatively low initial WSG harbored the highest diversity of fungi,
401 perhaps due to the higher proportion of labile carbon in the form of sugars. In addition, fungal
402 diversity and the proportion of saprotrophs and white-rot fungi peaked at 18 mo regardless of
403 wood species and then declined, suggesting an initial period of colonisation and weak
404 competitive interactions, followed by increasingly competitive interactions leading to decreased
405 diversity. As anticipated, fungal community structure varied with time, wood species identity
406 and habitat. However, fungal diversity was not a significant predictor of WSG loss. Our results
407 suggest that changes in functional traits, such as mechanisms of rot type, rather than species
408 diversity *per se* may better explain variation in WSG loss. Future studies should aim at
409 investigating the role of fungal functional traits and rot types, particularly those of Ascomycete
410 fungi whose roles in wood decay are less well characterized, as well as the effects of bark traits
411 on the dynamics of fungal decomposers in tropical systems.

412

413 **Materials & methods**

414 **Study site**

415 Our study site was located in Mengsong a small township within Bulong Nature Reserve
416 (Xishuangbanna, China, UTM/WGS84: 47 Q 656355 E, 2377646 N, 1100-1900 m above sea
417 level, Figure S 1). The climate in Mengsong is seasonal and monsoonal. Mengsong receives
418 1600-1800 mm of rainfall annually [57] of which 80 % occurs within 6 months of the year from
419 May to October. The vegetation found in Mengsong has been described by Zhu *et al.* [58].
420 Briefly, Mengsong is characterized by mountainous vegetation and shares many plant families
421 with temperate Asian forests, with Fagaceae and Lauraceae as dominant canopy families.

422

423 **Plot design to account for disturbance gradient**

424 A stratified and systematic protocol [59,60] was used to select plots, based on both satellite
425 imagery and ground truthing in 2009. The current landscape of Mengsong consists of a mosaic
426 that includes open land such as barren fields, grassland and terraced tea fields, as well as
427 regenerating forest and mature forest. In total, 28 one hectare plots were selected and established
428 in 2010 to represent the disturbance gradient found in the landscape. Specifically, after
429 classification 10, 12 and 6 plots classified as mature forests, regenerating forests and open land,
430 respectively, were selected. Each plot was then subdivided into 9 subplots on a 3 x 3 grid with 50
431 m interval among subplots (Figure S1 Panel C). Only 5 of the 9 subplots per plot were used for
432 the wood incubation experiment (subplots 1, 3, 5, 7, 9; Fig. S1).

433 **Experimental set up and wood species selection**

434 Based on a social survey conducted in September 2011 among farmers in Mengsong to
435 assess local knowledge and understand how they classify woody trees in their landscape, we
436 selected two native species contrasting in wood density: 1) *Litsea cubeba* (Lauraceae), which has

437 a relatively low wood specific gravity (0.42), and 2) *Castanopsis mekongensis* (Fagaceae), which
438 has a relatively high wood specific gravity (0.75).

439 We purchased 29 living individual trees of *Litsea* and 32 of *Castanopsis* from local
440 farmers' firewood plantations and harvested the main stem of these trees. The harvested stems
441 were ~9 cm in diameter and were cut into logs 0.5 m in length using a handsaw. We sterilized
442 the handsaw with ethanol and flamed it between cuts to prevent any microbial cross-
443 contamination among samples. All the logs were transported to the field station for further
444 preparation, such as fixing a unique tag number, and measurement of biometric variables (e.g.,
445 initial fresh weight, bark thickness, diameter, and total length). In order to establish initial wood
446 functional traits, initial wood chemistry, and to examine initial fungal composition, a disk of 10
447 cm thickness was collected from the bottom of each individual tree and stored at -20 °C.

448 The logs used for the experiment had a mean diameter of 9.53 ± 1.11 cm (sd) and $9.58 \pm$
449 1.02 cm, mean initial weight of 2.3 ± 0.53 kg and 1.4 ± 0.36 kg, and mean bark thickness of 6.06
450 ± 2.83 mm and 2.82 ± 0.82 mm for *Castanopsis mekongensis* and *Litsea cubeba*, respectively.
451 With respect to bark chemistry, *L. cubeba* had higher nitrogen (N), phosphorus (P), potassium
452 (K), water soluble sugar, hemi-cellulose and tannin concentrations than *C. mekongensis* and
453 similar concentrations of carbon (C), cellulose and lignin. For wood chemistry, *L. cubeba* had
454 higher concentrations of P, cellulose, hemi-celluloses and water soluble sugar, while *C.*
455 *mekongensis* wood had higher concentrations of C, N, fiber and lignin (Table S1). Detailed
456 chemical analysis protocols of the wood composition were reported in.[61]

457 At each of the five subplots within the established plots (see above), we set up a small
458 decomposition plot 2 m x 2 m approximately 5 m north of the subplot center and incubated one

459 log of each species. In total, 280 logs (28 plots x 5 subplots x 2 species x 1 log) were incubated
460 on the forest floor in 2011 and monitored for three years.

461

462 Sample collections

463 Wood cores were taken with a core borer (Forestry suppliers ®, Jackson, MS, USA). We
464 calculated WSG using the following formula;

$$WSG = \frac{Oven dry mass of woodcore}{Oven dry volume of woodcore} * \rho_{water}$$

465 where: WSG is the wood specific gravity (unit less), oven dry mass (g), oven dry volume (cm^{-3})
466 and ρ_{water} is density of water (1.00 g cm^{-3}) [62].

467 At the same time, the presence/absence of termites was recorded and a cordless drill (Doug Jones,
468 Doug Jones Jiwei company, Taiwan) was used to collect wood dust next to the core sample.

469 Wood dust samples were placed directly in a tube (Corning tube Corning®) and immediately
470 stored in -20 °C freezer for molecular analysis after being transported to the field laboratory on
471 ice bags. Each log was divided longitudinally into 5 cm sections and on each sampling occasion
472 one of these sections was randomly chosen for sampling. One core sample and one wood dust
473 sample were collected from the bottom (surface in contact with the ground) of the selected
474 section and one each from the top of the log. The sampling equipment was cleaned and flamed
475 between samples to avoid cross-contamination, and the holes in the log were plugged with
476 silicone (Tosseal® 381, Tokyo, Japan) to prevent inadvertent introduction of microbes. Samples
477 were collected at 3, 6, 12, 18, 24 and 36 mo. However, to reduce costs, only wood dust samples
478 collected at 18 mo and 36 mo, from four subplots (#1, 3, 7 and 9 each at the corner of the plot
479 like number four on a dice) and from the bottom of the log were used for molecular analyses.
480 Hence, we planned to do molecular analysis on a total of 432 field samples (27 plots x 4 subplots

481 x 2 species x 2 sample occasions), however only 384 field samples were conducted due to
482 missing samples and 34 samples from the initial wood discs. We elected to use the samples from
483 the bottom of the log to avoid interaction with photo-decomposition.

484

485 **Molecular analyses of fungal communities**

486 **DNA extraction**

487 Wood dust samples were homogenized to a fine powder with a mortar and a pestle in liquid
488 nitrogen. Subsequently, DNA was extracted from 150 to 250 mg of each homogenized wood
489 dust sample using the ZR Soil Microbe DNA MiniPrep kit (Zymo Research, Irvine, CA, USA)
490 according to the manufacturer's instructions. DNA quality was checked using a NanoDrop
491 ND1000 spectrophotometer (NanoDrop Technologies, Wilmington, DE, USA).

492 **DNA metabarcoding and next generation sequencing**

493 The DNA extracted from each sample was quantified using the Qubit fluorometer (Thermo-
494 Fischer) and approximately 10-25 ng of DNA for each sample were submitted to the University
495 of Minnesota Genomics Center (UMGC) for library amplification and sequencing. Additional
496 samples to assess the quality and accuracy of the amplification and sequencing steps included a
497 mock fungal community which contained equal quantities of 37 known fungal taxa (See
498 supplementary material Table S2 for the list of species in the mock community) and technical
499 replicates consisting of replicate libraries of the same DNA sample. A two-step dual-indexed
500 amplification method [63] was used for amplifying the fungal internal transcribed spacer 1 (ITS1)
501 barcode region. The universal fungal primers employed in this study are ITS1F
502 (CTTGGTCATTTAGAGGAAG*TAA) and ITS2R (GCTGCGTTCTTCATCGA*TGC) [64].
503 All the samples were amplified individually and the amplified PCR products were then barcoded

504 prior to pooling. The pooled sample was sequenced across two 300 base pair (bp) pair-end
505 Illumina Miseq lanes to get sufficient coverage for each sample. The sequences from all Miseq
506 lanes were aggregated together for the downstream quality control.

