Logging and soil nutrients independently explain plant trait expression in tropical forests 1 Sabine Both^{1*}, Terhi Riutta^{2,3}, C. E. Timothy Paine⁴, Dafydd M. O. Elias^{5,6}, Rudi Chino⁷, Annuar Jain⁸, 2 David Johnson⁹, Ully H. Kritzler⁹, Marianne Kuntz¹, Noreen Majalap-Lee¹⁰, Nora Mielke¹, Milenka X. 3 Montoya Pillco¹, Nicholas J. Ostle^{5,6}, Yit A. Teh¹, Yadvinder Malhi², David F. R. P. Burslem¹ 4 5 ¹Institute of Biological and Environmental Sciences, University of Aberdeen, 23 St Machar Drive, 6 7 Aberdeen, AB24 3UU, United Kingdom 8 ² Environmental Change Institute, School of Geography and the Environment, University of Oxford, 9 South Parks Road, Oxford, OX1 3QY, United Kingdom 10 ³ Imperial College London, Department of Life Sciences, Silwood Park Campus, Buckhurst Road, Ascot, SL5 7PY, United Kingdom 11 ⁴ Biological and Environmental Sciences, University of Stirling, Stirling, FK9 4LA, United Kingdom 12 13 ⁵ Lancaster Environment Centre, Lancaster University, Bailrigg, Lancaster, LA1 4YQ, United Kingdom ⁶ Centre for Ecology & Hydrology, Lancaster Environment Centre, Library Avenue, Bailrigg, Lancaster, 14 15 LA1 4AP, United Kingdom 16 ⁷ Instituto de Ciencias de la Naturaleza, Territorio y Energías Renovables, Pontificia Universidad Católica del Perú, Lima, Perú 17 18 ⁸ The South East Asia Rainforest Research Partnership (SEARRP), Danum Valley Field Centre, PO Box 60282, 91112, Lahad Datu, Sabah, Malaysia 19 20 ⁹ School of Earth and Environmental Sciences, The University of Manchester, Oxford Road, 21 Manchester, M13 9PT, United Kingdom ¹⁰ Forest Research Centre, Peti Surat 1407, 90715 Sandakan, Sabah, Malaysia 22 23 24 *Author for correspondence: 25 Sabine Both Tel: +44 1224274257 26 27 Email: <u>sboth@une.edu.au</u> 28 Current address: Environmental and Rural Science, University of New England, 2351 Armidale, 29 Australia 30 31 Total word count (excluding summary, references and legends): 4989 32 Summary: 195 Introduction: 1008 33

34 Materials and Methods: 1500

- 35 Results: 855
- 36 Discussion: 1439
- 37 Acknowledgements: 181
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- 39 No. of Tables: 2
- 40 No of Supporting Information files: 1 (Fig. S1; Table S1–S4)
- 41

42 Summary

43	٠	Plant functional traits regulate ecosystem functions but little is known about how co-occurring	
44		gradients of land use and edaphic conditions influence their expression. We test how gradients of	
45		logging disturbance and soil properties relate to community-weighted mean traits in logged and	
46		old-growth tropical forests in Borneo.	
47	•	In eight 1 ha plots, we studied 32 physical, chemical and physiological traits from 284 tree species	
48		and measured long-term soil nutrient supplies and plant-available nutrients.	
49	•	Logged plots had greater values for traits that drive carbon capture and growth, whilst old-growth	
50		forests had greater values for structural and persistence traits. Although disturbance was the	
51		primary driver of trait expression, soil nutrients explained a statistically independent axis of	
52		variation linked to leaf size and nutrient concentration. Soil characteristics influenced trait	
53		expression via nutrient availability, nutrient pools and pH.	
54	•	Our finding, that traits have dissimilar responses to land use and soil resource availability, provides	
55		robust evidence for the need to consider the abiotic context of logging when predicting plant	
56		functional diversity across human-modified tropical forests. The detection of two independent	
57		axes was facilitated by the measurement of many more functional traits than have been examined	
58		in previous <mark>studies</mark> .	
59			
60	Ke	eywords: anthropogenic disturbance, Borneo, functional diversity, functional traits, land use, Rao's	1

Commented [EDM1]: A suggestion: As reviewer 1 wanted recommendations of previously overlooked traits why not put them here in one sentence as this is an important outcome:

And we recommend inclusion of x... traits in future studies

- 61 Q, tropical rainforest, variance partitioning
- 62

63 Introduction

The differential expression of plant functional traits influences key ecosystem functions (Cornwell et 64 al. 2008; De Deyn et al. 2008; Fortunel et al. 2009; Finegan et al. 2015). Trait expression varies across 65 66 landscapes due to anthropogenic disturbance, soil characteristics, and other abiotic factors such as 67 climate (Ordoñez et al. 2009; Baraloto et al. 2012; Fortunel et al. 2014a; Dent & Burslem 2016). Fertile 68 soils are associated with traits conferring rapid nutrient acquisition and use, which support fast growth rates, whereas nutrient-poor soils are often associated with conservative strategies for the 69 70 maintenance of long-lived tissues (Aerts & Chapin 2000; Ordoñez et al. 2009; Jager et al. 2015). 71 Anthropogenic disturbances pervade ecosystems worldwide (Hansen et al. 2013) and can affect trait 72 expression in seeds, leaves and woody tissue (Gómez-González et al. 2011; Baraloto et al. 2012; 73 Carreño-Rocabado et al. 2012). Substantial effort has been dedicated to characterising the 74 independent effects of human disturbance (McIntyre et al. 1999; Mouillot et al. 2013a; Buzzard et al. 2016) and environmental gradients (Fortunel et al. 2014b; Fyllas et al. 2017) on plant trait expression 75 76 and ecosystem function. However, in practice, communities are influenced by multiple factors 77 simultaneously, and the effects of disturbance may vary along environmental gradients such as 78 nutrient availability.

