¹ **Global decoupling of functional and phylogenetic diversity in plant** ² **communities**

3 Georg J. A. Hähn^{1,2,3,*}, Gabriella Damasceno^{2,1}, Esteban Alvarez-Davila⁴, Isabelle Aubin⁵, 4 Marijn Bauters⁶, Erwin Bergmeier⁷, Idoia Biurrun⁸, Anne D. Bjorkman^{9,10}, Gianmaria Bonari¹¹, 5 Zoltán Botta-Dukát¹², Juan A. Campos⁸, Andraž Čarni^{13,14}, Milan Chytrý¹⁵, Renata 6 Ćušterevska¹⁶, André Luís de Gasper¹⁷, Michele De Sanctis¹⁸, Jürgen Dengler¹⁹, Jiri Dolezal²⁰, 7 Mohamed A. El-Sheikh²¹, Manfred Finckh²², Antonio Galán-de-Mera²³, Emmanuel 6arbolino²⁴, Hamid Gholizadeh¹¹, Valentin Golub²⁵, Sylvia Haider²⁶, Mohamed Z. Hatim²⁷, 9 Bruno Hérault^{28,29}, Jürgen Homeier³⁰, Ute Jandt^{1,2}, Florian Jansen³¹, Anke Jentsch³², Jens 10 Kattge^{33,2}, Michael Kessler³⁴, Larisa Khanina³⁵, Holger Kreft³⁶, Filip Küzmič³⁷, Jonathan 11 Lenoir³⁸, Jesper Erenskjold Moeslund³⁹, Ladislav Mucina^{40,41}, Alireza Naqinezhad⁴², Jalil 12 Noroozi⁴³, Aaron Pérez-Haase⁴⁴, Oliver L. Phillips⁴⁵, Valério D. Pillar⁴⁶, Gonzalo Rivas-Torres⁴⁷, 13 Eszter Ruprecht⁴⁸, Brody Sandel⁴⁹, Marco Schmidt⁵⁰, Ute Schmiedel⁵¹, Stefan Schnitzer⁵², 14 Franziska Schrodt⁵³, Urban Šilc⁵⁴, Ben Sparrow⁵⁵, Maria Sporbert^{1,2}, Zvjezdana Stančić⁵⁶, Ben 15 Strohbach⁵⁷, Jens-Christian Svenning⁵⁸, Cindy Q. Tang⁵⁹, Zhiyao Tang⁶⁰, Alexander Christian 16 Vibrans⁶¹, Cyrille Violle⁶², Donald Waller⁶³, Desalegn Wana⁶⁴, Hua-Feng Wang⁶⁵, Timothy 17 Whitfeld⁶⁶⁶, Georg Zizka⁶⁷, Francesco Maria Sabatini^{3,68,†} & Helge Bruelheide^{1,2,†}

18 $*$ Corresponding author, $*$ Shared senior authors

- 19 ¹ Martin Luther University Halle-Wittenberg, Institute of Biology / Geobotany and Botanical
- 20 Garden, Am Kirchtor 1, 06108 Halle, Germany