507

508 **Data analysis**

509 **Bioinformatics**

510 MOTHUR [65] was used to pair the sequences and make contigs, excluding sequences that had
511 less than 100 bp overlap. The remaining sequences that had less than 2 bp mismatch to the fungal
512 ITS1 region primer were retained for further filtering. The remaining sequences were filtered to
513 remove those that had more than one ambiguous base, more than eight homopolymers, or were
514 shorter than 150 bp or longer than 420 bp. The sequences that passed filtering in MOTHUR were
515 transferred into the QIIME platform [66]. Chimeras were removed based on both the de novo
516 and reference based chimera check algorithms of the USEARCH61 pipeline [67]. Representative
517 OTUs were picked de novo at 97% similarity using USEARCH [68]. The taxonomy of OTUs
518 was assigned using a 97 % similarity blast threshold. The UNITE database dynamic version
519 20.11.2016 [69] was used for the taxonomy assignment. The OTU table was transferred into R
520 for subsequent statistical analyses.

521 FUNGuild was used to map OTUs to trophic modes and ecological guilds [70]. Our
522 analyses first looked at the dynamics of the major trophic modes of fungi (e.g., pathotrophs,
523 saprotrophs and symbiotrophs). Second we further explored the taxonomic diversity of
524 saprotrophs, as these are the fungi that actively degrade wood constituents. Lastly, we focused on
525 three functional traits/guilds relevant to wood decay, namely white, soft and brown rot fungi

526 which denote the decay rot type, while other guild categories were aggregated under the category
527 “other”.

528

529 **Sequences**

530 All sequences are submitted to the NCBI database under the project bioproject accessible at
531 <https://www.ncbi.nlm.nih.gov/bioproject/PRJNA503471>. [Raw data file along with r script will
532 be uploaded upon acceptance of the MS]

533

534 **Statistical analyses**

535 **Wood specific gravity (WSG) dynamics**

536 WSG loss was reported in a previous study examining the habitat, species and abiotic effects on
537 wood decomposition (Dossa *et al.* submitted). Here our objective was to explain changes in the
538 diversity and composition of fungal decomposer communities and their effect on WSG loss.

539

540 **Fungal taxonomic diversity (Alpha diversity) and community structure (Beta-diversity)**

541 We used Chao 1 as an estimator of alpha diversity. The Chao 1 estimator was computed as
542 follows: $N + S^2 / (2 D)$ where N is the number of OTUs, S is the number of singleton OTUs and
543 D is the number of doublet OTUs, (i.e. OTUs with abundance 2) [71]. We estimated alpha
544 diversity per sample and examined its change across time and the disturbance gradient. We then
545 modeled alpha diversity across time using all the variables including incubation time, habitat,
546 and species with all two way interactions. We used a linear mixed model implemented with the
547 function *lmer* from the package “lme4” [72]. We simplified the maximal model to the optimal
548 model by subtracting variables one at a time starting from the higher level (interactions),

549 respecting the principle of marginality. We used the likelihood ratio test to determine whether
550 there was a significant shift in the likelihood of the predecessor model while dropping a
551 particular variable. We also used variance partitioning through linear modeling to assess how
552 much of the variation in WSG was explained by alpha diversity at the mid time point, as the
553 alpha diversity temporal pattern was consistent across habitats and species. We used liner mixed
554 effects models function *lme* from “nlme” package [73] and considered plot as random factor.

555 To assess community structure and turn over (beta diversity) we generated a dissimilarity
556 distance matrix based on Bray-Curtis distance by using the function *vegdist* method “bray” from
557 the package “vegan” [33]. We also conducted a non-metric multidimensional scaling (NMDS)
558 based on this dissimilarity matrix using the function *metaMDS* from the “vegan” package. We
559 then assessed the effects of the factors tree species, forest disturbance, and time on the
560 dissimilarity between fungal communities by performing a constrained permutational
561 multivariate anova (PERMANOVA) with the function *adonis* from the “vegan” package. We
562 used the argument strata = Wood log ID to account for the random factor. Prior to modeling
563 fungal community structure, we checked for any time effect due to repeated measures. We then
564 examined any priority effects by conducting a procrustes analysis, using the function *protest*
565 from the “vegan” package on OTU matrixes from 0 mo, 18 mo and 36 mo of incubation time.
566 Procrustes analysis superimposes two matrices and asks whether the degree of superimposition is
567 likely to occur by chance. If not, this would suggest that the initial community composition
568 constrains the community assemblage that develops during the decay process. We further used
569 the traits obtained from FUNGuild to compute the percent of each ecological guild category
570 within each forest disturbance category (mature, regenerating forest and open land) and per
571 harvesting time (initial = time 0 mo, 18 mo and 36 mo after incubation). We plotted the

572 dynamics of the percentage of each guild category against time. We further assessed not only the
573 dynamics of fungal guilds assigned to distinct rot types over time, but also examined how
574 different rot type fungi contributed to WSG loss. Finally, we used structural equation modeling
575 (SEM) to investigate both the direct and indirect effects of species, time, and habitat type on
576 WSG loss via fungal alpha diversity and white rot fungi abundance (Figure S2 illustrates the
577 initial SEM analysis model). We employed the package “lavaan” [74] to conduct SEM. For this
578 analysis, we first converted the habitat variable, which is a categorical variable, to dummy
579 variables using *dummy.code* function from the package “psych”, and we included time in the
580 modeling as an ordered categorical factor [75]. We examined the direct effects of main factors
581 (time, woody species and habitat type) on the total response variable (loss of WSG). As we
582 hypothesized that the fungal diversity and abundance of white-rot fungi would change over time,
583 we subsequently tested the indirect effect of the main factors on WSG loss mediated *via* partial
584 responses (fungal diversity and white rot abundance). We reduced the full model to best fit
585 model using the likelihood ratio test, which compares nested models (full model against reduced
586 model), using the function *LavTestLRT* within “lavaan” package. We removed non-significant
587 variables one at a time and retained them in the best fit model only if they produced a reduced
588 model that deviated significantly from the preceding more inclusive model by the likelihood
589 ratio test. All analyses were performed in R version 3.5.2 [76].

590

591 **Ethics approval and consent to participate**

592 Not applicable

593

594 **Consent for publication**

595 Not applicable

596

597 **Competing interests**

598 The authors declare that they have no competing interest.

599

600 **Funding**

601 This work benefitted financial support from the National Natural Science Foundation of China
602 (NSFC) via grant # 3181101433 to G.D., # 31470546 to R. D. H. Kathryn E Bushley and
603 Weiming Hu were supported by startup funds from the University of Minnesota and USDA
604 NIFA grant # 2015-67013-23419. Jian-Chu Xu was supported by Key Research Program of
605 Frontier Sciences of the Chinese Academy of Sciences (Grant # QYZDY-SSW-SMC014) and
606 Yong-Ping Yang was supported by the Major Program of NSFC (# 31590820, 31590823). In
607 addition, G.G.O. Dossa was supported by Yunnan provincial postdoctoral grant and young
608 international staff Chinese Academy of Sciences (CAS) president international fellowship
609 initiative (PIFI) grants # 2019FYB0001 and 2017PC0035 along with China postdoc foundation
610 grant #2017M613021.

611

612 **Authors' contributions**

613 G.G.O.D, E.P., D.S., K.F.C., and R.D.H. conceived the ideas and designed methodology;
614 G.G.O.D. and E.P. collected field data; Y.Q.Y., W.H., and K.E.B. Conducted DNA extraction
615 and molecular analyses; W.M. and KEB conducted bioinformatics analyses; G.G.O.D., W.H.,
616 K.E.B., and R.D.H. analyzed the data; G.G.O.D., R.D.H., and D.S. led the writing of the
617 manuscript. All authors contributed critically to the drafts and gave final approval for publication.

618

619 **Availability of data and materials**

620 All sequences are submitted to the NCBI database under the project bioproject accessible at

621 <https://www.ncbi.nlm.nih.gov/bioproject/PRJNA503471>.

622 [Raw data file along with r script are available from Harvard Dataverse (accession # upon
623 acceptance of the MS)]

624

625 **Acknowledgements**

626 This work benefitted financial support from the National Natural Science Foundation of China
627 (NSFC) via grant # 3181101433 to G.D., # 31470546 to R. D. H. Kathryn E Bushley and
628 Weiming Hu were supported by startup funds from the University of Minnesota and USDA
629 NIFA grant # 2015-67013-23419. Jian-Chu Xu was supported by Key Research Program of
630 Frontier Sciences of the Chinese Academy of Sciences (Grant # QYZDY-SSW-SMC014) and
631 Yong-Ping Yang was supported by the Major Program of NSFC (# 31590820, 31590823). In
632 addition, G.G.O. Dossa was supported by Yunnan provincial postdoctoral grant and young
633 international staff Chinese Academy of Sciences (CAS) president international fellowship
634 initiative (PIFI) grants # 2019FYB0001 and 2017PC0035 along with China postdoc foundation
635 grant #2017M613021. We also acknowledge the insightful discussion with Jonathan Schilling
636 and the Biogeochemistry laboratory of Xishuangbanna Tropical Botanical Garden (XTBG) for
637 the chemistry analysis. This work is linked to the CGIAR Research Program on Forests, Trees
638 and Agroforestry. G.G.O. Dossa is grateful to Lulu Chen for encouragement and support
639 throughout the redaction of the manuscript, to Atu our project local assistant in the field as well
640 as the entire Bulong nature reserve staff for their support throughout the execution of the project.