79 Comprehensively analysing trait expression in response to multiple gradients is challenging but essential for predicting the ecosystem-level consequences of anthropogenic disturbance. The leaf 80 economics spectrum (Wright et al. 2004; Díaz et al. 2016) suggests that the increase in resource 81 82 availability associated with disturbance and soil fertility will select for similar leaf trait syndromes. 83 Therefore, functional traits of plant communities should converge at the extremes of environmental gradients. Evidence from tropical tree communities suggests that foliar concentrations of N and P and 84 85 specific leaf area increase in response to gradients of both disturbance (Baraloto et al. 2012; Carreño-Rocabado et al. 2012; Carreño-Rocabado et al. 2016) and soil nutrient availability (Fyllas et al. 2009; 86 87 Fortunel et al. 2014a; Apaza et al. 2015; Jager et al. 2015; Turnbull et al. 2016; Van der Sande et al. 2016). Similarly, leaf dry matter content and branch and stem wood density decrease with both 88 89 disturbance (Verburg & van Eijk-Bos 2003; Baraloto et al. 2012; Carreño-Rocabado et al. 2012; 90 Carreño-Rocabado et al. 2016) and soil nutrients (Ordoñez et al. 2009; Fortunel et al. 2014b; Jager et al. 2015). All these studies, however, share twolimitations: they did not examine the influence of 91 92 multiple factors on trait expression, and they used a restricted set of traits. Moreover, many did not 93 consider traits associated with ecologically important processes, such as structural and defence 94 compounds (important for herbivory and hence trophic interactions); photosynthetic activity (essential for biomass production); and leaf δ^{15} N values (provides insight into sources and use of 95

96 nitrogen). Our understanding about the links between trait sensitivity to anthropogenic disturbance,
 97 soil properties, and ecosystem processes in tropical forests therefore remains incomplete.

98 The consequences of changes in community structure and diversity for ecosystem service 99 provision are determined by the impacts of disturbance on community-level trait expression, which is 100 a function of the type and intensity of disturbance. For example, in South American tropical forests, 101 disturbance due to logging and silvicultural activity increases light availability and triggers the recruitment of species with traits that promote rapid growth rates (Baraloto et al. 2012; Carreño-102 103 Rocabado et al. 2012). We expect a similar response to logging in Southeast Asian tropical forest. We 104 build upon these studies to additionally determine the influence of soil properties, including nutrient 105 availability on functional traits.

106 Tropical lowland forests in Southeast Asia are amongst the most species-rich communities 107 worldwide, but are also the most threatened by logging and conversion to agriculture (Hansen et al. 2013; Edwards et al. 2014; Stibig et al. 2014). The high density of commercially valuable species 108 109 explains the high intensity of logging in Southeast Asian forests (Osman et al. 2012; Gaveau et al. 110 2014), which suffer rates of extraction that far exceed those in tropical forests elsewhere (see Asner 111 et al. 2005 for the Brazilian Amazon and Rutishauser et al. 2015 for various sites in the Amazon Basin). Logging creates a spatially patchy disturbance, with gaps and skid trails characterised by high light and 112 temperature distributed among fragments of relatively unmodified forest (Johns 1997). The selective 113 removal of target species, logging-induced mortality and recruitment of pioneer species in disturbed 114 115 areas affects tree species composition and the pools and fluxes of biomass and nutrients (Cannon et al. 1998; Verburg & van Eijk-Bos 2003; Pfeifer et al. 2016; Riutta et al. 2018). Although the magnitude 116 of anthropogenic disturbance is much greater in forests in Southeast Asia than in South America, they 117 118 have received far less attention regarding the modification of plant functional traits. Specifically, the potential for intense logging to override the effects of environmental gradients, including soil 119 properties, has not been investigated. 120

121 Here, we measured 32 leaf, wood and physiological traits of 284 tropical tree species to capture 122 community level trait expression in response to selective logging across a gradient of soil properties 123 in species-rich tropical rainforest in Sabah, northern Borneo. We consider traits reflecting nutrient status, light capture, photosynthesis, and allocation to structure and defence, to provide a whole-124 125 plant perspective and assess many aspects of functional diversity. We tested the hypothesis that 126 functional trait values and functional diversity shift in response to anthropogenic disturbance and soil 127 properties. We used community-weighted mean (CWM) values of traits to quantify average trait values, and a multi-trait index of functional diversity (FD) to quantify trait variation, which can occur 128 independent of variation in CWM trait values (Ricotta & Moretti 2011). 129

Specifically, we predict that (1) increasing disturbance and soil nutrient availability will increase CWM traits related to tissue nutrient concentrations and carbon assimilation rates, but reduce tissue densities and investments in structural defences. Given the high logging intensity in Southeast Asia, we further predict that (2) a greater proportion of the variance in CWM traits will be explained by logging than by soil properties, emphasizing the pervasive impact of anthropogenic land use on functional trait expression. Finally, due to the high overall tree species richness, we predict that (3) functional diversity will remain high in response to disturbance, despite shifts in overall CWM traits.

137

138 Material and Methods

139 Study sites

140 Sampling was conducted in eight 1 ha plots in Sabah, Malaysian Borneo. The plots are part of the 141 Global Ecosystems Monitoring (GEM) network of permanent sample plots with intensive, regular carbon cycle measurements (Malhi et al. 2015; Riutta et al. 2018) and were selected to capture 142 143 variation in logging intensity across a range of lowland tropical forests in northern Borneo. Old-growth 144 lowland mixed dipterocarp forest plots (hereafter OG) were located in the Maliau Basin Conservation 145 Area (MBCA, two plots) and the Danum Valley Conservation Area (DVCA, two plots), while the other four plots were distributed between these two areas in the selectively logged Kalabakan Forest 146 Reserve (hereafter SL). The four logged plots are part of the Stability of Altered Forest Ecosystem 147 (SAFE) project (Ewers et al. 2011). This area has been logged two times with the first round of logging 148 149 in the mid-1970s and subsequent repeated logging during 1990-2008. Approximately 150–179 m³ ha⁻ 150 ¹ of timber was removed over this time period (Struebig *et al.* 2013), bracketing the mean extraction volume across Sabah (152 m³ ha⁻¹, Fisher et al. 2011). 151

152 All three areas are part of the Yayasan Sabah Forest Management Area and belong to a formerly 153 connected area of lowland dipterocarp rainforest characterised by high species richness and many 154 tall, emergent trees. The region has a moist tropical climate with an annual daily mean temperature of 26.7 °C and annual precipitation of approximately 2600-2700 mm (Walsh & Newbery 1999). 155 156 Although the climate is aseasonal there are occasional droughts and dry spells associated with supra-157 annual El Niño Southern Oscillation events (Walsh & Newbery 1999; Newbery & Lingenfelder 2009). 158 The forest soils in Sabah are mostly orthic Acrisols or Ultisols (for more details see Marsh & Greer 159 1992; Nainar et al. 2015).