21 ² German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Puschstrasse

- 22 4, Leipzig, 04103, Germany
- 23 ³ University of Bologna, Department of Biological, Geological and Environmental Sciences,
- 24 Via Irnerio 42, Bologna, 40126, Italy
- ⁴ 25 Universidad Nacional Abierta y a Distancia (Colombia), Escuela ECAPMA, Street 14 Sur #
- 26 14-23, Bogotá, Postal Code 111511, Colombia
- ⁵ 27 Canadian Forest Service, Great Lakes Forestry Centre, 1219 Queen St. East, Sault Ste Marie,
- 28 ON, P6A 2E5, Canada
- ⁶ 29 Ghent University, Department of Environment, Coupure Links 653, 9000 Gent, Belgium
- ⁷ 30 University of Göttingen, Deptartment of Vegetation & Phytodiversity Analysis, Untere
- 31 Karspüle 2, Göttingen, 37073, Germany
- 8 University of the Basque Country UPV/EHU, Department of Plant Biology and Ecology,
- 33 Apdo. 644, 48080, Bilbao, Spain
- ⁹ University of Gothenburg, Biological & Environmental Sciences, Box 463, 40530,
- 35 Gothenburg, Sweden
- 36 ¹⁰ Gothenburg Global Biodiversity Centre, Box 463, 40530, Gothenburg, Sweden
- 37 ¹¹ University of Siena, Department of Life Sciences, Via P.A. Mattioli 4, 53100, Siena, Italy
- 38 ¹² Centre for Ecological Research, Institute of Ecology and Botany, Alkotmány 2-4, Vácrátót,
- 39 2163, Hungary
- ¹³ Research Centre of the Slovenian Academy of Sciences and Arts, Jovan Hadži Institute of
- 41 Biology, Novi trg 2, SI 1000 Ljubljana, Slovenia
- ¹⁴ University of Nova Gorica, School for Viticulture and Enology, Vipavska cesta 13, 5000
- 43 Nova Gorica, Slovenia
- 44 ¹⁵ Masaryk University, Faculty of Science, Department of Botany and Zoology, Kotlářská 2,
- 45 611 37 Brno, Czech Republic
- ¹⁶ University of Ss. Cyril and Methodius, Faculty of Natural Sciences and Mathematics,
- 47 Institute of Biology, Arhimedova Str. 3, 1000, Skopje, North Macedonia
- ¹⁷ 48 Universidade Regional de Blumenau, Rua Antonio da Veiga, 140, 89030903, Blumenau,
- 49 Santa Catarina, Brazil
- 50 ¹⁸ Sapienza University of Rome, Department of Environmental Biology, P.le Aldo Moro 5,
- 51 Rome, 00185, Italy
- 52 ¹⁹ Zurich University of Applied Sciences (ZHAW), Wädenswil, Switzerland
- 53 ²⁰ Czech Academy of Science, Institute of Botany, Dukelská 135, 379 01 Trebon, Czechia
- 54 ²¹ King Saud University, College of Science, Botany and Microbiology Department, P.O. Box
- 55 2455, Riyadh 11451, Saudi Arabia
- ²² 56 University of Hamburg, Institute of Plant Science and Microbiology, Ohnhorststr., 18,
- 57 Hamburg, 22609, Germany
- 58 ²³Universidad San Pablo-CEU, CEU Universities, Botany Lab, Carretera de Boadilla Km 5,300,
- 59 28660- Boadilla del Monte, Madrid, Spain