641 **Supplementary information**

642 Supplementary information is available in separate file.

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869 **Figure legends**

870 **Fig. 1:** Percentage wood specific gravity (WSG) loss from logs installed across 28 plots in the
871 Mengsong landscape after 18 mo and 36 mo incubation. The experiment used two species, *Litsea*
872 *cubeba* and *Castanopsis mekongensis*. Points represent predicted mean values ($\pm 95\%$ confidence
873 interval) for two species (*Litsea cubeba* and *Castanopsis mekongensis*) with respect to
874 disturbance category (mature forest, regenerating forest and open-land) and incubation time
875 during 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna,
876 SW, China (Dossa *et al.* submitted).

877

878 **Fig. 2:** A) Average relative abundance of OTUs assigned to higher taxonomic units (Ascomycota,
879 Basidiomycota, Other), B) Average relative abundance of OTUs assigned by FUNGuild to
880 different tropic modes (Pathotroph, Saprotrroph, Symotroph) and C) Average relative abundance
881 of OTUs assigned by FUNGuild to different rot types (white-rot, brown-rot, and soft-rot fungi).
882 In order to have comparable values, the relative abundance was calculated across all our samples
883 regardless of habitats and species. And this relative abundance represents the proportion of
884 OTUs assigned to each fungal guild identified *via* FUNGuild. Thus within each panel the total
885 percentage sums to 100.

886

887 **Fig. 3:** Change in fungal alpha diversity (Chao 1) across time and forest types for two wood
888 species (*Litsea cubeba* and *Castanopsis mekongensis*) across habitat (mature forest in red,
889 regenerating forest in blue and open forest in green) during 36 month of wood decomposition in
890 tropical montane forest, Mengsong, Xishuangbanna, SW, China. Points represent predicted
891 mean values ($\pm 95\%$ confidence interval) for two wood species (*Litsea cubeba* and *Castanopsis*

mekongensis) with respect to disturbance category (mature forest, regenerating forest and open-
land) and incubation time during 36 month of wood decomposition in tropical montane forest,
Mengsong, Xishuangbanna, SW, China. Note that for 0 mo error bars represent standard error of
the mean (from pooled logs) while for the remainder time points the error bars are +/- 95 % from
the best predicted model.

897

Fig. 4: Change in fungal composition through time based on Bray-Curtis dissimilarity over 36
month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW,
China (each point representing a sample; 95% confidence intervals around centroids are shown
(ellipses)). The upper two panels show ellipses (colored dashed lines) for incubation time. The
lower two panels show ellipses for forest disturbance categories. Initial in the lower two panels
represent the communities at 0 mo before incubation.

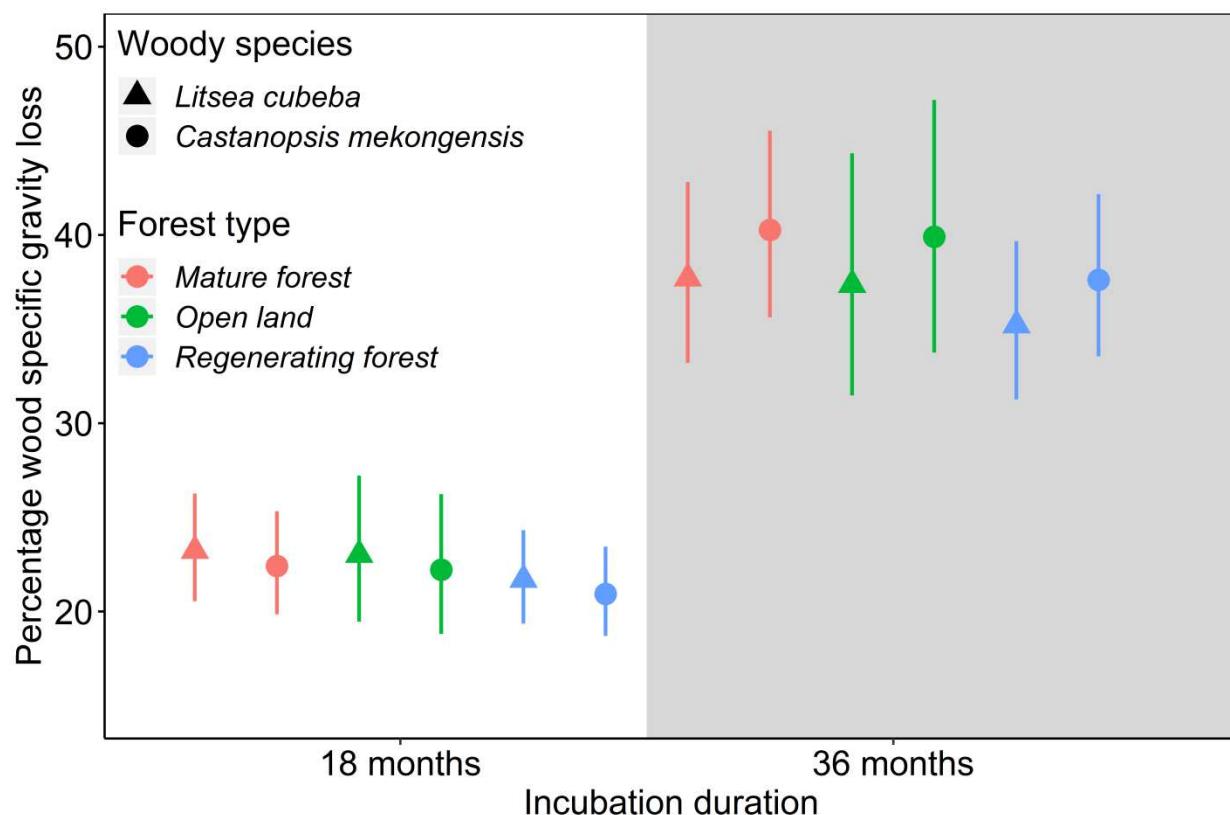
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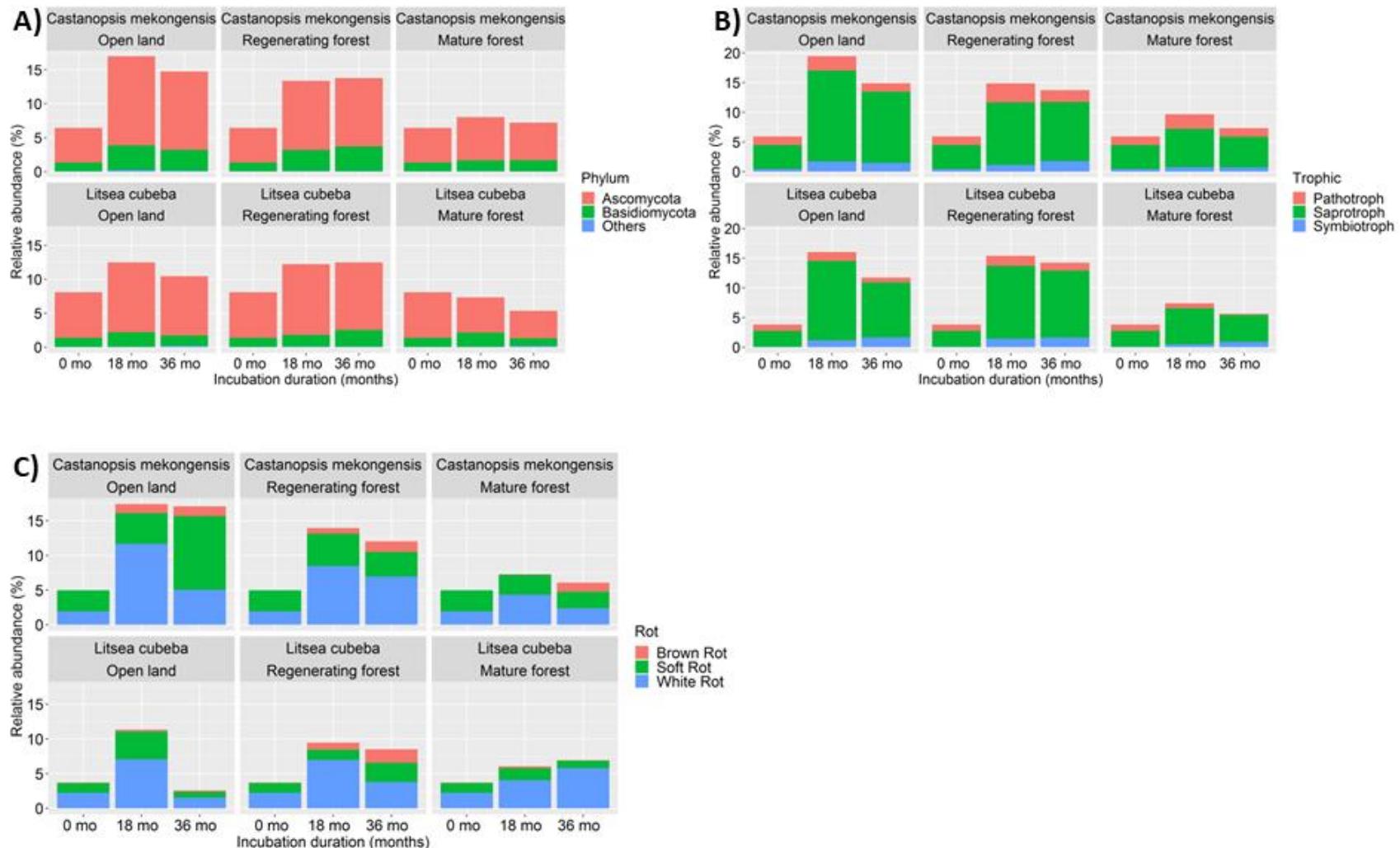
Fig. 5: Venn diagram for displaying the temporal dynamics of unique and shared fungal species
(OTUs) harbored by logs of A) *Castanopsis mekongensis*, B) *Litsea cubeba*, C) both species at
initial time 0 mo, D) both species at 18 mo, and E) both species at 36 mo after incubation during
36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW,
China.

