

1 **Temporal trait plasticity and neighborhood crowding predict the growth of tropical trees**

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18 **Abstract**

19 Functional traits and neighborhood composition have been used to predict tree growth dynamics.

20 Temporal changes in trait values (temporal trait plasticity) is one of the mechanisms for adaptive
21 plastic response to environmental change. However, the consequence of temporal change in trait
22 values and neighborhoods on the growth performance of individuals has rarely been investigated.

23 We, therefore tested the effect of temporal changes in trait values and neighborhood crowding on

24 the growth rate of individuals in a tropical forest using a dataset containing individual level
25 growth and functional trait data for *Ficus* individuals. We collected trait and size data at two time
26 points (2010 and 2017) for 472 individuals of 15 *Ficus* species in Xishuangbanna tropical forest
27 dynamics plot, southwest China. We used linear mixed effect model to predict the effect of
28 temporal trait plasticity and neighborhood crowding on the relative growth rate of individuals
29 using these data. We found significant temporal changes in individuals' functional traits
30 suggesting a shift in ecological strategies from being functionally acquisitive to conservative. We
31 also found differences in neighborhood crowding between the two census years indicating that
32 the strength of individual interactions might change over time. The temporal changes in trait
33 values and neighborhood crowding were found to predict better the relative growth rate of
34 individuals, compared to static trait or crowding values in the initial and final censuses. We also
35 found major axes of tree functional strategies in a principal component analysis, highlighting
36 potentially adaptive trait differences. Our results in general highlight to consider the temporal
37 dimension of functional traits and biotic interactions, as our result suggest that growth-trait
38 relationships may vary between time points, allowing us to understand the demographic response
39 of species to temporal environmental change.

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41 Key words: *Ficus*, functional traits, forest temporal dynamics, neighborhood crowding, species
42 growth, temporal trait plasticity, tropical trees.

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47 **INTRODUCTION**

48 Biotic interactions and environmental heterogeneity overlap spatially and temporally in effects
49 on community assembly, creating dynamic and ecologically complex tropical forest community
50 (Wright 2002; Zambrano et al. 2017). Biotic interactions at local scales partly drive the
51 demographic pattern of species that ultimately shape tree community assembly (Fortunel et al.
52 2018). Heterogenous abiotic environments also sort species based on species ecological
53 requirements, and regulate species performance and community dynamics in diverse systems
54 (Lasky et al. 2013). Functional traits have been widely used to make inferences about community
55 dynamics, as traits are believed to provide insights into the role of environment in assembly
56 (Poorter and Bongers 2006; Yang et al. 2018). Although testing trait-growth relationships has
57 become more common and fundamental to understand community dynamics (Swenson et al.
58 2017), a remaining goal is to understand this relationship from a temporal perspective.

59 In practice, community trait data are often collected only at a single time point. These
60 static data are then used for downstream analyses to species demography and to understand
61 community change through time and space (Swenson et al. 2017). While collecting a single
62 timepoint of trait data may be pragmatic, particularly in diverse systems, a vast evolutionary
63 ecology literature shows how traits influence individual performance (Lande and Arnold 1983,
64 Wade and Kalisz 1990), and how traits change in adaptive (Moran 1992, Baythavong 2011), and
65 maladaptive response to environment (Ghalambor et al. 2007). Furthermore, traditional
66 implementation of correlating community variation in traits to demographic traits may lead to
67 weak or mislead models and inferences (Umaña et al. 2018). How trait values and neighborhood
68 interactions change over time, and how their temporal changes impact trees demography have
69 not been widely tested, despite the fact that species interactions and growth strategies are known

70 to be temporally dynamic. This may reflect the limitation of trait-based ecology as it usually
71 gives static trait values for individuals that ignores the temporal variation of traits, and this limits
72 the ability to understand how temporal variability in traits and biotic interactions regulates the
73 performance of individuals over time (Swenson et al. 2017).

74 Adaptive phenotypic plasticity, i.e. when trait changes increase fitness, is a key strategy
75 by which organisms respond to changes in their environment (Pigliucci 2001). Maladaptive
76 plasticity, which is a symptom of a failure of an organism to maintain homeostasis, could also be
77 resulted when a change in trait values through time reduce fitness of organisms (Ghalambor et al.
78 2007). Temporal trait plasticity is expected to increase as conditions vary over time (Lázaro-
79 Nogal et al. 2015). Long-lived organisms have to have some level of adaptive plasticity to
80 survive and persist through such a wide range of conditions over their lifespan, relative to short
81 lifespan organisms such as annual plants. While a growing evolutionary ecology literature has
82 tested for the effects of trait plasticity on intraspecific fitness variation (Dudley and Schmitt
83 1996, Van Kleunen and Fischer 2005), less is known about how temporal trait plasticity
84 influences community assembly. Much of the earlier trait-based studies have focused on
85 assessing forest community dynamics using traits measured once in the life span of trees that
86 lacks the temporal domain of ecology (e.g., Wright et al. 2010, Lasky et al. 2014a, Paine et al.
87 2015, Visser et al. 2016). Temporal trait variation of communities has been less studied than
88 temporal shifts in species composition, though traits are known to be temporally dynamic
89 (Enquist and Enquist 2011, Fauset et al. 2012). Few studies have characterized the temporal trait
90 changes and associated demographic consequences at community level. Van Der Sande et al.
91 (2016) reported that community trait values (wood density increased; specific leaf area
92 decreased) changed over time in all of the five studied forest types in the Neotropics suggesting

93 that species shifted from being fast-growing to slow-growing species. Temporal shifts of trait
94 distributions, mainly at the community level, have also been reported (Lasky et al. 2014b,
95 Katabuchi et al. 2017). The decrease of specific leaf area (SLA) and leaf phosphorus content
96 over time in the wet tropical forests also suggested a change in functional strategies of species
97 (Muscarella et al. 2017). A long-term shift of species' mean trait values through time showing
98 directional change was also found in a tropical dry forest (Swenson et al. 2020). There are many
99 studies that have inferred functional turnover in forests through time, using traits measured at a
100 single time point and assumed to be the same for all individuals of a species. However, these
101 studies did not measure traits of individual plants, meaning that trait plasticity could not be
102 quantified. Testing whether the effect of traits on tree growth differs between time points and
103 how the temporal shift of traits (i.e. temporal trait plasticity) plays a role in shaping the growth
104 dynamics of communities may help to better understand the direction of forest structural and
105 functional change.