- 160
- 161 Sampling design
- 162 Thirty-two functional traits were measured on 651 individual trees ≥ 10 cm diameter at breast height
- 163 (dbh) representing 284 species during an intensive sampling campaign from July to December 2015.

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164 We combined two strategies to sample the functional trait values in each plot. In the first, weighted basal area strategy, we sampled species that most contributed to the total plot basal area. This 165 approach assumes that species accounting for a larger proportion of plot basal area also make a 166 167 greater contribution to ecosystem functioning. Species were ranked based on their contribution to 168 total basal area at the most recent census for each plot (2011 to 2015), which ranged from 10.9-41.8 169 m² ha⁻¹. All species that contributed to 70% of plot basal area (in decreasing order of species basal 170 area) were identified for sampling. In 57% of cases only one individual per species occurred; otherwise, 171 the individual with the greatest dbh within a species was sampled. This strategy disproportionately 172 sampled large-statured and abundant species. To ensure that smaller and potentially rare species 173 were also represented, we adopted a second strategy: stratified random and taxon-independent 174 sampling of all trees \geq 10 cm dbh in three randomly selected 20 × 20 m subplots within each 1 ha plot. 175 As this strategy allowed for repeated samples of the same species, as well as sampling from all height strata, it contained understory and shaded trees. This combination of different sampling strategies 176 provided a comprehensive representation of the tree community (Paine et al. 2015) and resulted in 177 178 an overall representation of > 90% of the total basal area per plot (except one plot with 65%) and 51-179 71% of the species \geq 10 cm dbh (Fig. S1).

180

181 Soil properties

182 We measured total nutrients and exchangeable nutrient pools to estimate both long-term nutrient 183 supply as well as plant-available forms. Two randomly located soil cores were taken per plot in 2014-2015. Surface soil (0-10 cm) was analysed for pH, cation exchange capacity and total concentrations 184 of P, C, N, Mg, K and Ca using the protocols of Quesada et al. (2010, 2012). To assess availability of K, 185 186 Ca, Mg, P, NO₃⁻ and NH₄⁺ we measured nutrient supply rates using in-situ ion exchange membranes (PRSTM Probes, Western AG, Saskatoon, Canada). To account for spatial variability we installed four 187 188 probe pairs (each composed of one cation and anion probe) vertically at corners of three 50 × 50 cm quadrats to 10 cm depth within each of the three subplots used in the stratified random sampling. 189 190 These were collected after two weeks, washed with distilled water and sent to the manufacturer for 191 analysis. They pooled the four probe pairs from each quadrat prior to elution with 0.5M HCl for 1 hr, 192 yielding 72 samples. NO₃⁻ and NH₄⁺ were measured colorimetrically using automated flow injection 193 analysis (FIA). All other elements were analysed using Inductively Coupled Plasma Mass Spectrometry 194 (ICP-MS). Results are reported as supply rates over the burial period (micrograms/10 cm²/14 days).

195

196 Trait measurements

197 From each target tree, we attempted to sample a fully sunlit canopy branch and a fully shaded branch; 198 however, branches of only one type were available for most trees (91%) because it was uncommon 199 for large canopy trees to possess fully shaded branches and for small understorey trees to have fully 200 sunlit branches. Branch samples were collected by tree climbing or by cutting from the ground with 201 telescopic branch cutters. Target tree height ranged from 2.3 to 78.1 m, and sample height ranged 202 from 2.3 m to 53 m. Branches were approximately 2-4 cm in diameter and provided sufficient leaf 203 material for all analyses. Photosynthetic activity was only measured on trees selected by the basal 204 area sampling strategy due to time constraints (N = 298), whereas all other functional traits were 205 determined on all trees. Undamaged mature leaves were collected and cleaned with water for 206 subsequent analyses. Fresh and dry leaf weight, (specific) leaf area, leaf thickness, leaf dry matter content (LDMC), (specific) force to punch and branch wood density were determined in a field 207 208 laboratory. Dried bulked and milled leaf material was used for determination of Ca, K, Mg, P, C and N 209 concentrations, δ^{13} C and δ^{15} N stable isotope composition, cellulose, hemicellulose and lignin 210 concentrations. Analyses of pigments (chlorophyll a, chlorophyll b, and carotenoids), phenols and tannins were conducted on 0.7 cm diameter leaf discs punched from fresh leaves immediately after 211 212 field collection and frozen in liquid nitrogen. Herbarium voucher specimens were taken for 213 identification of trees and were deposited in the herbarium at Danum Valley Field Centre. All trait 214 measurements follow standardised protocols (Pérez-Harguindeguy et al. 2013), and detailed methods 215 and an overview of sampling and replication are provided in Table S1.