910

Fig. 6: Structural equation modeling summarizing the direct and indirect effects of time, fungal
alpha diversity, woody species, white rot abundance and forest type on wood specific gravity
(WSG) loss on logs of *Litsea cubeba* and *Castanopsis mekongensis* during 36 month of wood
decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China. Thickness of

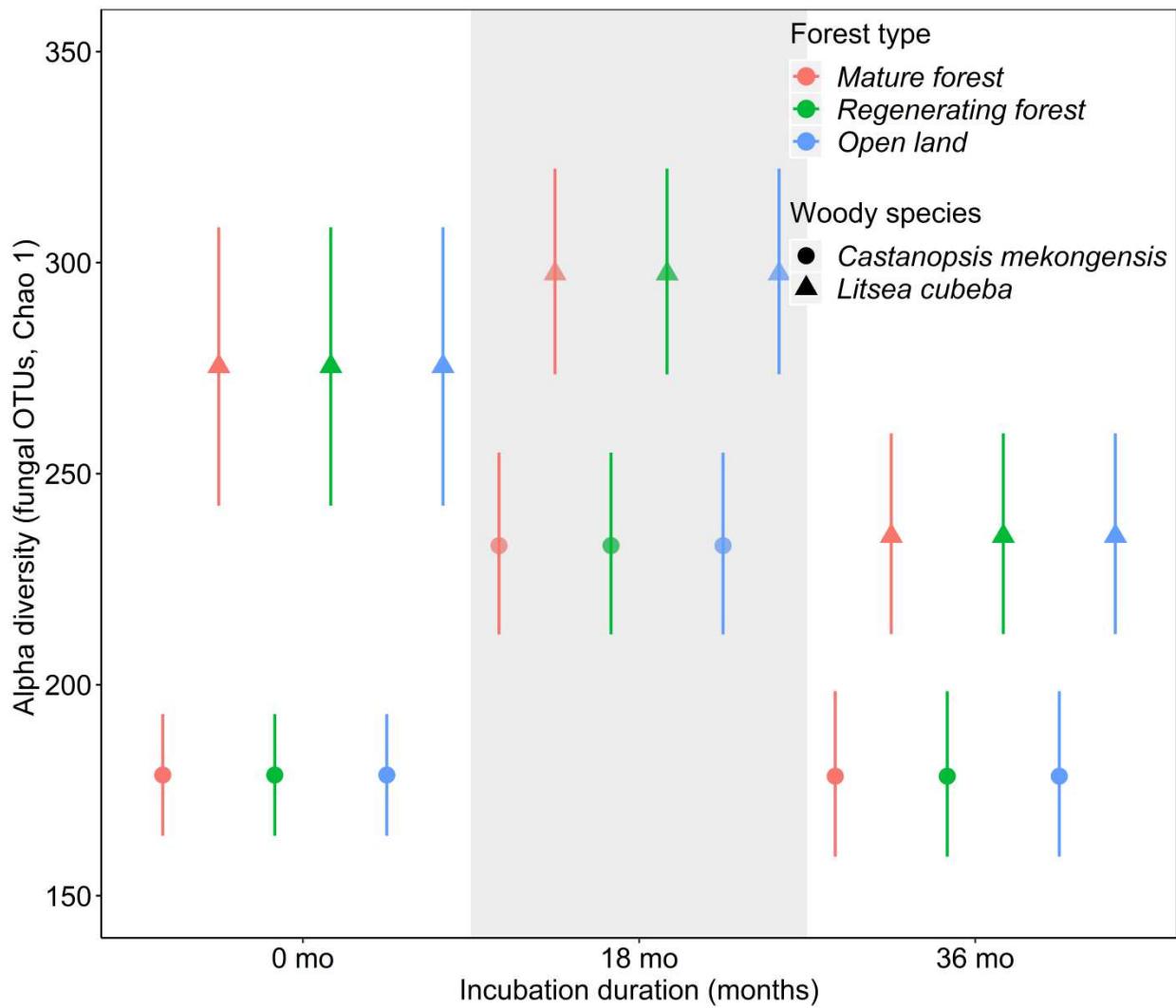
915 the path equates to the strength of path coefficient. Black and red arrows indicate positive and
916 negative paths respectively. For clarity we did not put the non-significant path coefficients in the
917 diagram (but see Table S5 for full SEM results). Chi square = 4.17, P-value = 0.53 , degrees of
918 freedom (DF) = 5, Comparative Fit Index (CFI) = 1. As habitat is a categorical variable with
919 three levels, we created dummy variables with mature forest as the baseline level so any path
920 regression coefficient for the other two levels represents the difference of that level from the
921 baseline. Time was included as ordered categorical variable with 18 mo < 36 mo.