106 Trait-growth relationships have been used to reveal plant growth strategies and predict
107 the demographic trajectories of species (Adler et al. 2013, Yang et al. 2020 in press). However,
108 the predictive power of traits has been sometimes weak which raises a question about the
109 significance of traits (Paine et al. 2015). One reason for this could be, apart from the trade-offs
110 between demographic rates that may conceal the effect of traits on species performance
111 (Laughlin et al. 2020 in press), trait-growth relationships usually are computed at the species
112 level using mean trait values and mean growth rates of individuals, despite the fact that trait-
113 driven resource competition occurs at the individual level (Liu et al. 2016). Averaging trait
114 values of individuals across the species ignores individual level trait variation, limiting the ability
115 of traits to predict individual growth rates (Liu et al. 2016, Umaña et al. 2018). Individuals traits

116 may predict better the growth performance of individuals, as trait differences determine
117 individuals' growth strategies (Yang et al. 2018, Worthy & Swenson 2019).

118 Neighborhood interactions influence tree growth, and can promote species diversity
119 (Lasky et al. 2014b, Chen et al. 2016, Lamanna et al. 2017, Zambrano et al. 2017, Fortunel et al.
120 2018). The growth rate of individuals depends on the density of immediate neighbors with
121 positive or negative effects. High density of neighbors often reduces the growth or survival rate
122 of trees (Comita et al. 2010, Johnson et al. 2017, Lamanna et al. 2017). However, studies of
123 neighborhood interactions have rarely considered temporal dynamics in biotic interactions. That
124 is, how do neighborhood interactions change over time, and do these changes affect individual
125 vital rates? Changes in neighborhoods over time, if overlooked, might obscure the effects of
126 neighbors on individual growth (Bachelot et al. 2015). The number and identity of neighbors
127 could change through time due to recruitment and mortality, and as a result the strength of
128 neighborhood effect on growth may change over time (Newbery and Stoll 2013). One of the
129 challenges of using neighborhood crowding covariates is that neighborhoods may change
130 spatially in response to variation in resources (light, water, nutrients), so that the actual available
131 resource supply might differ from what we expect from the level of crowding. And so, it may be
132 that neighborhood dynamics are better at capturing the variation in actual resource availability,
133 because we might expect an increase in crowding over time actually does correspond to less
134 available resources to individuals. Thus, the effect of neighbors may not be captured unless
135 changes in local neighborhoods are considered. However, the temporal change in neighbors and
136 its subsequent effect on tree demography has not been widely studied, though few studies being
137 reported.

138 We tested how changes in functional traits and neighborhood interactions affect the
139 growth of species in the diverse genus of *Ficus* trees in a tropical forest. We asked the following
140 specific questions: (i) How do traits, neighborhood crowding, and growth rate of individual trees
141 change over time? (ii) Are functional traits and neighborhood crowding temporally consistent in
142 predicting the relative growth rate of individuals? (iii) Does temporal trait plasticity and changes
143 in neighborhood crowding predict better the relative growth rate of individuals compared to
144 using only a single snapshot of traits and neighborhood crowding?

145

146 **METHODS**

147 **Study site**

148 We carried out this study in the 20-ha Xishuangbanna seasonal tropical rainforest dynamics plot
149 (FDP) in southwest China (21°37'08" N, 101°35'07" E) (Figure S1). Dry and rainy seasons are
150 typical features of the region with mean annual rainfall and temperature of 1493 mm and 21.8°C
151 respectively (Cao et al. 2006). The plot ranges from 709 to 869 m in elevation (Lan et al. 2009).
152 In 2007, all free-standing woody stems ≥ 1 cm in diameter at 130 cm from the ground (Diameter
153 at Breast Height, DBH) were measured, mapped and identified to species (Condit 1998).

154

155 **Focal species**

156 We used the *Ficus* (Moraceae) genus as a case study, as it is a pantropical genus with more than
157 800 species in the lowland tropical forest and contains functionally diverse species (Harrison
158 2005). *Ficus* assemblages provides a useful system to investigate the mechanisms that maintain
159 high tropical species diversity (Lasky et al. 2014a). Furthermore, *Ficus* is the most speciose
160 genus in the 20-ha plot, with 15 identified species and 4.6% of the total basal area in the plot, and

161 a large quantity of soil seedbank (Tang et al. 2006). Most of the individuals are distributed on the
162 steep slopes of the plot, and some of them are limited to ridges and valleys (Hu et al. 2012). In
163 2010, leaf functional traits were measured on *Ficus* individuals with a DBH of at least 10 cm
164 with leaves accessible with pole shears (Lasky et al. 2014a) and then re-measured these trees in
165 2017. Thus, we used trait data for the *Ficus* trees separated by seven years and DBH data
166 separated by ten years interval in the Xishuangbanna FDP. A species list is given in Table S1.

167

168 **Functional traits**

169 We measured eight functional traits data in two census years for the 472 individuals of the 15
170 *Ficus* species in the plot. We collected five matured, healthy and sun exposed leaves for each
171 individual in each census year and measured traits following the standardized protocols
172 (Cornelissen et al. 2003). We measured leaf area (cm^2), specific leaf area ($\text{cm}^2 \cdot \text{g}^{-1}$), leaf
173 chlorophyll content, leaf fresh mass (g), leaf dry mass (g), leaf dry mass content, leaf thickness
174 (mm), and leaf succulence ($\text{g} \cdot \text{cm}^{-2}$). These traits are expected to represent the fundamental
175 ecological strategies of individuals for resource acquisition. Leaf area is related to light capture
176 and heat balance (Poorter and Rozendaal 2008). Specific leaf area is linked to light interception
177 efficiency and the main part of leaf economic spectrum (Wright et al. 2004). Leaf chlorophyll
178 content is related to light harvesting capacity of the plant (Coste et al. 2010). Leaf thickness is
179 related to the mechanical strength of the leaf (Onoda et al. 2011). Leaf dry matter content is
180 associated with leaf defense ability and decomposition (Van Der Sande et al. 2016). Leaf
181 succulence represents the trade-off of productivity and life span of the leaf (Garnier and Laurent
182 1994). We measured the leaf chlorophyll content using SPAD-502 Chl meter (Minolta Camera
183 Co., Osaka, Japan), and three readings were taken at the widest portion of the leaf blades

184 (Marenco et al. 2009). We used electronic digital micrometer to measure leaf thickness (mm) at
185 the center of fresh leaves with multiple readings, and average was taken (Seelig et al. 2012).