216

217 Statistical analyses

218 Replicated leaf-level functional traits were averaged for sun and shade leaves for the few individuals 219 that possessed both to generate a tree-level dataset. Our results were not significantly different for 220 analyses on sun leaves alone, where available, or otherwise shade leaves, so we combined data from 221 sun and shade leaves together. Leaf chemical properties that are most relevant for photosynthetic 222 activity (chlorophyll a, chlorophyll b, bulk carotenoids, N, and P) were expressed as mass-based as well 223 as area-based values. For 43% of species, multiple individuals were measured and trait values were 224 averaged to result in species-level values. For all analyses, if necessary, species-level leaf traits were 225 log-transformed to improve the normality of residuals. A CWM was calculated for each trait, weighted 226 by the number of individuals of each species in each plot (Pla et al. 2012). Values of dark respiration fluxes and δ^{13} C were converted to positive values for ease of interpretation. To characterise soil 227 228 properties in relation to land use, we performed a principal component analysis (PCA) of soil chemical properties across the eight plots with the measurements of total concentrations of P, C, N, Mg, K, Ca, exchangeable Mg, K, Ca, NH₄⁺ and NO₃⁻, extractable P, pH and cation exchange capacity (CEC). To visualise the distribution of CWM traits across forest types and test hypothesis 1, we conducted a PCA using centred and standardised CWM trait values for each study plot.

233 In order to test hypothesis 2, site scores from the first two PCA axes of soil properties, along with a 234 binary variable representing logging history, were used as predictors in linear models to partition the 235 variance in each CWM trait. The first two principal components from the soil PCA were both 236 statistically independent of logging history (linear model: $p \ge 0.48$). Nevertheless, because the three 237 predictors were weakly but non-significantly inter-correlated ($R^2 \leq 0.29$), we used the hierarchical 238 partitioning method of Chevan and Sutherland (1991), as implemented in the hier.part library of R, to 239 estimate the variance in functional traits explained by each. This technique calculates the R^2 of every 240 possible model, then averages over this set of models to allocate the variance explained by each predictor variable. It thereby overcomes the effect of the order that inter-correlated variables enter a 241 242 model on the inference of variance explained by each variable (Chevan & Sutherland 1991). Tests of 243 significance are less important than partitioning the variance in CWM trait values in this analysis. 244 Nevertheless, given that this analysis generated 99 p-values (3 tests on each of 32 functional traits, plus functional diversity), we corrected the p-values using the false discovery rate (García 2004). 245

To address hypothesis 3, we computed plot-level values of functional diversity (FD) as Rao's quadratic entropy (Rao's Q), which is the sum of the pairwise distances between species in multidimensional trait space weighted by their relative abundance (Rao 1982). It is the functional equivalent of Simpson's diversity index. We compared Rao's Q among forest types with ANOVA.All analyses were performed using R 3.4.0 (R Core Team 2017).

251

252 Results

253 Forest structure, species composition and soil properties of plots

The study plots varied substantially in basal area (BA) and stem density, with BA varying fourfold (10.9 m - 41.8 m² ha⁻¹, Table 1). Basal area was significantly lower in the SL plots but the range among plots within each forest type was similar (means: SL 17.8 ± 12.7, OG 34.8 ± 14.9 m² ha⁻¹; ANOVA: $F_{1,6}$ = 15.26, p = 0.008). Stem density ranged from 331 to 565 ha⁻¹, peaking in plots with intermediate BA but was not associated with logging ($F_{1,6}$ = 0.02, p = 0.90). Species richness was similar in OG and SL plots, ranging from 124 to 211 tree species ha⁻¹ ($F_{1,6}$ = 0.55, p = 0.49).

A PCA of soil chemical properties explained 69.5% on the first two principal axes (Fig. 1). The strongest gradient was defined by variation in total Mg, total P and CEC, whereas the second axis represented a gradient of total C, total N and exchangeable Ca to exchangeable K and NH₄⁺. Nutrient concentrations varied markedly among plots, including 10-fold and 5-fold variation in total Mg and total P concentrations, and 9-fold and 10-fold variation in exchangeable K and NH₄⁺ (Table 1). Soil properties differed among plots, but were independent of logging history, indicated by the overlapping distribution of OG and SL plots in the PCA (Fig. 1).

267

268 Community-weighted mean traits

269 Major gradients in CWM trait expression were visualised by PCA, with the first two axes 270 explaining 77.7% of the variance in functional traits (Fig. 2). There was a clear differentiation of 271 functional composition between OG and SL plots along the first principal component, indicated by a distinct clustering of the study plots. Tree communities in OG plots were characterised by greater 272 273 investment in defence and tissue density, whereas SL tree communities expressed higher 274 photosynthetic activity and reduced investment into structural components (Table 2). Old-growth 275 forests were characterized by denser wood and tougher leaves. These traits reflect enhanced 276 structural investment, implying longer leaf life span and slower growth rates. Tree communities in SL forest had higher photosynthetic activity represented by higher CWM values of Amax and Asat, and 277 higher R_d. These higher rates of gas exchange were supported by the expression of higher CWM area-278 279 based pigment concentrations in SL communities and higher N_a , N_m and P_a concentrations. Tree 280 communities in SL were enriched in ¹³C compared to OG communities, indicating greater water-use 281 efficiency.

The second axis of functional trait space represented tissue nutrient concentrations and leaf area but was independent of logging history (Fig. 2). This axis reflects covariance among CWM values of leaf area, leaf P_m, N_m, Mg_m and Ca_m concentrations, and a negative association of these traits with leaf C_m and tannin concentrations. Variability of these traits within both logged and unlogged forests was high, which suggests that the expression of these traits is driven by underlying soil properties rather than logging history.

289 Variance partitioning

288

290 Partitioning the CWM response of traits to logging and the first two principal components of soil 291 properties showed that these factors explained up to 90% of the variation in traits. Overall, the 292 proportion of variance explained was on average 74.4%. (Fig. 3, Table S4). To present these results, , we group the functional traits based on their main association with leaf nutrients, photosynthesis or 293 294 structure. Variation in mass-based concentrations of leaf Cam, Pm, Nm and Km and to a lesser extent Mg_m were associated with variation in soil properties, both with soil PC1 and 2. Particularly soil PC1, 295 296 enveloping a gradient from exchangeable Mg to cation exchange capacity (CEC) and total P, strongly 297 affected the variance in leaf Cam, Pm, Cm. However, expressed on area basis, foliar Pa and Na **Commented [cetp4]:** I deleted this text because the variation occurs between plots, not only inside the PCA, I think.