924 **Fig. 1**



925

926 Fig. 2

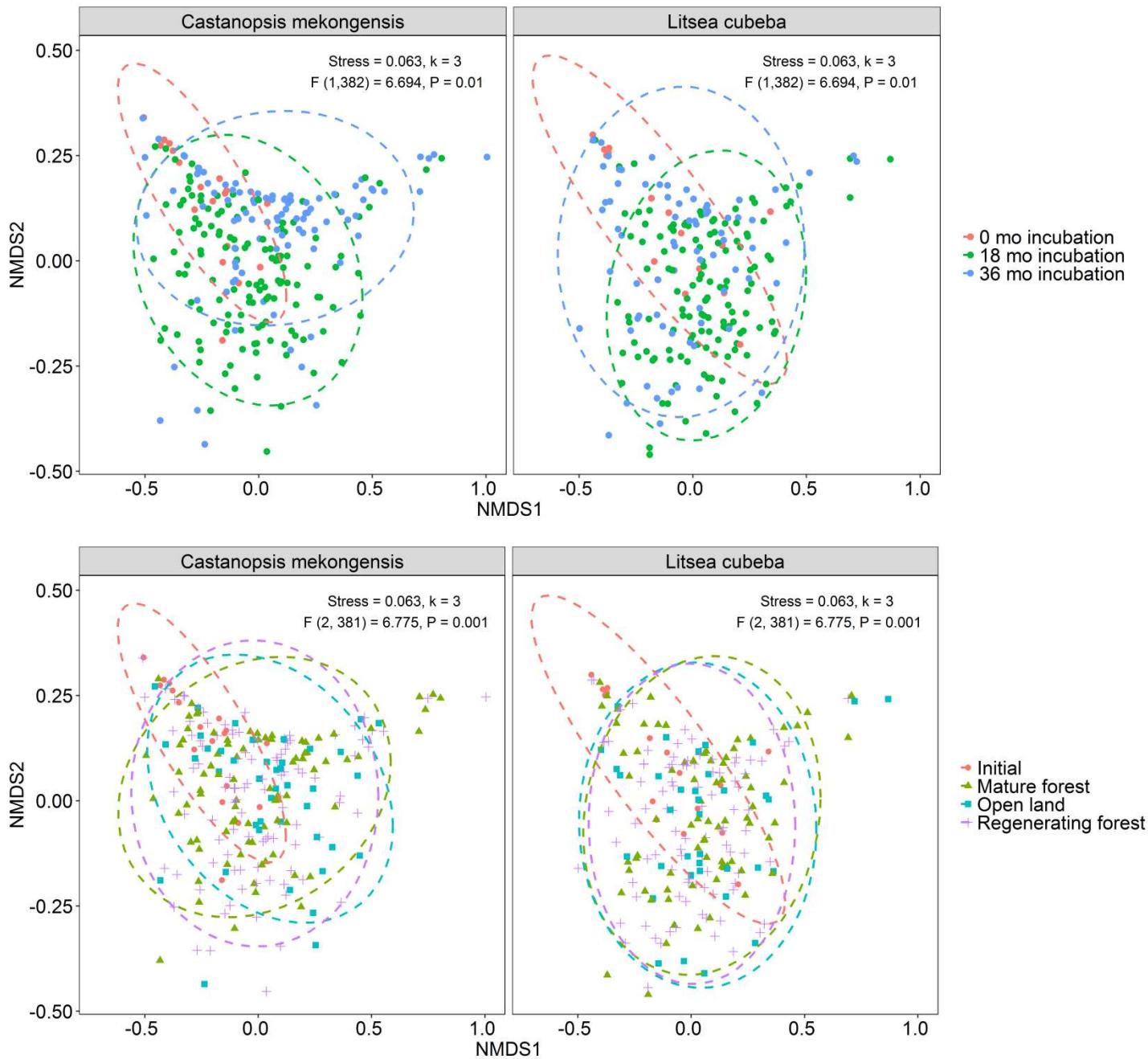


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928 **Fig. 2**

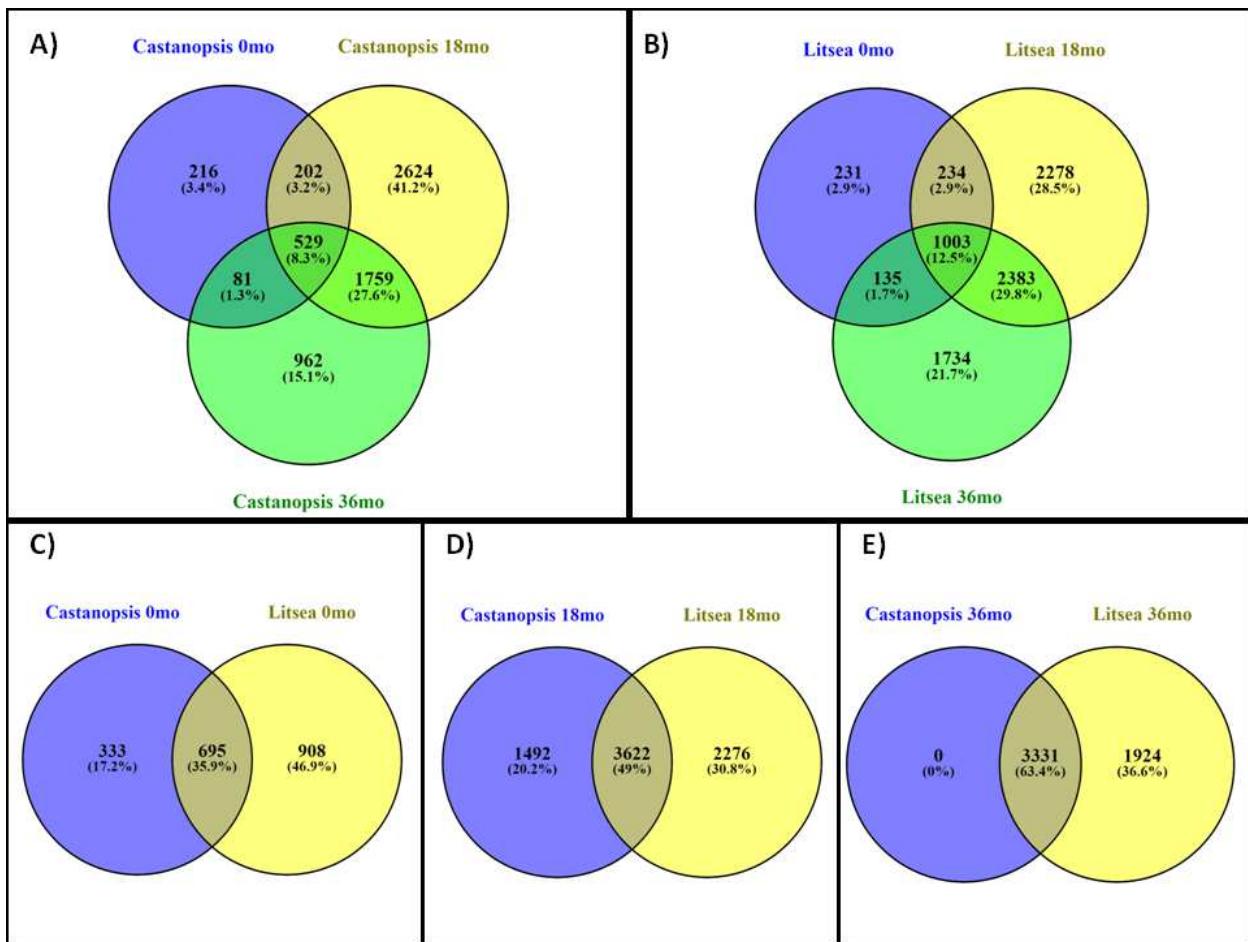
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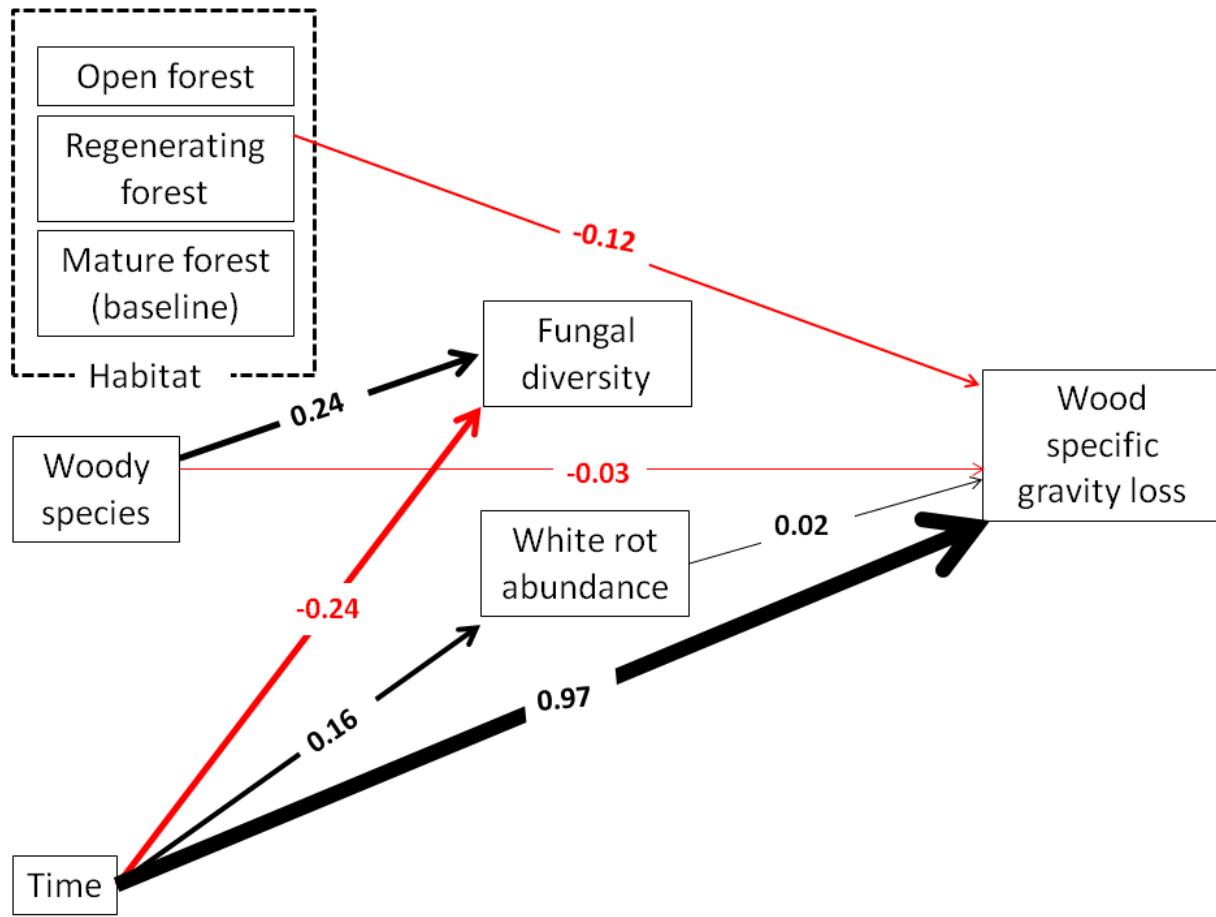
932 **Fig. 4**



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934

935 **Fig. 5**



936

937

938 **Fig. 6**

939 **Tables**

940 **Table 1:** Analysis of factors affecting Bray-Curtis dissimilarity between fungal communities
941 using permutational multivariate analysis PERMANOVA with repeated measurement
942 implemented in adonis for fungal communities found in log of *Litsea cubeba* and *Castanopsis*
943 *mekongensis* during 36 month of wood decomposition in tropical montane forest, Mengsong,
944 Xishuangbanna, SW, China. DF = Degree of freedom.