- 60 ²⁴ MINES Paris PSL ISIGE, 35 rue Saint-Honoré, 77300 Fontainebleau, France
- 61 ²⁵ Samara Federal Research Scientific Center, Institute of Ecology of the Volga River Basin,
- 62 Komzina 10 Togliatti, 445003, Russia
- ²⁶ 63 Leuphana University of Lüneburg, Faculty of Sustainability, Institute of Ecology,
- Universitätsallee 1, 21335 Lüneburg, Germany
- 65 ²⁷ Wageningen University, Plant Ecology and Nature Conservation Group, Environmental
- Sciences Department, P.O. Box Postbus 47, Droevendaalsesteeg 3, 6700 AA, Wageningen,
- The Netherlands
- ²⁸ CIRAD, UPR Forêts et Sociétés, Campus de Baillarguet, F-34398 Montpellier, France
- ²⁹ University Montpellier, CIRAD, Forêts et Sociétés, Campus de Baillarguet, F-34398
- Montpellier, France
- ³⁰ HAWK Goettingen, Resource Management, Daimlerstraße 2, 37075 Goettingen, Germany
- ³¹ University of Rostock, Justus-von-Liebig-Weg 6, 18059 Rostock, Germany
- 73 ³² University of Bayreuth, Bayreuth Center of Ecology and Evironmental Research,
- Department of Disturbance Ecology, Bayreuth, Germany
- ³³ Max Planck Institute for Biogeochemistry, Hans Knöll Str. 10, 07745 Jena, Germany
- ³⁴ University of Zurich, Systematic and Evolutionary Botany, Zollikerstrasse 107, CH-8008
- Zurich, Switzerland
- ³⁵ IMPB RAS, Branch of the M.V. Keldysh IAM RAS, 1 Prof. Vitkevicha Str., Pushchino,
- 142290, Russia
- 36 University of Göttingen, Department of Biodiversity, Macroecology & Biogeography,
- Büsgenweg 1, 37077 Göttingen, Germany
- 82 ³⁷ Research Centre of the Slovenian Academy of Sciences and Arts, Jovan Hadži Institute of
- Biology, Novi trg 2, 1000, Ljubljana, Slovenia
- 84 ³⁸ UMR CNRS 7058 Ecologie et Dynamique des Systèmes Anthropisés (EDYSAN), Université
- de Picardie Jules Verne, 1 rue des Louvels, 80000 Amiens, France
- 86 ³⁹ Aarhus University, Department of Ecoscience, C. F. Møllers Allé 6-8, DK-8000, Aarhus C,
- Denmark
- 88 ⁴⁰ Murdoch University, Harry Butler Institute, 90 South Street, Murdoch 6150, Perth,
- Western Australia, Australia
- 90 ⁴¹ Stellenbosch University, Department of Geography & Environmental Studies, Private Bag
- X1, 7602 Matieland, Stellenbosch, South Africa
- 92 ⁴² University of Mazandaran, Pasdaran, Campus of the University, Babolsar, 47416-74765,
- Iran
- 94 ⁴³ University of Vienna, Department of Botany and Biodiversity Research, Rennweg 14,
- Vienna, 1220, Austria
- ⁴⁴ Universitat de Barcelona, Departament de Biologia Evolutiva, Ecologia i Ciències
- Ambientals, Institut de Recerca de la Biodiversitat (IRBio), Av. Diagonal 643, Barcelona,
- 08036, SpainUniversitat de Barcelona, Facultat de Biologia, Institut de Recerca de la