186

187 **Tree growth**

188 All *Ficus* individuals' diameter at breast height (DBH) was measured in the Xishuangbanna FDP
189 in 2007 and 2017. Relative growth rates (RGR) used in this study were calculated as

190 $\ln\left(\frac{DBH_f/DBH_i}{t_f-t_i}\right)$, where t is year and the subscripts of f and i are respectively the final and initial

191 values of the diameter at breast height (Wright et al. 2010). The relative growth rate of species is
192 graphically indicated in Figure S2.

193 **Neighborhood crowding**

194 Neighborhood competition is one of the biotic driving forces that largely determines the growth
195 performance of individuals at the local scale (Fortunel et al. 2018). The effect of neighborhood
196 crowding is expected to decline with distance increases from the focal stem (Uriarte et al. 2010).

197 Here, we calculated the neighborhood competition of trees using the neighborhood crowding

198 index (NCI) separately for the two census years in order to evaluate its temporal effect on tree

199 growth. We computed the neighborhood crowding index (NCI) for each focal stem i of species s

200 based on the size (DBH) and distance (d) of its neighbors ($j=1\dots J$) within a 15 m radius for each

201 census year (t) (Lasky et al. 2014b, Uriarte et al. 2016). We excluded focal stems within 15 m of

202 plot boundaries to avoid edge effects in our analysis. A 15 m radius was chosen following the

203 previous work (Yang et al. 2020 in press).

$$NCI_{tsi} = \sum_{j=1, i \neq j}^J \frac{DBH^2}{d_{ij}^2} \quad (1)$$

204 **Statistical analyses**

205 **The temporal shift in traits and neighborhood crowding**

206 We first tested whether there were temporal shifts in traits (i.e. plasticity) and neighborhood
207 crowding over time. We used a linear mixed model to test whether significant changes in
208 univariate traits and *NCI* values occurred between the two censuses, with census as fixed effect
209 and the variable of interest, and species identity as random factor. Furthermore, we also used the
210 principal component analysis (PCA) on the mean centered and standardized trait values (by
211 dividing the centered trait values by their standard deviations) to find major axes of trait
212 variation and trait plasticity using the two censuses data.

213 Since functional traits were sampled twice over time on the same individuals,
214 we were able to compare the magnitude of trait variation explained by different sources. Using
215 traits as response variables, we included leaves, individuals, species, and census interval as
216 random variables in our mixed-effect models to decompose and estimate the variance explained
217 by each random variable, and expressed it in percentage as the total variance explained by each
218 of the random components. We standardized all parameters by subtracting the minimum value
219 from each observed value and then divided by its range value for the ease of interpretation and
220 comparisons. Data transformation was done for all functional traits, and other variables to meet
221 the assumption of normal distribution before analysis. Pearson correlation was carried out to
222 check for trait covariation and hence we removed leaf fresh mass from analysis as it strongly
223 correlated to leaf dry mass (Table S2, S3, and S4).

224

225

226

227 **Effect of functional traits and neighborhood crowding on tree growth**

228 The second objective of this study was to evaluate the relative importance of each functional trait
229 and neighborhood crowding on the relative growth rate of individuals. To address this question,
230 we built three different models: one model using the first census data, second model using the
231 second census data, third model is using the temporal changes in trait and neighborhood
232 crowding (i.e. the difference of traits, and neighborhood crowding between the first and second
233 census data). For each model, we fitted individual RGR as a function of traits and neighborhood
234 crowding using linear mixed-effects model. To handle model complexity, we fit separately the
235 growth model for each functional trait. The first two models take the following form:

$$RGR_i = \beta_0 + \beta_1 dbh_0 + \beta_2 traits_{i,t} + \beta_3 NCI_{i,t} \quad (2)$$

236 Where dbh_0 is the initial tree size (DBH) at the first census year, $traits_{i,t}$ represents the trait
237 values of individual i in year t . $NCI_{i,t}$ represents the NCI values of individual i in year t . β_0 is the
238 intercept for all individuals. For the third model, though it is the same in form with the above
239 model, we took the temporal difference in traits and NCI values. We subtracted the traits/ NCI
240 values in 2010 from the corresponding values in 2017 (trait/ NCI values in 2017 – trait/ NCI
241 values in 2010), and were used to describe temporal changes in traits/ NCI values. We selected
242 among models using Akaike Information Criterion (AIC) (Table S5, S6, and S7).

243 Additionally, we used piecewise structural equation models (SEMs) to determine any
244 possible pathways by which traits, neighborhood crowding and initial DBH size could
245 interactively influence the relative growth rate of individuals. We hypothesized that initial DBH
246 size and neighborhood crowding affect individuals' growth indirectly through their effects on
247 functional traits. Also, the DBH size may determine the canopy position and crowding
248 conditions of trees which may in turn influence trait expressions and ultimately affect growth of

249 individuals. We computed a series of piecewise SEMs separately for each census data (i.e. 1st
250 census data, 2nd census data, and temporal changes in traits and neighborhood crowding data).
251 We developed a conceptual framework model that shows possible direct and indirect casual
252 relationships among predictors and response variable (Figure S3). These hypothesized
253 relationships help to optimize the piecewise SEMs. Functional traits, initial DBH size and
254 neighborhood crowding were predictor variables, whereas relative growth rate of individuals was
255 a response variable. Species were taken as random effects in our piecewise SEMs analysis. To
256 minimize model complexity, functional traits were reduced using PCA and we used the first two
257 PCA axes representing traits as predictors. A series of piecewise SEMs were fit to the data, and
258 insignificant pathways were removed progressively from models to improve fitness of the model.
259 We used Fishers's C statistics to evaluate the goodness fit of the models with high P-values
260 showing good fit (Lefcheck 2016). We used AIC to select the best fit and parsimonious model.