298 concentrations were mainly explained by logging. Variation in SLA and leaf thickness appears to underlie the contrasting response of mass and area based traits. For leaf traits related to 299 300 photosynthesis, 33.5-78.6% of variance was explained by logging and a much smaller proportion by soil PC1 (1.5-21.8%) or soil PC2 (0.9-35.6%; Table S4). Structural traits were explained by a 301 302 combination of both logging history and the independent effects of soil properties. Logging explained 303 on average 39.2% of variance in traits reflecting tissue density and structural investment, such as 304 specific force to punch and branch wood density, which had consistently lower values in logged forest 305 plots. Community-weighted mean LDMC was unusual in that it was poorly explained by the predictor 306 variables. In contrast, leaf size, expressed as CWM leaf area and leaf mass, incr eased with increasing 307 values of soil PC1, which was linked to plots with higher total N and exchangeable Ca concentrations 308 (Fig. 1). There was an increase in CWM tannin concentrations in logged forest plots and at higher 309 values of soil PC1. The CWM values of C_m and N_a were significantly explained by the first principal component of soil properties, and forest type, respectively, whereas other traits were statistically 310 311 independent of the predictors (Fig. 3)

312

313 Functional diversity

Functional diversity, expressed as Rao's Q, was similar between forest types (Fig. 4; $F_{1,6} = 0.16$, p = 0.70), and neither logging nor soil properties explained a significant proportion of its variance (Fig. 3). The main proportion of variance was explained by soil PC2. The negative relationship with soil PC2 indicates xxx. Variability in FD was greater among SL than OG forests (Fig. 4), potentially indicating the heterogeneous conditions resulting from logging.

319

320 Discussion

Logging profoundly affected the expression of plant functional traits in Bornean tropical forests. 321 322 Logging was the primary driver of variation in community-weighted mean (CWM) values of functional 323 traits (Fig. 2), and explained more variation than soil properties for 20 of 32 traits (Fig. 3). Similar 324 impacts of logging on functional trait expression have been demonstrated in Neotropical forests 325 (Baraloto et al. 2012; Carreño-Rocabado et al. 2012), although those studies did not analyse soil-326 related factors. Together, these studies confirm that CWM traits are highly sensitive to land-use 327 change in tropical forests, but results from our study additionally highlight the considerable relevance 328 of the environmental context for trait expression. This is an important outcome in the light of the fact 329 that logging has impacted over half of all tropical forests globally, and over 70% of forests in Sabah (Bryan et al. 2013; Potapov et al. 2017). Therefore, the effect of logging on the expression of functional 330 331 traits is likely to pervade tropical forest landscapes and impact ecosystem processes with cascading 332 effects on other trophic levels. Moreover, logging-associated changes in forest structure and CWM traits drive altered patterns of productivity in tropical forests (Pfeifer et al. 2016; Riutta et al. 2018). 333 334 In our study, the principal axis of functional trait space defined a clear gradient from values of 335 traits that maximise carbon capture and growth, which were predominantly expressed in selectively 336 logged forests, to greater allocation to tissue persistence and stability, which were predominantly 337 expressed in old-growth forests. This strong signal of anthropogenic disturbance is partly congruent with the leaf economics spectrum, which differentiates species along a gradient based on leaf traits 338 339 contributing to resource acquisition and conservation (Wright et al. 2004; Díaz et al. 2016). Thus, 340 species in logged forest communities expressed higher CWM values of area-based measures of N, P 341 and pigments, whereas old-growth forest communities expressed low CWM values of these traits and 342 higher values of traits conferring structural stability and resistance to herbivory, such as branch wood 343 density and leaf toughness. Supporting hypothesis 1, disturbance enhanced the occurrence of species possessing traits that confer rapid carbon capture and investment in fast growth rates (Baraloto et al. 344 345 2012; Carreño-Rocabado et al. 2012, 2016). We add to previous results by additionally demonstrating 346 that logged forest communities expressed higher CWM values of $A_{sat,}A_{max}$ and R_d , whereas old-growth 347 forest communities were characterised by higher values of traits conferring structural stability of wood 348 and leaves.

We observed lower CWM values of specific leaf area (SLA) in logged forests, in contrast to 349 results from French Guiana (Baraloto et al. 2012), and contrary to the expectation that SLA scales 350 351 positively with Amax, foliar Na, and foliar Pa concentrations among species (Wright et al. 2004). The lack of association between SLA and other leaf-economic traits may be explained by the abundance of 352 pioneer species, which recruit following disturbance and are adapted to resist the more exposed and 353 354 potentially desiccating conditions created by logging (Hardwick et al. 2015). A reduction in SLA may contribute to photosynthetic water-use efficiency, especially when combined with enhanced 355 356 investment in photosynthetic enzymes, to ensure draw-down of internal CO₂ concentrations at a given stomatal conductance (Reich *et al.* 2003). Greater enrichment of CWM δ^{13} C of logged forest tree 357 358 communities demonstrates reduced discrimination for the heavier ¹³C isotope and provides 359 independent evidence of enhanced, integrated water-use efficiency for trees in this hotter and drier environment (Farquhar et al. 1989; Rumman et al. 2018). The absence of a shift in SLA in response to 360 361 logging in French Guianan forests (Baraloto et al. 2012) suggests that logging imposes a more extreme 362 environmental contrast for trees occurring in the less seasonal climate of Borneo. Species that have 363 evolved in a seasonal climate such as in French Guiana, may be better adapted to changes in 364 microclimatic conditions, like those driven by logging (Blonder et al., unpublished data). The impact of 365 logging may be more severe in tree communities not adapted to drought and emphasises the potential sensitivity of Bornean forests to future climatic change. Mean temperature for Borneo is predicted to
 rise by 0.9 – 3.2 °C, annual precipitation is predicted to become increasingly drier in central to western
 Borneo and wetter in northern and north-western Borneo (ICCP 2013; Scriven *et al.* 2015).