Biodiversitat (IRBio), Av. Diagonal 643, Barcelona, 08036, Spain

- 100 ⁴⁵ University of Leeds, Leeds LS2 9JT, United Kingdom
- 101 ⁴⁶ Universidade Federal do Rio Grande do Sul, Department of Ecology, Department of
- Ecology, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, 91501-970, BRAZIL
- 47 Estación de Biodiversidad Tiputini, Universidad San Francisco de Quito USFQ, Colegio de
- Ciencias Biológicas y Ambientales, Diego de Robles sn e Interoceanica, Quito,
- EcuadorUniversidad San Francisco de Quito USFQ, Estación de Biodiversidad Tiputini,
- $\,$ $\,$ Colegio de Ciencias Biológicas y Ambientales. Diego de Robles sn e Interoceanica. Quito,
- Ecuador
- 108 ⁴⁸ Babeș-Bolyai University, Faculty of Biology and Geology, Hungarian Department of Biology
- and Ecology, Republicii street 42., 400015 Cluj-Napoca, Romania
- 110 ⁴⁹ Santa Clara University, Department of Biology, 500 El Camino Real, Santa Clara CA, 95053,
- USA
- 112 ⁵⁰ Palmengarten der Stadt Frankfurt am Main, Wissenschaft, Siesmayerstraße 61, 60323
- Frankfurt am Main, Germany
- ⁵¹ University of Hamburg, Institute of Plant Science and Microbiology, Ohnhorststraße 18,
- 22609 Hamburg, Germany
- ⁵² Marquette University, PO Box 1881, Milwaukee WI 53202
- 117 ⁵³ University of Nottingham, University Park, Nottingham, NG7 2RD, United Kingdom
- 118 ⁵⁴ ZRC SAZU, Institute of Biology, Novi trg 2, Ljubljana, Slovenia
- ⁵⁵ University of Adelaide, TERN, The School of Biological Sciences, Waite Campus, PMB 1,
- Glen Osmond, SA, 5064, Australia
- ⁵⁶ University of Zagreb, Faculty of Geotechnical Engineering, Hallerova aleja 7, HR-42000
- Varaždin, Croatia
- 57 Namibia University of Science and Technology, Biodiversity Research Center, Faculty of
- Health, Natural Resources and Applied Sciences, 13 Jackson Kaujeua street, Windhoek,
- Namibia
- 126 ⁵⁸ Aarhus University, Department of Biology, Center for Ecological Dynamics in a Novel
- Biosphere (ECONOVO), Ny Munkegade 114, DK-8000 Aarhus C, Denmark
- 59 Yunnan University, Institute of Ecology and Geobotany, College of Ecology and
- 129 Environmental Science, Building Shixun, Chenggong Campus, Dongwaihuan South Road,
- 130 University Town, Chenggong New District, Kunming, Yunnan 650504, China
- ⁶⁰ Peking University, Department of Ecology, College of Urban and Environmental Sciences,
- 132 Yiheyuan Road 5, Haidian, Beijing 100871, China
- 133 ⁶¹ Universidade Regional de Blumenau (FURB), Rua São Paulo, 3250, Blumenau-Santa
- 134 Catarina Zipcode 89030-000, Brazil
- ⁶² CEFE, Univ Montpellier, CNRS, EPHE, IRD, Campus CNRS, 1919 route de Mende, 34293
- 136 Montpellier, France
- ⁶³ University of Wisconsin Madison, Botany, 2150 West Lawn Ave, Madison WI, 53711, USA
- 138 ⁶⁴ Addis Ababa University, Department of Geography & Environmental Studies, Bole street,
- 139 Addis Ababa, P.O. Box 150178, Ethiopia
- ⁶⁵ Hainan University, Sanya Nanfan Research Institute, Sanya, 572500, Hainan, China
- ⁶⁶ University of Minnesota, Bell Musuem, 1479 Gortner Avenue, St. Paul, MN 55108, USA
- 142 ⁶⁷ Senckenberg Research Institute and Natural History Museum Frankfurt and Goethe
- 143 University, Department Botany and Molecular Evolution, Senckenberganlage 25, 60325
- 144 Frankfurt/Main, Germany
- ⁶⁸ Faculty of Forestry and Wood Sciences, Czech University of Life Sciences Prague, 165 00
- 146 Praha, Czech Republic

Abstract

 Plant communities are composed of species that differ both in functional traits and evolutionary histories. Understanding how species' traits and histories interact with the environmental conditions of a site and drive the assembly of ecological communities is the basis for predicting the impacts of climate change on biodiversity and ecosystem functioning. As species' functional traits partly result from their individual evolutionary history, the functional diversity (FD) of communities is expected, on average, to covary positively with their phylogenetic diversity (PD). However, this expectation has only been tested at local scales, for specific growth forms or specific habitat types, e.g. grasslands. Here, we compared the standardized effect sizes of FD and PD for 1,781,836 vegetation plots using the global sPlot database. In contrast to our expectations, the correlation between FD and PD was weak, not positive but negative, and these two facets of diversity were more often decoupled than coupled. While PD reflected recent climatic conditions and vegetation type, being higher in forests, FD depended on recent (1981-2010) and past climatic conditions (21,000 years ago). The independent nature of functional and phylogenetic diversity makes it crucial to consider both aspects of diversity when analyzing ecosystem functioning or prioritizing conservation efforts.