261 We used R version 3.5.3 to run all the analyses. 'lme4' package was used to fit linear
262 mixed-effect models (Pinheiro and Bates. 2016). Principal component analysis was conducted
263 with the 'rda' function in vegan package (Oksanen et al. 2014). We used 'psem' function in
264 'piecewiseSEM' package for piecewise SEMs analysis (Lefcheck 2016).

265

266 **RESULTS**

267 **Temporal shifts in trait values, growth and neighborhood crowding**

268 We tested the extent of trait, growth and neighborhood variation at the individual level and
269 temporal time points in a tropical forest. We found significant temporal changes in trait values
270 for at least half of the functional traits being tested (Figure 1; see also Figure S4 that compares
271 individual traits on the scatter plot). SLA decreased significantly from the first census to the

272 second census, whereas leaf chlorophyll content, leaf dry mass and leaf succulence increased
273 from the first to the second census. However, we did not find significant temporal changes in
274 trait values for Leaf fresh mass, Leaf thickness, Leaf area, and LDMC. Individuals' size,
275 expressed as DBH, also increased significantly over time indicating significant growth of focal
276 trees, whereas significant change was not observed on the neighborhood crowding of individuals,
277 consistent with the late-successional stage of the forest.

278 We also analyzed the amount of trait variation explained by the species, individuals,
279 years and leaves. We found that most functional traits showed significant variation among
280 leaves, individuals, species and between census years (Figure 2). Most functional trait variations
281 are explained by the species followed by the individual level.

282

283 **Axes of functional variation**

284 To evaluate trait associations and plant strategies, we used a PCA of the seven traits of species
285 (Figure 3). The first two PCA axes explained almost 66 % of the variation and showed a
286 spectrum of trait variation. The first PCA axis shows species with a large leaf area, leaf thickness
287 and dry mass at the left to species with high SLA at the right. The second axis represents species
288 with high chlorophyll content at the top to species with high LDMC and succulence at the
289 bottom. These axes, therefore, represent the leaf trait spectrum tradeoff. We also conducted the
290 PCA on the temporal change in traits (trait values in 2010 were subtracted from traits in 2017) to
291 see axes of temporal plasticity (Figure S5). Along the first axis, individuals were separated
292 between those species with decreasing SLA and leaf area on the right-hand side and those with
293 increasing leaf dry mass on the left side. Species with high leaf thickness and succulence were
294 represented at the top of the second axis.

295 **Effect of traits and neighborhood crowding on the relative growth rate of individual trees**

296 We tested how growth was correlated with temporal variation of traits and neighborhood
297 crowding. We found that traits and neighborhood crowding have not explained significantly the
298 relative growth rate of individual trees in the first census (Figure 4a). However, in the second
299 census leaf chlorophyll content, leaf area, leaf dry mass, LDMC, leaf succulence and
300 neighborhood crowding significantly explained the relative growth rate of individuals (Figure
301 4b). We also used the temporal changes in functional traits and neighborhood crowding to
302 predict the growth rate of individuals, and interestingly found that almost all of the change in
303 trait values and neighborhood crowding explained better the relative growth rate of the
304 individuals (Figure 4c). See Table S5, S6, and S7 for model AIC values.

305 We also used SEMs to investigate any possible pathways by which traits and
306 neighborhood crowding has interactively predicted growth of individuals. We found no
307 significant causal relationships among traits, neighborhood crowding and initial DBH size to
308 determine individuals' growth rates (Figure S6). However, initial DBH size (in addition to its
309 direct significant negative effect on RGR) has indirect significant positive effect on the RGR of
310 individuals through its negative effect on PC1 and PC2 of the second census and temporal
311 change data (Figure S6 b & c). We also found initial DBH to negatively be interacted with
312 neighborhood crowding which in turn negatively influenced the RGR of individuals in the
313 temporal change data (Figure S6 c). However, we did not find a pathway through which
314 neighborhood crowding and traits interactively affect individuals' growth in all census data.

315

316

317

318 **DISCUSSION**

319 While past studies of community functional dynamics have focused on turnover in species
320 identity, here we show patterns arising due to temporal trait plasticity of long-lived individuals.
321 We predicted individual tree growth using traits measured on individuals while considering at
322 the same time the biotic context in which that individual was found across time points. We
323 showed trait-growth relationships, and negative effects of neighborhood crowding on the growth
324 rate of individuals. The significant change of traits over time (temporal trait plasticity) and the
325 association of functional traits with the leaf economics spectrum was also detected. Half of the
326 functional traits measured changed significantly over time and were able to predict individual
327 growth rates. The covariation of traits also revealed the presence of, to a certain extent, a leaf
328 economics spectrum.

329

330 **Temporal trait plasticity and neighborhood crowding**

331 Tropical forests inhabit dynamic environments, and therefore some changes in functional
332 strategies of trees might be adaptive. Consistently, we found significant temporal changes of
333 some functional traits in our plot that could potentially alter individual ecological requirements.
334 SLA decreased and leaf dry mass increased, possibly suggesting a change in strategies for
335 resource acquisition. Similar observations have been previously reported using data on turnover
336 in species identities and assuming fixed trait values for species. For example, in Neotropical
337 forests changes in species composition over time shifted toward conservative functional
338 strategies, mainly due to disturbances (Van Der Sande et al. 2016). Muscarella et al. (2017) also
339 found that communities shifted from species with resource acquisitive to conservative functional
340 strategies in Mexico. Disturbances like tree fall and landslides have been common on the

341 topographically steep plot, potentially influencing the tree community (Hu et al. 2012),
342 especially *Ficus* species which tend to be found on the slopes. Furthermore, as species grow
343 larger, larger amounts of energy could be invested to build non-photosynthetic tissue of the plant
344 to maximize survival (King 2011). Thus, the formation of high leaf dry mass and succulent
345 leaves over time could protect species from herbivore and pathogen attack, and provide
346 mechanical support that maximize the life span of leaves and individual trees (Kitajima and
347 Poorter 2010, Onoda et al. 2011, Poorter et al. 2018). The temporal development of this
348 functional strategy could be associated with the resource distribution of the plot. The steep slopes
349 of the plot, where most of the study *Ficus* species are distributed, have poor soil nutrients (Hu et
350 al. 2012). These poor soils might influence the species to gradually develop more conservative
351 traits (low SLA and leaf area, high leaf dry mass and leaf succulence) to maximize investment on
352 structural components (minimize construction costs) and survival rate. Similarly, a long-term
353 shift in functional composition due to species turnover (increased leaf area and SLA, decreased
354 leaf succulence and wood density) was reported in a tropical dry forest (Swenson et al. 2020).
355 Therefore, the observed temporal changes in trait values in our study, regardless of the direction
356 (decreasing or increasing) reflects that the system of the forest is highly dynamic.