945

Parameters	DF	Sums of Squares	Mean Squares	F. Model	R ²	Pr(>F)
Time	1	1.565	1.565	3.560	0.009	0.001
Forest	2	1.166	0.583	1.327	0.007	0.001
Termites	1	0.409	0.409	0.930	0.004	0.176
Time:Termites	1	0.602	0.602	1.369	0.004	0.003
Residuals	377	165.726	0.440		0.976	

946

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948

Figures

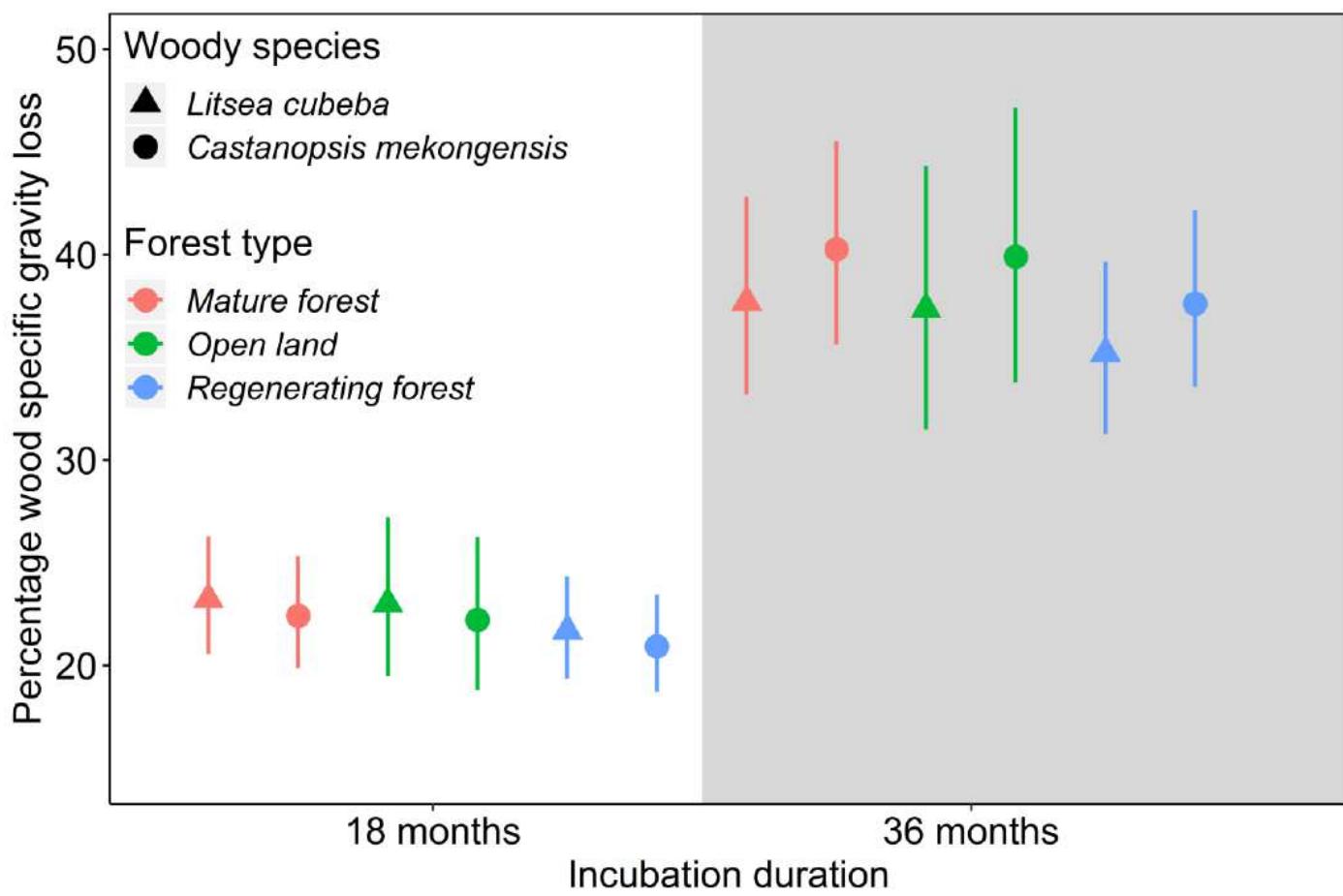


Figure 1

Percentage wood specific gravity (WSG) loss from logs installed across 28 plots in the Mengsong landscape after 18 mo and 36 mo incubation. The experiment used two species, *Litsea cubeba* and *Castanopsis mekongensis*. Points represent predicted mean values ($\pm 95\%$ confidence interval) for two species (*Litsea cubeba* and *Castanopsis mekongensis*) with respect to disturbance category (mature forest, regenerating forest and open-land) and incubation time during 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China (Dossa et al. submitted).

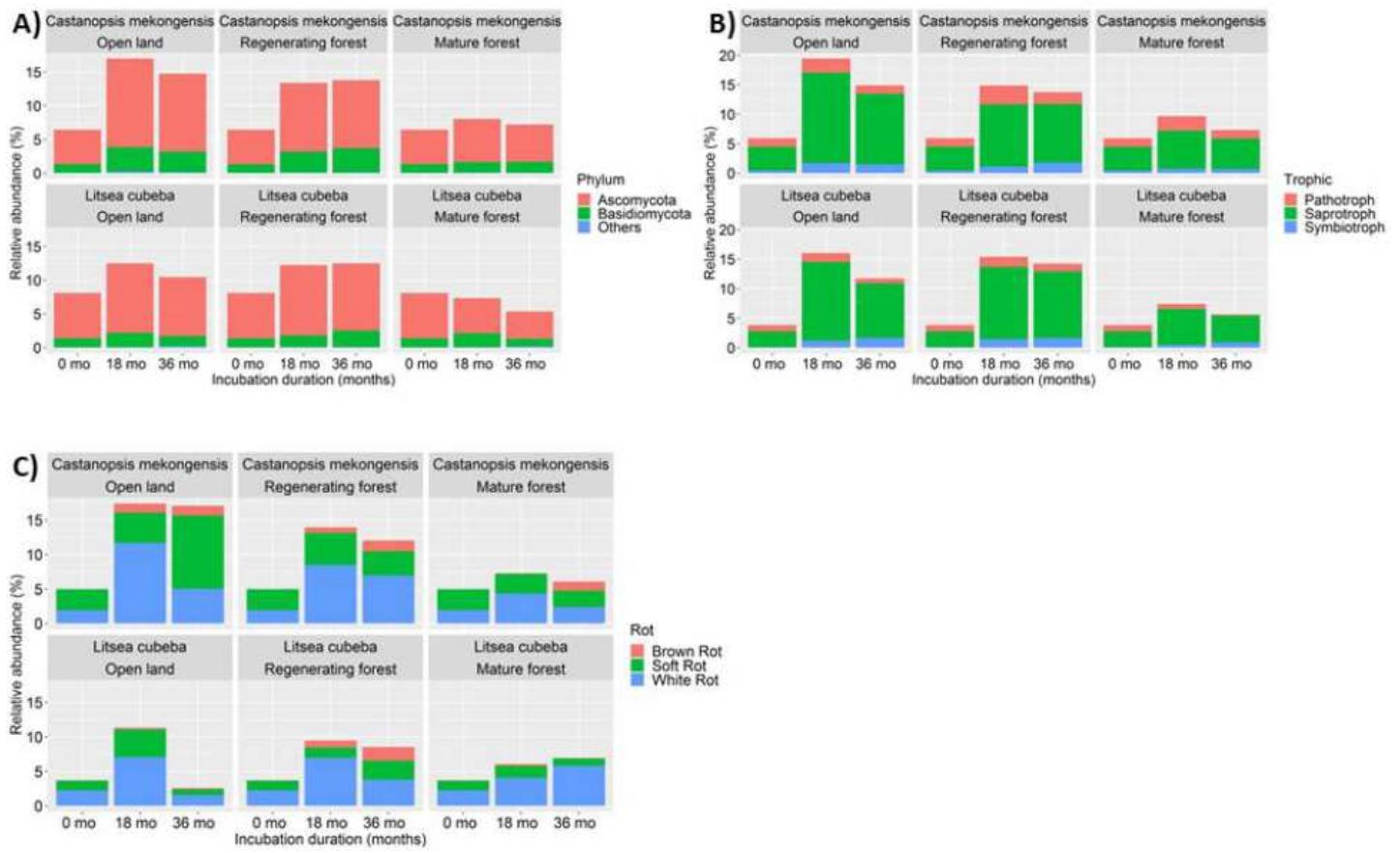


Figure 2

A) Average relative abundance of OTUs assigned to higher taxonomic units (Ascomycota, Basidiomycota, Other), B) Average relative abundance of OTUs assigned by FUNGuild to different trophic modes (Pathotroph, Saprotroph, Symotroph) and C) Average relative abundance of OTUs assigned by FUNGuild to different rot types (white-rot, brown-rot, and soft-rot fungi). In order to have comparable values, the relative abundance was calculated across all our samples regardless of habitats and species. And this relative abundance represents the proportion of OTUs assigned to each fungal guild identified via FUNGuild. Thus within each panel the total percentage sums to 100.