369 We show that trait expression responded independently to logging disturbance and soil 370 properties. Variation in soil properties can be attributed to interactions between underlying soil 371 texture and mineralogy, on one hand, and the impacts of logging disturbances including soil inversion, 372 removal, and compaction on the other (Pinard et al. 2000). However, soil properties did not differ 373 systematically between old-growth and selectively logged forests (Fig. 1), owing to variation in 374 underlying soil types and the heterogeneous nature of logging. This allowed us to assess their 375 independent effects on the expression of CWM functional traits. For most of the mass-based nutrient 376 concentrations, variation in soil properties explained more variation in CWM trait values than did 377 logging, whereas traits linked to photosynthesis and carbon capture were more sensitive to logging than to variation in soil properties (Fig. 3). The mechanisms underlying these associations deserve 378 379 further study. An obvious field of research should be the study of post-logging alterations in the fungal 380 community, in particular the occurrence and diversity of ectomycorrhizal fungi (McGuire et al. 2015). 381 They are almost exclusively associated with tree species of the family Dipterocarpaceae, which are also the main family logged for timber (but see Essene et al. 2017). The interacting effects between 382 tree species dominance, logging and below-ground microbial diversity and ecosystem functions are 383 384 largely unknown.

385 Moreover, we provide clear evidence that soil properties act on trait expression in two independent ways; the first axis reflected total pools of nutrients, and the second reflected nutrient 386 availability (Fig. 1). Community-weighted mean values of leaf area, leaf dry mass and foliar 387 388 concentrations of P_m, P_a, N_m and Ca_m all increased in response to the first axis of variation in soil properties, whereas leaf C_m and tannin concentrations decreased along this gradient (Fig. 3). The 389 390 second component of soil variation also influenced some leaf traits, particularly δ^{13} C, N_a and P_a concentrations (Table 2, Table S4). Moreover, most traits were influenced either by the first or second 391 392 axis of variation in soil properties, but rarely both. This finding may reflect a trade-off in how plants 393 interact with local edaphic conditions, as suggested in other systems (Laliberte et al. 2015); a key future challenge will be to disentangle the mechanisms underpinning these contrasting responses of 394 functional traits to the soil environment. Our results highlight the need to consider the context 395 396 dependency of drivers of variation in functional traits. Landscape-level predictions of change in 397 functional trait expression in response to anthropogenic disturbance will need to account for the 398 additional effects of soil properties.

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399 Despite the large variation in CWM traits, functional diversity (FD) did not differ between logged and old-growth forest, which is consistent with our third hypothesis and with results from Neotropical 400 401 forests (Fig. 4; Baraloto et al. 2012; Carreño-Rocabado et al. 2012). This finding emphasises that 402 forests can retain species richness and trait variation, yielding similar FD, despite logging. In line with 403 Mayfield et al. (2010), logging did not result in loss of FD but in shifts of numerous CWM trait values, 404 indicating a lower sensitivity of multi-trait FD to these changes (Ricotta & Moretti 2011). FD was more 405 variable among logged forests than old-growth forests (Fig. 4), probably owing to variation in logging 406 history and intensity, which affect forest structure (Cannon et al. 1994; Berry et al. 2008), 407 microclimatic conditions (Hardwick et al. 2015) and ecosystem functions (Mayfield et al. 2006; Both 408 et al. 2017; Riutta et al. 2018). The substantial variance in FD among the disturbed plots highlights the 409 challenge of predicting the impacts of anthropogenic modification on FD in environments where the outcomes may be highly context-dependent (Costantini et al. 2016). 410

Assessments of functional composition and diversity at a community scale are critical as human-411 412 modified landscapes become more extensive and play an increasing role in the provision of ecosystem 413 services (Berry et al. 2010; Gibson et al. 2011). However, uncertainty remains over how changes in 414 community trait expression will affect ecosystem functioning and resilience after selective logging and other forms of disturbance (Laliberté et al. 2010; Mayfield et al. 2010; Edwards et al. 2014). Part of 415 that uncertainty arises because rare tree species may contribute substantially to resilience (Mouillot 416 et al. 2013b), but tend to be under-represented in traditional sampling designs adopted for measuring 417 418 ecosystem functions. Our nested sampling design explicitly resolved this issue by selecting both 419 common and rare species across the full range of size classes. We therefore advocate this approach in 420 future assessments of trait expression at the community scale.

421 We demonstrate a consistent shift in community-level trait expression in response to logging, 422 reflecting a transition from an old-growth forest dominated by individuals with resource conserving, 423 structurally persistent tissues to logged forests manifesting greater capacity for carbon assimilation and vegetative growth. Strikingly, there was a second, independent, axis of functional trait variation 424 425 reflecting variation in soil properties (i.e. nutrient availability and chemistry including pH), which 426 explained variation in leaf size and mass-based foliar nutrient concentrations. The elucidation of these orthogonal dimensions of plant trait variation was made possible by the measurement of numerous 427 428 functionally relevant traits and by their consideration at the community level, as well as by the 429 inclusion of rare species. These results provide a basis for predicting how pervasive logging 430 disturbance combines with natural gradients to determine trait expression and ecosystem functioning 431 across human-modified tropical landscapes.

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449 Author contributions: SB, DB and YM designed the study with input from DJ, NO and YAT. SB, DE, TR, 450 UHK, RC and MMP collected field data, SB, RC, DE, AJ, UHK, MK, NML, NM and MMP conducted 451 laboratory analyses. SB and CETP analysed the data. SB led the writing of the manuscript with 452 contributions from all co-authors. YAT, DB, DJ, YM and NO secured the funding. All authors declare no 453 conflict of interest.

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643 Figure captions

Figure 1: Principal component analysis (PCA) of plot-level soil properties. The highest loadings on the
first axis are CEC (12.6%), total Mg (12.3%) and total P (12.2%). The highest loadings on the second
axis are exchangeable K (12.0%), total N (11.1%) and exchangeable Ca (11.1%). See Table S2 for all PCA
loadings.