357 We also used the PCA of these traits to explore species functional strategies. The first
358 two PCA axes explained 66% of the variation, and we found two lines of trait variation showing
359 the ecological strategies of plants. The first axis corresponded to species with high SLA at one
360 extreme, versus species with high leaf thickness and area at the other extreme. The second axis
361 corresponded to species with high leaf chlorophyll content versus high leaf dry matter and
362 succulent leaves. This resource use strategy trade-off is a common phenomenon in the tropical
363 trees and is well documented (Wright et al. 2004, Katabuchi et al. 2012, Asefa et al. 2017). The

364 negative correlation of SLA and leaf area might suggest that these two important traits were not
365 integrated to determine the growth performance of the species (Poorter et al. 2018). Similarly,
366 SLA and leaf area were found to be negatively correlated, probably indicating that costs to
367 deploy SLA for large leaves was more expensive than small leaves (Milla and Reich 2007). The
368 negative correlation of SLA with leaf thickness and/or positive correlation of LDMC with leaf
369 thickness and succulence suggested that thick leaves maximize the longevity of trees by
370 providing protection from herbivore attack, pathogens and physical damage. In summary, the
371 functional trait variation of *Ficus* species supports the globally known leaf economics spectrum.

372 We also determined the factors associated with the greatest portion of functional trait
373 variation. All traits were varied significantly among individuals within species and among
374 different species. However, the largest extent of trait variations was mainly explained by species
375 identity, with a range of 23.39% for leaf fresh mass to 58.49% for LDMC, suggesting that trait
376 variation was stronger at the species level than the individual level. The species differences in
377 traits might be enhanced by niche-driven evolutionary trait divergence among different species.
378 Phylogenetically conserved traits might show small trait variation within species, suggesting less
379 trait plasticity among individuals (Poorter et al. 2018). The detection of significant individual
380 trait variation, however, in general highlights ecological difference among individuals. A
381 previous study also indicated the variation of *Ficus* traits at the individual level, reflecting
382 differences of ecological requirements among individuals co-occurring together at small scales
383 (e.g. 10 m) (Lasky et al. 2014a). Our result highlights that individual trait variation supports the
384 species level variation of functional traits suggesting that both the individual and species level
385 approach together helps to better understand community dynamics.

386

387 **Effect of traits on the relative growth rate of individuals**

388 We tested to what extent individual trait variation predicts the individual variation of growth
389 rate. The relative growth rate of individuals was found to vary substantially among individuals of
390 the same species and among different species (Figure S2). We found that initial DBH has
391 consistent relationships with growth of individuals in both censuses. Our results indicate that the
392 relationship between functional traits and relative growth rate varied through time. Functional
393 traits measured at the first census did not predict the growth rates of individuals. However,
394 in the second census, leaf dry mass, LDMC and leaf area negatively predicted individuals'
395 growth rates, whereas chlorophyll content and leaf succulence were positively associated with
396 the growth rate of individuals.

397 Detection of weak trait–growth relationships in the first census could be attributed to
398 different factors. Using stem tree diameter as a growth indicator might be a poor parameter to
399 describe the entire plant growth pattern, especially for small plants due to the fact that plants
400 could invest their energy in height and leaf growth to capture adequate amount of sunlight as
401 height growth is more ecologically important than diameter growth, or underground investment
402 to maximize nutrient acquisition (Paine et al. 2015, Poorter et al. 2018). The trait-growth
403 relationship might also be confounded by developmental stages of trees, as ontogenetic stages of
404 trees were found to determine trait-growth relationships (Iida et al. 2014, Lasky et al. 2015,
405 Visser et al. 2016), suggesting size-dependent changes in growth strategies (Gibert et al. 2016).
406 However, these developmental differences should be relatively subtle given the short time
407 interval between censuses (7 years) relative to the lifespan of many trees (many decades).

408 The relative growth rate of individuals in the second census, however, was found to be
409 positively correlated with SLA and chlorophyll content of the species. This is consistent with the

410 expectation that high chlorophyll content and SLA are considered to maximize the efficiency of
411 biomass investment for light interception (Poorter et al. 2008). Similarly, Poorter and Bongers
412 (2006) found that SLA predicted higher growth rate of rainforest species. Lack of consistent
413 predictive power of traits on the relative growth rate of individuals over time points in this study,
414 however, might indicate how sensitive tropical forests are to the temporal dynamics of the
415 environment or trait plasticity, indicating the importance of complexity and temporal dynamics
416 in tropical rainforests. However, temporal trait plasticity did explain the relative growth rate of
417 individuals. Increases in leaf chlorophyll content and leaf succulence over time had positive
418 correlations with growth, while a decrease in leaf area, leaf dry mass and LDMC over time had a
419 negative effect on growth, suggesting that temporal shifts in trait values appeared to be more
420 predictive of growth rate than initial census trait values. These functional traits showed large
421 variation across time points and subsequently were found to be growth determinants.
422 Considering the effect of temporal trait plasticity helps to better predict growth dynamics of
423 trees. Our findings in general highlight that considering the dynamic ecological dimension of
424 species such as traits, helps to gain a temporal understanding of plant growth dynamics.