Introduction

 Climate change and biodiversity loss are two of the most pressing environmental issues of our 167 time, with rising temperatures and shifting precipitation patterns increasingly becoming one 168 of the main drivers of the extinction of many plant species¹. These changes have significant implications for ecosystems and human societies alike, with impacts ranging from altered 170 agricultural yields to increased risk of natural disasters^{2,3}. To understand and mitigate the effects of climate change and biodiversity loss, it is crucial to determine how plant species are assembled into communities and how these communities respond to changing environmental 173 and climatic conditions^{4,5}. This means that we need to understand the underlying mechanisms of plant community assembly, and how these mechanisms are mediated by the interactions 175 between species' functional traits, evolutionary histories and environmental conditions⁶.

 Community assembly is the net result of several processes that partially reinforce or oppose 177 each other⁷. On the one hand, environmental filtering may result in a phenotypic clustering

178 of traits in a community^{8,9}. On the other hand, biotic interactions, and in particular competitive exclusion, may limit the similarity of the phenotypes in a community, since species can more readily coexist when they have different traits, and result in trait 181 divergence^{10,11}. The attribution of convergence or divergence to specific mechanisms is not 182 clearcut, however₋₅ since cConvergence could also be caused by the competitive exclusion of 183 species whose traits are associated with low competitive abilities⁷, and divergence might stem 184 from habitat filtering in case of correlated traits under different environmental controls¹², or 185 . In addition, trait divergence can arise from interacting environmental factors that select the 186 resident species in a community¹³. Whatever the underlying mechanism, species functional traits clearly play a big role in community assembly, while also being the result of the evolution of a species in its environment. In other words, functional traits are subject to selection and are often conserved within phylogenetic lineages. This means that species that are closely related on the evolutionary tree are more likely to share similar traits compared to species that are less closely related. Depending on the velocity of evolution, specific traits 192 can be more or less conserved on the phylogenetic tree^{14,15}. Different *indices based on* Brownian motion models of evolutionary modelstrait evolution (e.g. Blomberg`s *K* and Pagel`s 194 $\lambda^{16,17}$) exist to test whether a trait is phylogenetically conserved, which are based on the correlation between the species distances in trait values and their distances in the 196 phylogeny $6,18,19$.

 If species in a community share similar traits, the community is said to show phenotypic clustering, which is equivalent to having a low functional diversity (FD). Phenotypic clustering can be associated with two patterns, either a combination of phylogenetic clustering with trait conservatism (*Fig. 1*, bottom left) or a combination of phylogenetic dispersion with trait 201 convergence (Fig. 1, bottom right)^{6,14,20}. In the former case, there is a positive covariation between phylogenetic and functional distances, which is why we call the resulting communities coupled. In the latter case, the phylogenetic and functional distances are inversely related, and thus, we call the resulting communities decoupled.

 In contrast, if species in a community have dissimilar traits, the community has a high phenotypic variation, which is equivalent to a high FD. High FD can either happen in combination with high phylogenetic variation (*Fig. 1*, top right) or phylogenetic clustering (*Fig. 1*, top left). Again, in the former case phylogenetic and functional diversities are coupled, 209 while they are inversely related, and therefore decoupled, in the latter case^{20,21}. Many local 210 studies found a prevalence of coupled communities with positive covariation of functional 211 and phylogenetic diversity (FD, PD)²²⁻²⁴, but negative covariations^{25,26} and unclear patterns 212 have also been encountered²⁷. However, it is not yet known under which conditions 213 communities express coupled or decoupled functional and phylogenetic diversities.

214 By calculating functional and phylogenetic diversity for 1,781,836 vegetation plots from 215 sPlot²⁸, the global vegetation plot database, we tested whether patterns of coupling or 216 decoupling 1) dominate at the global level, 2) have regional patterns, 3) differ between forest 217 and non-forest ecosystems, and 4) correlate with current and past climatic gradients. We 218 hypothesized an overall coupled pattern of functional and phylogenetic diversity, since 219 phylogenetic diversity has often been found to reflect functional trait diversity, especially for 220 those phylogenetically conserved traits which are not easily measurable in plants, such as 221 herbivore and pathogen resistance^{14,19,29}. We expected higher phylogenetic diversity in 222 forests than in non-forest ecosystems due to the co-occurrence of woody and non-woody 223 plant species, given that the herbaceous habit has evolved from the ancestral woody state 224 multiple times and in different lineages $30-33$. Since phylogenetic and functional diversity 225 metrics are correlated with species richness, we used null models to calculate standardized 226 effect sizes and quantify how much phylogenetic and functional diversity differed from 227 random expectations, before comparing them³⁴.