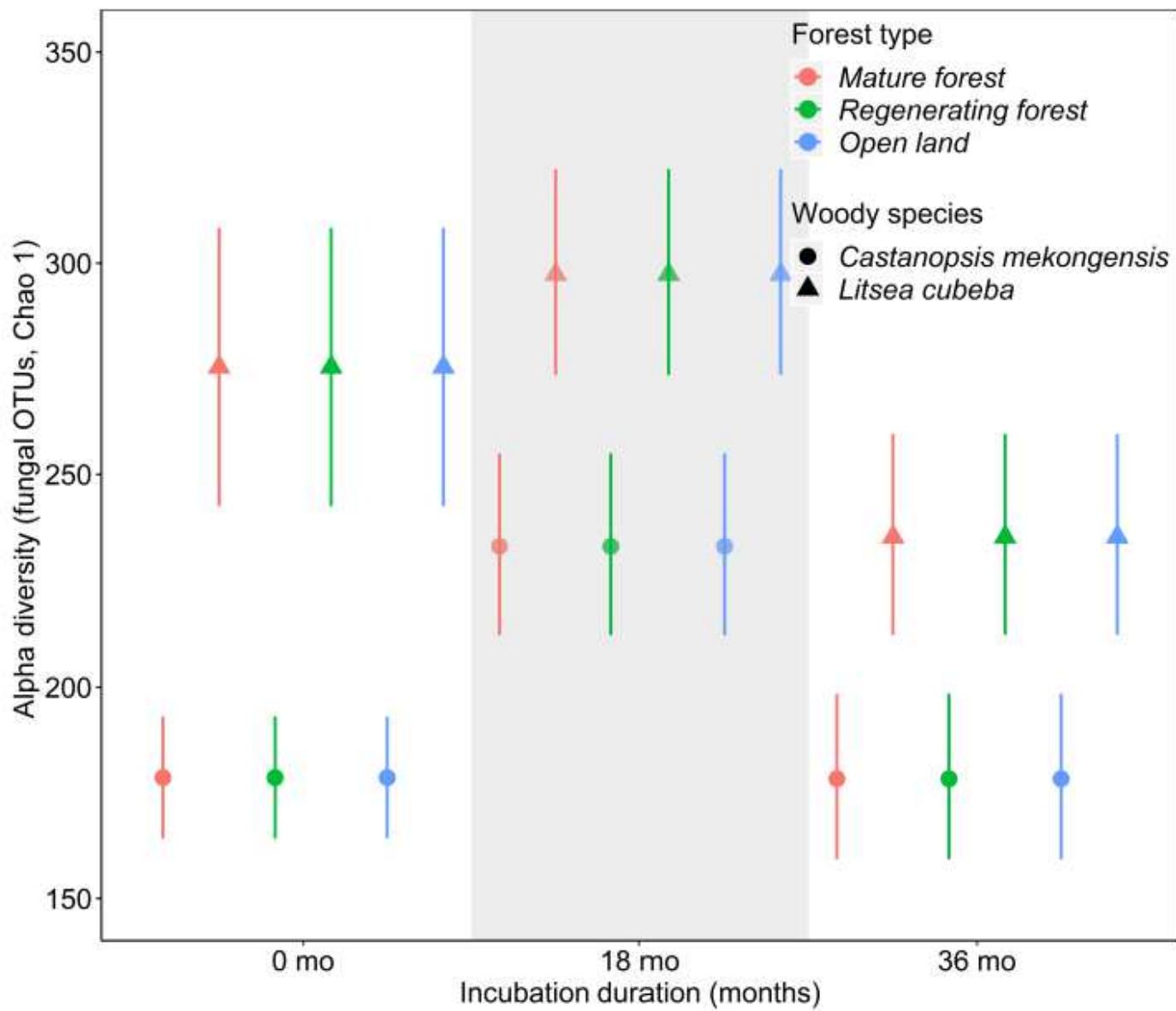


Figure 3

Change in fungal alpha diversity (Chao 1) across time and forest types for two wood species (*Litsea cubeba* and *Castanopsis mekongensis*) across habitat (mature forest in red, regenerating forest in blue and open forest in green) during 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China. Points represent predicted mean values ($\pm 95\%$ confidence interval) for two wood species (*Litsea cubeba* and *Castanopsis mekongensis*) with respect to disturbance category (mature forest, regenerating forest and open-land) and incubation time during 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China. Note that for 0 mo error bars represent standard error of the mean (from pooled logs) while for the remainder time points the error bars are +/- 95 % from the best predicted model.

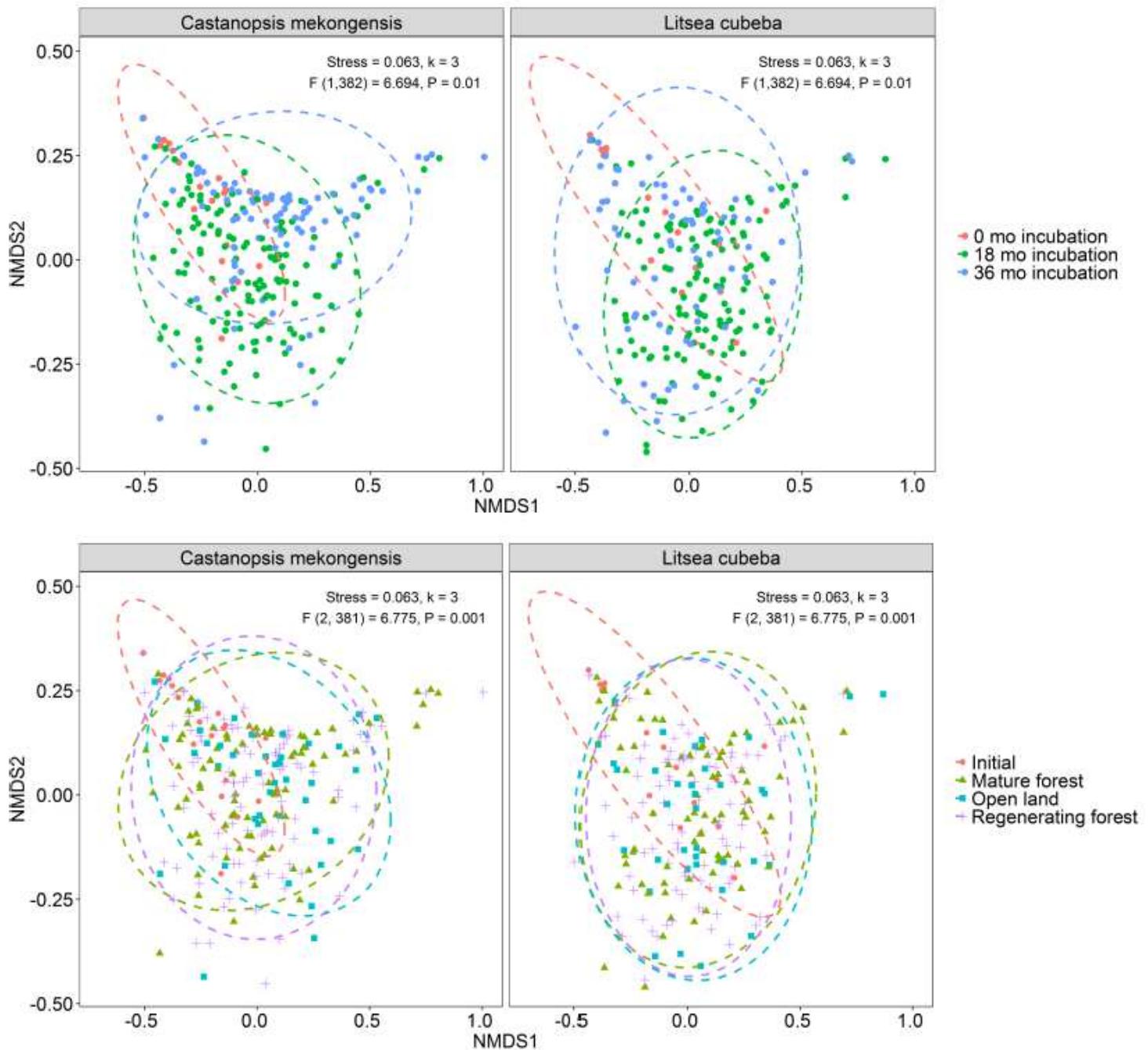


Figure 4

Change in fungal composition through time based on Bray-Curtis dissimilarity over 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China (each point representing a sample; 95% confidence intervals around centroids are shown (ellipses)). The upper two panels show ellipses (colored dashed lines) for incubation time. The lower two panels show ellipses for forest disturbance categories. Initial in the lower two panels represent the communities at 0 mo before incubation.