425 We also found both direct and indirect effects of initial DBH of trees on the growth rate
426 of individuals from our SEMs analyses. Initial DBH of trees was found to directly negatively
427 affect the relative growth rate of individuals, as we found in the mixed effects models. This
428 might be because small adult size plants could allocate more resources to height than diameter
429 growth, as height is more important for interception of light resource (Paine et al. 2015).
430 However, initial DBH of trees indirectly positively affected the relative growth rate of trees
431 through its significant negative effect on PC1 and PC2 in the second census and PC1 in the
432 temporal change data. The PC1 both in the second and temporal change data were mostly

433 represented by leaf dry mass and LDMC, while SLA and succulence were largely represented by
434 PC2 in the second census data (Table S8). Initial DBH size of trees could be negatively related
435 with resource conservative traits mentioned above that may provide protection against herbivores
436 and pathogens (Van Der Sande et al. 2016). Plants could prioritize their survival by building
437 non-photosynthetic tissues particularly at small adult size at which susceptibility to herbivory
438 and physical damages is higher. This reduces mortality and maximizes the longevity of trees
439 (Onoda et al. 2011), and provides time for trees to gradually shift to the strategy by which more
440 energy could be invested for their growth rates (Iida et al. 2014). Consistently, our result may
441 demonstrate that initial DBH size of trees could indirectly promote the growth rate of individuals
442 in a long-term by controlling trait expressions in response to many biotic and abiotic factors.
443 Initial DBH size of trees also negatively interacted with neighborhood crowding to significantly
444 limit the RGR of individuals in the temporal change data. The crowding conditions of
445 individuals could be influenced by the size of neighboring trees. Large trees might dominate
446 small neighborhood individuals through competition thereby reducing neighborhood density
447 and/or limit individuals' growth, as they may have large canopy, crown and deep root systems
448 (Yang et al. 2020 in press). Our result therefore, suggests that various factors may interactively
449 influence species performance through multiple pathways.

450 **Effect of neighborhood crowding on the relative growth rate of individuals**

451 We evaluated the effect of neighborhood interactions on individual growth, and how the effect
452 changes over time. We found that neighborhood crowding significantly limits the growth rate of
453 individuals, which is consistent with previous studies (Bagchi et al. 2014, Lasky et al. 2014b,
454 Fortunel et al. 2016, Liu et al. 2016, Fortunel et al. 2018, Umaña et al. 2018). Also, species-
455 specific negative density dependence was found to drive seedling survival (Lin et al. 2012). This

456 further confirmed our result that species growth might be influenced by biotic interaction with
457 neighbors. Interestingly, our result demonstrates not only the negative effect of neighborhood
458 crowding on growth but also its effect found to vary through time.

459 Similarly, the growth rate of individuals was negatively affected by changes in the
460 number of conspecifics over time (Umaña et al. 2018). We detected a coordinated shift (temporal
461 plasticity) of species from acquisitive to conservative, which may enhance the density-dependent
462 effect of neighbors on growth rate due to niche overlap (Uriarte et al. 2010). However, the effect
463 of neighborhood crowding on individuals' performance in the first census was not significant,
464 suggesting that interactions between tree neighbors might not be consistent over time. This
465 inconsistency may be related to trait differences among individuals, which may be an
466 important mechanism of coexistence (Lasky et al. 2014a). The relationship of growth and
467 neighborhood competition might not be completely captured under current environmental
468 dynamics. As a result, it is always a challenge to explore the effect of neighborhood competition
469 dynamics on the tree performance unless a temporal change in local neighbor density is
470 considered. We found that temporal changes in neighborhood crowding affected tree growth,
471 suggesting the importance of the approach we used to test the impact of temporal shifts of
472 neighborhood competition on the demography of species. The result of this study highlights the
473 importance of the temporal dimension of ecology to understand better how species interactions
474 change over time and predict individual performance.

475 In conclusion, our result demonstrates that functional traits and neighborhood crowding
476 have changed over time. This temporal trait plasticity was found to best predict the growth rate
477 of individuals. Neighborhood interactions also limited the growth of individuals. This all
478 together suggested that the temporal dynamics of traits and biotic interactions need to be

479 considered to explain better the growth dynamics of tropical trees. Furthermore, trees tended to
480 shift their functional strategies from being acquisitive to conservative, as we observed the
481 increment of leaf dry mass and succulence, and decrement of SLA and leaf area through time
482 points. We also found major axes of tree functional strategies in PCA, highlighting potentially
483 adaptive trait differences. This study in general highlights that a temporal-based approach of
484 investigating the relationship between traits and biotic interactions, and growth for each
485 individual tree, can help gain insights into forest dynamics. To better predict future changes in
486 community structure, function and dynamics, it is therefore important to consider the temporal
487 change of environments together with changes in traits and biotic interactions over time, as trait-
488 neighborhood-performance relationships vary temporally with environmental conditions.

489

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501

502 **AUTHORS' CONTRIBUTIONS**

503 MA, YJ and XS designed the study; YJ, JRL and XS collected the field data; MA, YJ and XS
504 analyzed the data; MA, YJ, XS and JRL wrote the manuscript, and all authors provided
505 comments.

506

507 **DATA AVAILABILITY STATEMENT**

508 Data will be available online upon manuscript acceptance.

509

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732 **FIGURE LEGENDS**

733 Figure 1. Comparison of trait values, growth and neighborhood crowding between the two
734 census years. Asterisk (*) indicates significant differences between the censuses for each
735 functional trait. DBH-Diameter at breast height.