 Figure 1: Conceptual figure of the relationship between functional and phylogenetic diversity after Ref. 19 & 20. If functional diversity is proportional to community phylogenetic diversity, we consider the community to be coupled (diagonal). The extremes are the results either of phylogenetic clustering in combination with trait convergence (bottom left) or phylogenetic overdispersion in combination with trait divergence (top right). Decoupled communities can be either observed if a community shows phylogenetic overdispersion in combination with trait convergence (bottom right) or if it shows phylogenetic clustering with trait divergence (top left).

Results

The relationship of functional and phylogenetic diversity

 We modelled the relationship between functional and phylogenetic diversity indices expressed as a standardized effect size of Rao´s quadratic entropy based on functional traits 242 (SES.FD_Q) and phylogenetic distances (SES.PD_Q), when considering three selected functional traits representative of the main dimensions of the global spectrum of plant form and function, namely the leaf economics spectrum (specific leaf area), the size-seed mass 245 dimension (plant height), and the root collaboration gradient (specific root length)^{35,36}. Both indices were calculated using Rao's quadratic entropy and transformed to standardized effect sizes, based on biome-specific null models that account for the uneven species richness across plots, and use the relative frequencies of species occurrences within each biome to weight species resampling probabilities. We did this because both functional and phylogenetic diversity are tightly related to species richness. Out of 1,781,836 vegetation plots, 31.38% 251 showed trait and phylogenetic coupling as $SES.FD_Q$ and $SES.PD_Q$ were equally high or low. 252 53.03% of the vegetation plots had higher SES.FD_Q than SES.PD_Q and 15.6% had higher 253 SES.PD_Q than SES.FD_Q, suggesting that decoupled plant communities are twice as common than coupled ones and that, on average, global communities are more functionally than phylogenetically diverse (*Fig. 2A*). These results did not change after removing non-significant 256 standardized effect values, i.e. values between -1.96 and 1_{72} 96 (6.9% coupled communities, 45.8% decoupled with high FD values and 17.3% decoupled with high PD values).

 We did not find any clear geographical pattern at the global scale (*Fig. 2B*). Decoupled 259 communities with high SES.FD_Q and low SES.PD_Q, (see Methods for definition of high and low 260 values of SES.FD_Q and SES.PD_Q) occurred in the western USA and locally across Europe, while 261 communities with low SES.FD_Q and high SES.PD_Q were found close to the Arctic circle in Scandinavia and Siberia, and in New-Zealand and Japan. Coupled communities with high values of both diversity indices were encountered in the eastern USA, Central-Europe as well as in New-Zealand and Japan.

265 Overall, we found a negative relationship between SES.FD_Q and SES.PD_Q. Accounting for the spatial structure of the data by adding a smoothing spline, our general additive model 267 explained 7.8% of the deviance in SES.FD_Q (*Fig. 2A*). Modelling the raw values of FD_Q against 268 the raw values of PD_Q, i.e., not accounting for the effect of species richness, also returned a negative relationship with 18.5% of deviance explained (*Fig. S 1 A*). The explained deviance increased to 36.2% when the distance matrix of phylogenetic distances was square root-transformed, accounting for the non-linearity of trait evolution (*Fig. S 1 B*).