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650 Figure 2: Principal component analysis (PCA) of plot-level community-weighted mean functional traits. 651 Plots cluster by logging history, with increased values of traits that maximise carbon capture and 652 growth in logged forest communities and greater allocation to tissue persistence and structural 653 stability in old-growth forests. The highest loadings on the first axis are chlorophyll b_m (4.44%), N_a 654 (4.37%), branch wood density (4.25%), A_{sat} (4.25%), A_{max} (4.21%) and SLA (4.17%). The highest loadings on second axis are P_m (7.45%), LA (7.02%), tannins (6.22%), C_m (5.88%) and leaf dry weight (5.75%). 655 Mass-based nutrients are denoted by superscript "m" and area-based values by superscript "a". See 656 657 Table S3 for all PCA loadings.

658

Figure 3: Proportion of variance in community-weighted mean functional trait values explained by 659 660 forest type and the first two principal components of soil properties (Fig. 1). Functional traits are grouped by the ecosystem function to which they most contribute. Statistical significance is derived 661 662 from linear regression models following false discovery rate correction, asterisks indicate p < 0.05, '+' and '-' indicate the direction of the relationship. For forest type '+' indicates that trait values were 663 greater in selectively logged than old-growth forests (i.e. positive with first PC axis). For variance 664 explained by soil, '+' indicates positive relationship with the respective PC axis. See Table 2 and Table 665 S4 for detailed results. 666

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Figure 4: Box-and-whisker plots showing the median, upper and lower quartile of functional diversity calculated as Rao's Q with no significant difference between forest type (ANOVA: $F_{1,6} = 0.16$, p = 0.70).

670 Tables

Table 1: Study plot description and soil properties, plots are listed with decreasing basal area. Basal

area, stem density and number of tree species refers to all tree individuals \ge 10 cm dbh.

Plot name	location	Total basal area [m² ha⁻¹]	Stem	Number	_	N [%]				Total Mg [mg kg ⁻¹]		рН 1 (н. о)	NO ₃ ⁻	NH4 ⁺ [µg 10 cm ² 14 days ⁴]	Exchangable Ca	Exchangable Mg	Exchangable K	Extractab
			uensity	orspecies	[70]	[70]	fink vR 1	fing vg 1	THR PR 1	fink vR 1	[IIIIIOI Kg	1 (1120)	[hg to cm 14 days	j[µg to un 14 uays	[hg to un 14 days]	[hg to chi 14 days]	[hg to all 14 days	
Old-growt	h forest (OG)																
MLA-01	MBCA	41.8	396	141	1.67	0.14	163.01	50.06	101.03	39.67	36.44	3.95	59.6 ± 45.2	10.5 ± 3.11	237 ± 130	152 ± 80.6	265 ± 154	0.23 ± 0.2
MLA-02	MBĆA	37.3	484	170	2.00	0.17	266.44	194.68	80.62	99.41	43.18	4.25	184 ± 103	6.37 ± 1.52	417 ± 476	303 ± 215	151 ± 80.2	0.433 ± 0.
DAN-04	DVCA	30.8	456	128	1.80	0.18	557.21	603.28	16.12	389.63	63.88	5.81	75.2 ± 57.2	11.9 ± 12.7	480 ± 596	235 ± 187	268 ± 158	0.177 ± 0.
DAN-05	DVCA	29.1	413	144	1.84	0.17	255.59	140.50	77.03	180.37	44.90	4.46	154 ± 164	5 ± 1.88	737 ± 682	271 ± 183	305 ± 269	1.03 ± 1.
Selectively	logged fore	st (SL)																
SAF-03	SAFE project	25.8	565	211	1.89	0.16	231.05	40.42	115.55	38.65	35.66	3.68	83.8 ± 63.7	26.4 ± 44.9	392 ± 265	318 ± 201	332 ± 308	8.51 ± 1
SAF-04	SAFE project	t 19.5	465	188	7.15	0.32	117.07	107.71	67.21	41.36	14.55	3.90	83.4 ± 60.5	2.68 ± 4.32	1.35*10 ³ ± 621	310 ± 94.1	45.1 ± 58	1.18 ± 1.
SAF-02	SAFE project	t 14.8	416	124	1.51	0.12	137.33	160.50	105.86	41.80	49.38	4.04	340 ± 239	23.9 ± 33.2	182 ± 187	191 ± 173	401 ± 239	0.464 ± 0.
SAF-01	SAFE project	t 10.9	331	129	3.08	0.28	375.15	887.03	96.37	266.36	70.76	4.66	20±17.5	16.8 ± 18.7	212 ± 269	79 ± 67.6	245 ± 90.6	3.03 ± 2.

674 Table 2: Results from linear regression models from which the explained variance was generated, factors are the categorical 'forest type' (OG – old-growth,

SL – selectively logged), and continuous 'soil PC1' and 'soil PC2'. For analyses values of dark respiration R_d fluxes and $\delta^{13}C$ were converted to positive values

676 for ease of interpretation, here untransformed values are shown. For abbreviations and description of the functional traits, see table S1.

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Commented [SB7]: I'll pimp up that table