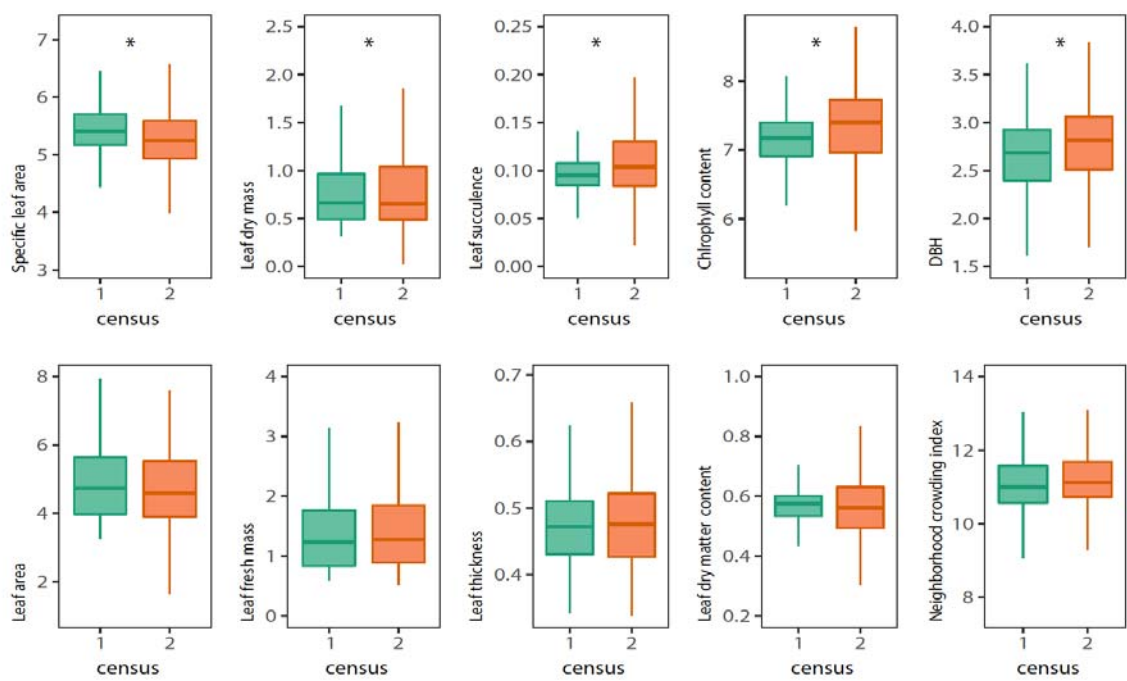
736 Figure 2. Variance in trait values explained by species, individuals, census interval, and leaves.

737 Figure 3. PCA representing multivariate associations among functional traits of the 472 *Ficus*
738 individuals. The numbers in parentheses in the PC1 and PC2 axes are the variances explained by
739 each axis.

740 Figure 4. Standardized regression coefficients modelling initial size effects, traits and
741 neighborhood effects on tree relative growth rate. (a) the first census of traits and neighborhood
742 effect; (b) the second census of traits and neighborhood effect; (c) the effect of the change in
743 traits and neighborhood crowding values (the trait values in 2010 were subtracted from traits in
744 2017) on the relative growth rate of individuals during seven years. Circles indicate posterior
745 medians for each studied parameter and lines indicate 95% confidence intervals, with filled
746 circles representing significant effect.

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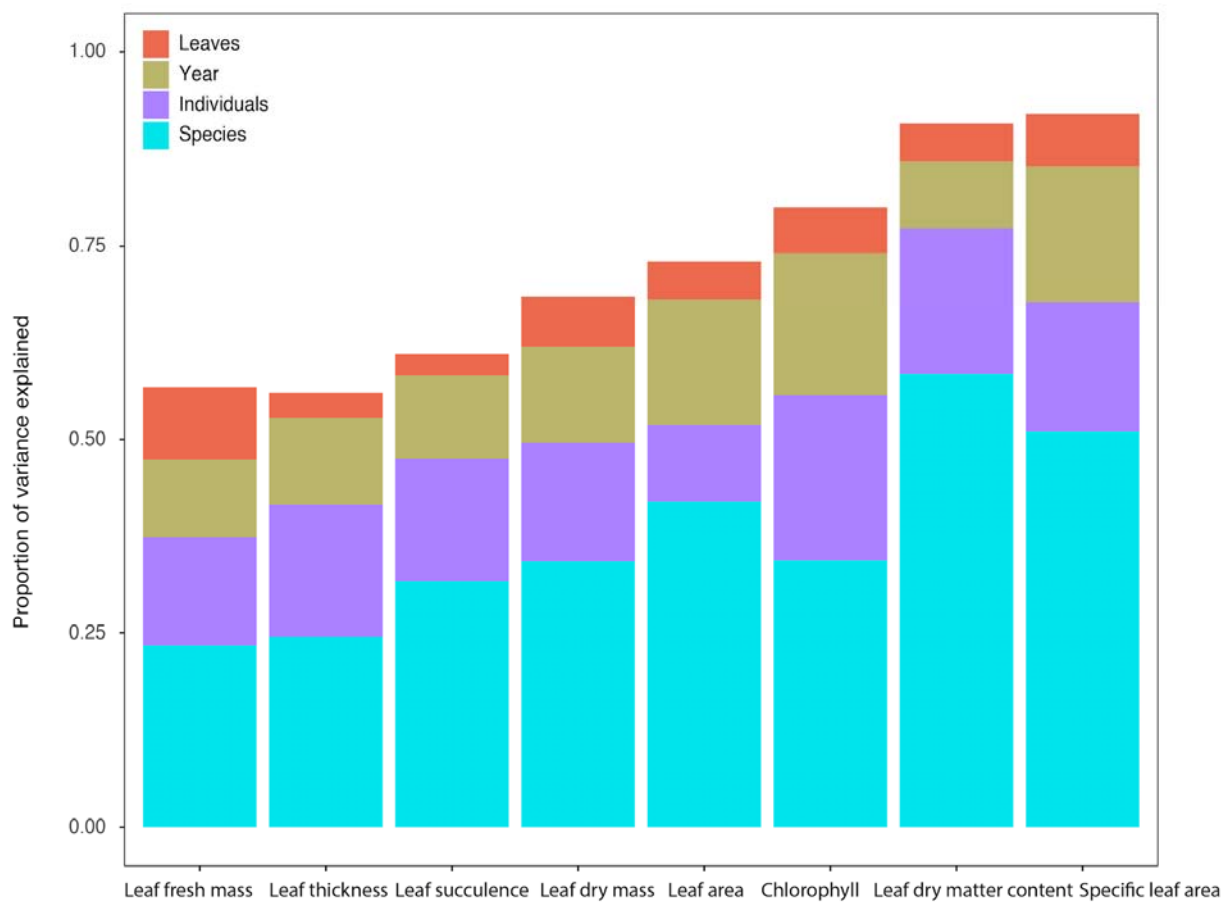
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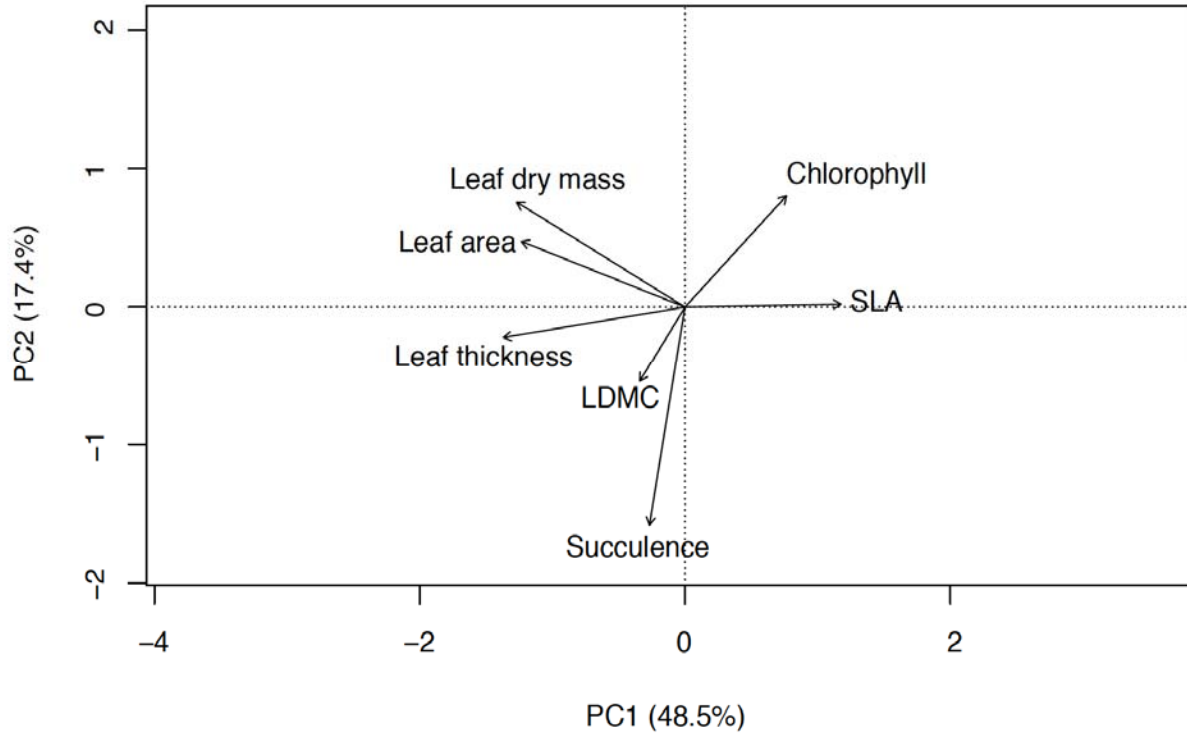
750 Figure 1