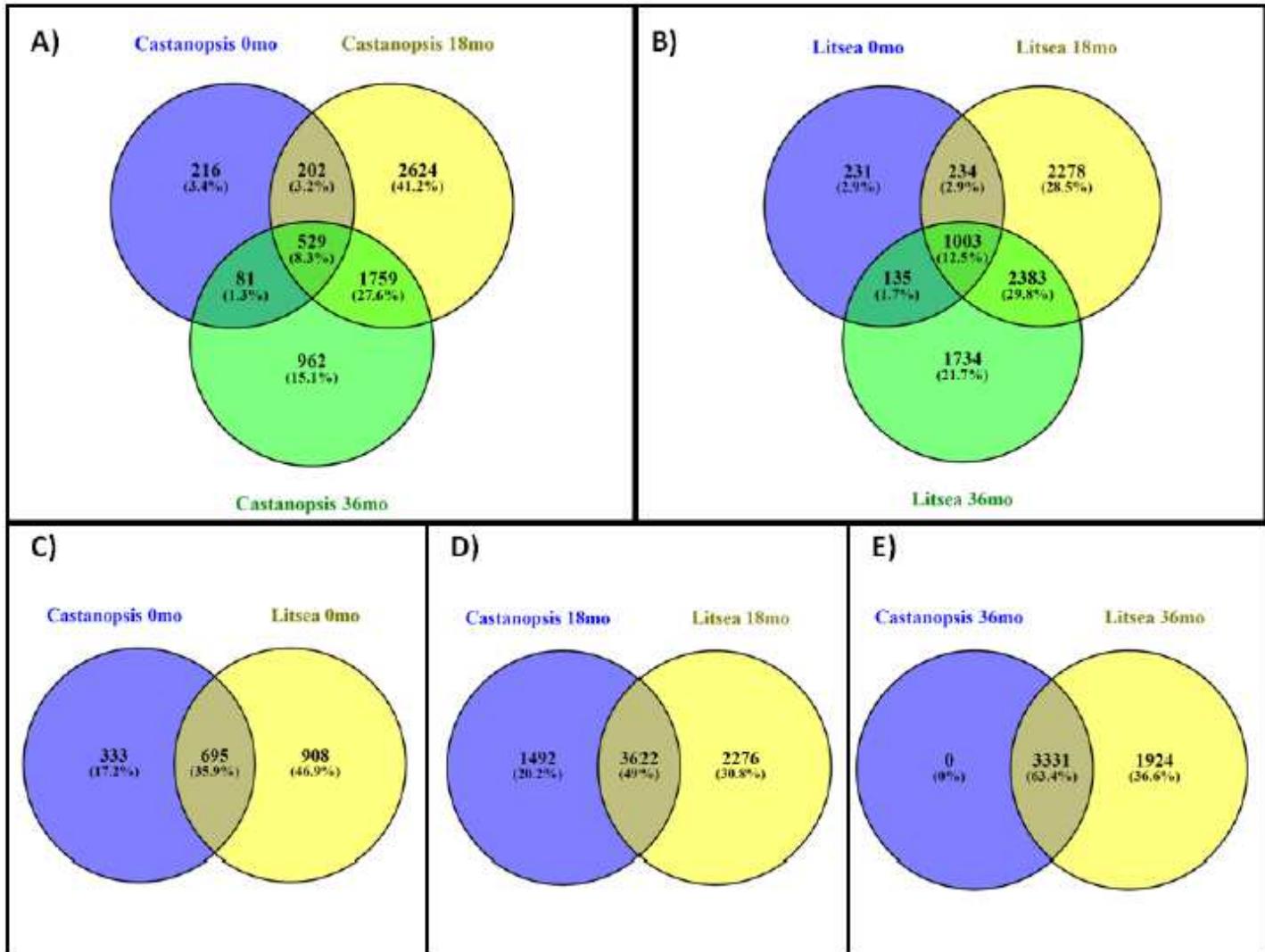


Figure 5

Venn diagram for displaying the temporal dynamics of unique and shared fungal species (OTUs) harbored by logs of A) *Castanopsis mekongensis*, B) *Litsea cubeba*, C) both species at initial time 0 mo, D) both species at 18 mo, and E) both species at 36 mo after incubation during 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China.

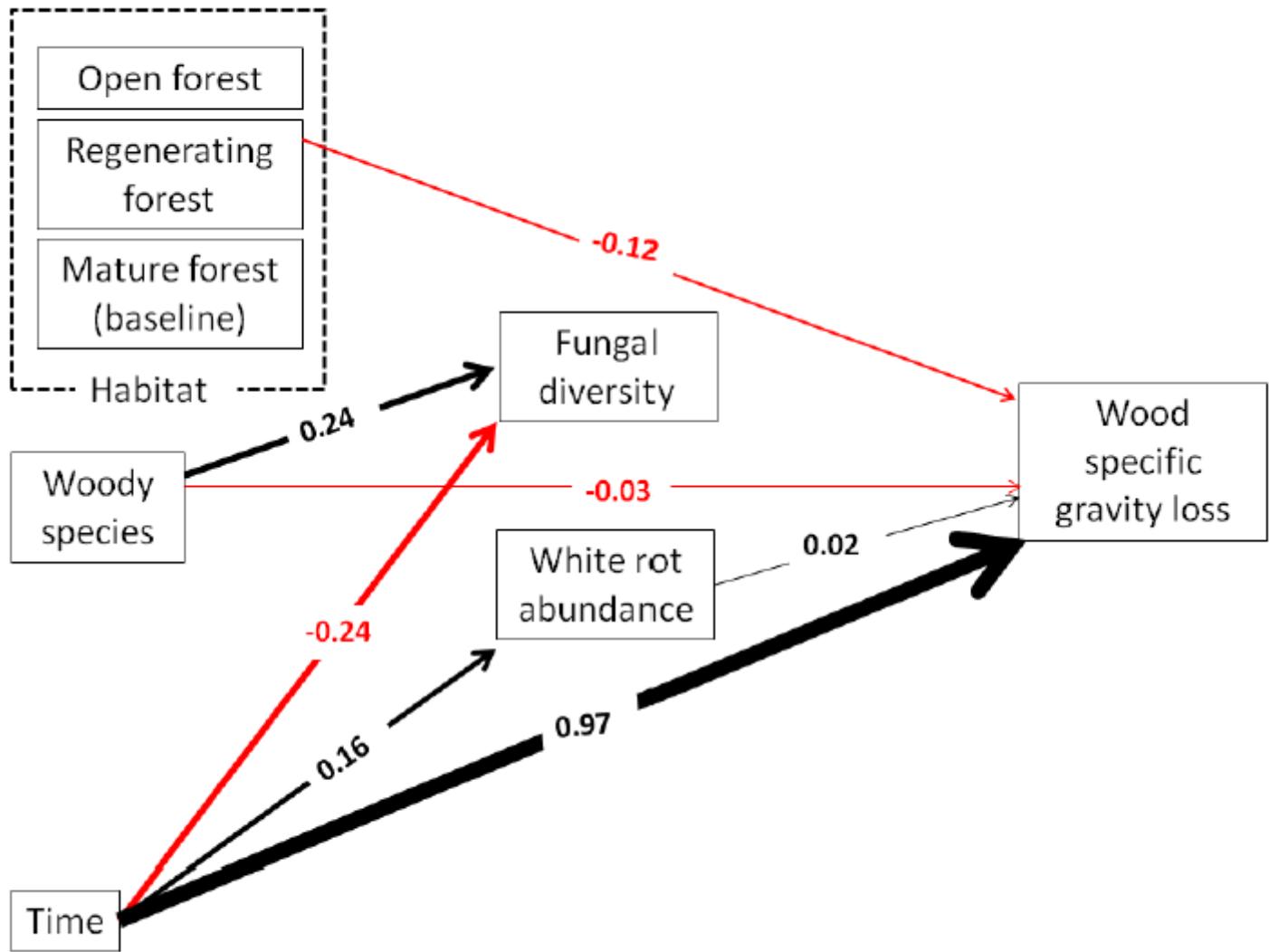


Figure 6

Structural equation modeling summarizing the direct and indirect effects of time, fungal alpha diversity, woody species, white rot abundance and forest type on wood specific gravity (WSG) loss on logs of *Litsea cubeba* and *Castanopsis mekongensis* during 36 month of wood decomposition in tropical montane forest, Mengsong, Xishuangbanna, SW, China. Thickness of the path equates to the strength of path coefficient. Black and red arrows indicate positive and negative paths respectively. For clarity we did not put the non-significant path coefficients in the diagram (but see Table S5 for full SEM results). Chi square = 4.17, P-value = 0.53 , degrees of freedom (DF) = 5, Comparative Fit Index (CFI) = 1. As habitat is a categorical variable with three levels, we created dummy variables with mature forest as the baseline level so any path regression coefficient for the other two levels represents the difference of that level from the baseline. Time was included as ordered categorical variable with 18 mo < 36 mo.

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