	CWM trait value (95%	confindence intervals)	For	rest type		Soil PC1	Soil PC2		
Functional trait	OG	SL	F value	p-value	F value	p-value	F value p-value		
hemicellulose_perc	12.3 (11.4 - 13.1)	11.8 (11 - 12.6)	1.7284	0.4371 ns	0.7672	0.5839 ns	0.27	0.725 ns	
cellulose_perc	22.5 (20.9 - 24)	20.9 (19.4 - 22.4)	3.3431	0.3055 ns	0.3132	0.725 ns	0.995	0.538 ns	
lignin_recalcitrants_perc	19.4 (17.3 - 21.4)	17.3 (15.3 - 19.2)	2.7065	0.3403 ns	3.333	0.3055 ns	0.0803	0.8265 ns	
Total_tannin_mg_gDW	8.56 (7.7 - 9.41)	9.41 (8.6 - 10.2)	8.8879	0.1586 ns	8.0687	0.1626 ns	0.0043	0.9508 ns	
Total_phenol_mg_gDW	36.4 (33.7 - 39.1)	42.7 (40.2 - 45.3)	29.9599	0.0641 ns	5.0043	0.2147 ns	2.762	0.3403 ns	
WD_B	0.564 (0.528 - 0.599)	0.493 (0.46 - 0.526)	15.3085	0.1227 ns	2.4421	0.3608 ns	1.5223	0.4406 ns	
LDMC_mg_g_mean	416 (391 - 440)	410 (387 - 433)	0.1426	0.78 ns	0.3322	0.725 ns	0.0786	0.8265 ns	
Fp_N_mm_mean	0.266 (0.227 - 0.311)	0.212 (0.183 - 0.247)	7.611	0.1626 ns	0.2997	0.725 ns	0.2597	0.725 ns	
specific_Fp_mean	1.23 (1.03 - 1.47)	0.889 (0.751 - 1.05)	13.209	0.1285 ns	0.4308	0.686 ns	0.013	0.9337 ns	
leaf_thickness_mm_mean	0.221 (0.209 - 0.233)	0.236 (0.224 - 0.249)	7.1956	0.1697 ns	0.2132	0.7434 ns	2.3189	0.3712 ns	
dry_weight_mg_mean	922 (784 - 1.08e+03)	1.08e+03 (930 - 1.27e+03)	2.0771	0.4013 ns	10.6002	0.1385 ns	6.1195	0.1891 ns	
LA_mm2_mean	1.37e+04 (1.13e+04 - 1.65e+04)	1.31e+04 (1.1e+04 - 1.57e+04)	1.6779	0.4371 ns	11.1158	0.1367 ns	1.8983	0.4249 ns	
SLA_mm2_mg_mean	16.3 (15.3 - 17.4)	13.2 (12.2 - 14.1)	52.0691	0.057 ns	3.0363	0.3225 ns	5.338	0.2081 ns	
chla_mg.g	2.62 (2.54 - 2.71)	2.49 (2.41 - 2.57)	13.8526	0.1285 ns	0.967	0.539 ns	0.0201	0.922 ns	
chla_mg.mm2	0.00018 (0.000169 - 0.000192)	0.000206 (0.000195 - 0.000217)	29.1407	0.0641 ns	1.4573	0.4408 ns	7.0602	0.1697 ns	
chlb_mg.g	1.09 (1.05 - 1.13)	0.97 (0.931 - 1.01)	40.3793	0.0622 ns	0.0054	0.9508 ns	2.6047	0.3462 ns	
chlb_mg.mm2	7.42e-05 (6.79e-05 - 8.04e-05)	7.95e-05 (7.36e-05 - 8.55e-05)	5.5521	0.2032 ns	1.6784	0.4371 ns	1.3329	0.4618 ns	
carot_mg.g	0.687 (0.667 - 0.708)	0.667 (0.647 - 0.687)	6.3526	0.1891 ns	1.5548	0.4406 ns	0.2638	0.725 ns	
carot_mg.mm2	4.74e-05 (4.47e-05 - 5.02e-05)	5.54e-05 (5.28e-05 - 5.79e-05)	47.7257	0.057 ns	1.7074	0.4371 ns	7.9565	0.1626 ns	
Asat_mean	4.08 (2.66 - 5.5)	7.03 (5.69 - 8.38)	20.2667	0.0936 ns	0.2841	0.725 ns	4.4952	0.2333 ns	
Amax_mean	11.7 (8.94 - 14.5)	18 (15.4 - 20.6)	23.2366	0.0844 ns	0.8777	0.5526 ns	4.2675	0.2424 ns	
DR_mean	1.03 (0.871 - 1.19)	1.25 (1.09 - 1.4)	7.7079	0.1626 ns	1.546	0.4406 ns	5.7587	0.199 ns	
N_mg.mm2	0.128 (0.12 - 0.136)	0.166 (0.158 - 0.174)	97.6994	0.0343 *	0.5198	0.6654 ns	19.7036	0.0936 ns	
total_P_mg.mm2	6.62e-05 (6.21e-05 - 7.06e-05)	8.04e-05 (7.57e-05 - 8.54e-05)	33.2076	0.0641 ns	12.2667	0.1294 ns	10.3913	0.1385 ns	
X13C	32.4 (32.1 - 32.8)	31.4 (31.1 - 31.8)	28.7751	0.0641 ns	8.7471	0.1586 ns	11.3558	0.1367 ns	
C_perc	44.6 (44.3 - 44.9)	44.7 (44.4 - 45)	12.2663	0.1294 ns	89.7169	0.0343 *	0.2403	0.7309 ns	
total_P_mg.g	0.998 (0.912 - 1.09)	0.99 (0.909 - 1.08)	1.4839	0.4408 ns	13.2189	0.1285 ns	0.444	0.686 ns	
N_perc	1.83 (1.74 - 1.91)	1.97 (1.89 - 2.05)	9.1914	0.1586 ns	7.7457	0.1626 ns	4.523	0.2333 ns	
total_K_mg.g	9.99 (8.4 - 11.9)	10.8 (9.13 - 12.7)	0.9229	0.5454 ns	0.3208	0.725 ns	2.7576	0.3403 ns	
total_Mg_mg.g	2.57 (2.06 - 3.2)	2.41 (1.96 - 2.97)	0.7237	0.5925 ns	1.2751	0.4687 ns	0.4897	0.672 ns	
total_Ca_mg.g	7.09 (6.12 - 8.2)	6.6 (5.75 - 7.59)	6.1143	0.1891 ns	17.5554	0.1051 ns	1.5777	0.4406 ns	
X15N	1.64 (0.966 - 2.32)	0.846 (0.204 - 1.49)	5.032	0.2147 ns	0.1854	0.7495 ns	0.5269	0.6654 ns	
RaoQ	0.791 (0.735 - 0.847)	0.789 (0.736 - 0.842)	0.1971	0.748 ns	0.1187	0.7961 ns	3.0601	0.3225 ns	