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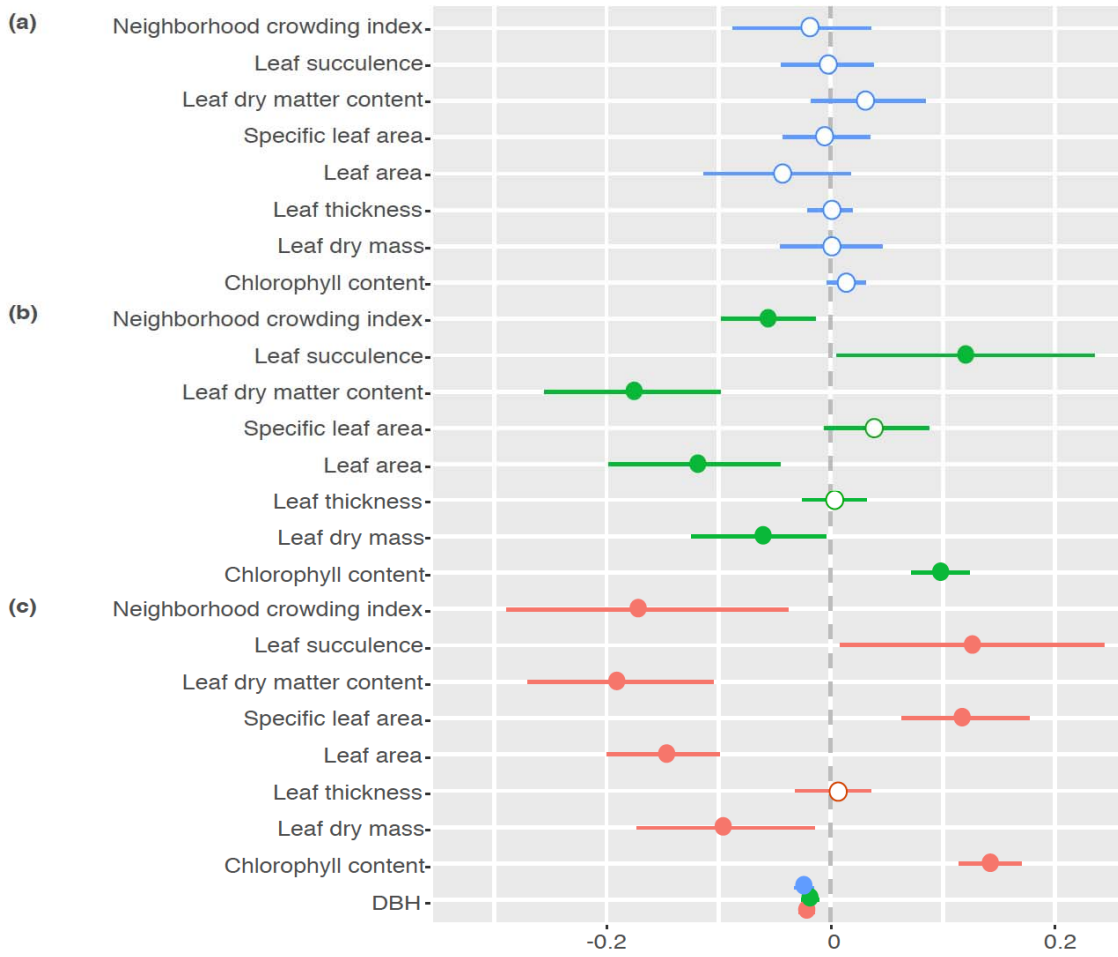
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753 Figure 2



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755 Figure 3



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757 Figure 4

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- 766 Supporting information
- 767 Figure S1. Location map of the study area
- 768 Figure S2. Relative growth rate of species
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773 relationship with growth
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- 780 Table S7. AIC values of mixed-effect models of the temporal change in traits and NCI
- 781 Table S8. Trait loads on the PCA axes