272 The negative relationship between SES.FD_Q and SES.PD_Q was robust to the use of alternative null models, diversity indices, selections of functional traits and subsets of vegetation plot 274 data (see Methods for details). Using a null model based on a global species pool, SES.PD_Q 275 together with the spatial smoothing spline explained 5.8% of the deviance in SES.FD_Q, which increased to 6.2% when the phylogenetic distances were square root-transformed (*Fig. S 1 C, D*). Based on a biome-specific, but unweighted species pool, the explained deviance was 6.8% 278 (*Fig. S 1 F*). When null models were constrained based on a -and for a phytogeographic³⁷ species pool the explained deviance was 7.8% (*Fig. S 1 G*). The same negative relationship was found when using alternative indices of functional and phylogenetic diversity, i.e., when modelling standardized effect size of functional dispersion against mean pairwise distance (MPD). The explained deviance in this case was 7.1% (*Fig. S 1 E*). Considering each trait individually, or including additional traits (eight) but only for an environmentally-balanced 284 subset of vegetation plot data (i.e., sPlotOpen³⁸), also returned a negative relationships 285 between FD_Q and PD_Q (*Fig. S 87, Table S 1*).

SES.PD_Q

 $\sf B$

 Figure 2: The relationship of standardized effect size of quadratic functional (SES.FDQ) and phylogenetic diversity (SES.PDQ). SES.FD^Q is based on three functional traits: specific leaf area, plant height and specific root length. A SES.FD^Q as a function of SES.PD^Q with the linear regression slope (blue) after accounting for spatial autocorrelation with a general additive model (7.8% explained deviance). Additionally, the line of coupling with the 1:1 relationship (black) and the confidence interval (grey, see Methods). 31.38% observations are lying within the confidence interval. 53.03% and 15.6% of all observations show decoupling, with either FD > PD or FD < PD, respectively. B Mean log ratio of standardized effect sizes of functional (SES.FDQ) and phylogenetic diversity (SES.PDQ) per raster cell (863.8 km²). Negative values indicate higher observed SES.PD^Q than SES.FD^Q and vice versa. The extracted values from the spatial smoothing spline from the General Additive Model (GAM) can be found in Fig. S 2 D.

The environmental drivers of functional and phylogenetic diversity

 We used Boosted Regression Trees (BRT) to select the environmental variables that best 302 explain either SES.FD_Q or SES.PD_Q. The BRTs suggested climate variables to be most relevant for shaping patterns of SES.FDQ (*Fig. 3 A*). Temperature of the coldest quarter and coldest month (both reflected by PC2 in a principal component analysis based on 19 bioclimatic 305 variables) had the highest relative influence on SES.FD $_{\text{Q}}$, followed by the climate variability after the Last Glacial Maximum (LGM) and precipitation seasonality (PC5). Partial dependence 307 plots suggested a predominantly positive relationship between SES.FD_Q and climate variability 308 after the LGM and a negative one with precipitation seasonality (PC5, *Fig. S* 3). SES.FD_Q first increased and then decreased with increasing temperatures of the coldest quarter and coldest month (PC2).

311 Regarding phylogenetic diversity, $SES.PD_Q$ was especially related to the vegetation type (forest vs. non-forest, classified based on cover of the tree layer and species traits, such as growth form and height, see methods), being higher in forest compared to non-forest ecosystems, and tend to increase with annual precipitation (PC1; *Fig. 3 A, Fig. S 4*).

317
318 *Figure 3: Results of the Boosted Regression Trees for A SES.FDQ, B SES.PD^Q and C the relationship of both expressed as the logarithm of the ratioquotient betweenof SES.FD^Q and SES.PDQ. An explanatory variable was considered relevant in the model when its relative influence was greater than 12.5%, indicated by the dashed line, which is the expected influence of a variable if all eight predictors had the same relative importance. The signs indicate the direction of the significant effects arisen from the partial dependence models (Fig. S 3 – 5).*

324 When modelling the log ratio of $SES.FD_Q$ and $SES.PD_Q$, as log($SES.FD_Q/SES.PD_Q$), the BRTs showed that the classification of forest or non-forest and annual precipitation (PC1) were the variables with the highest relevant influence, which was mostly equivalent to what observed for SES.PD^Q (*Fig. 3 B, S 5*).

 Only those variables with relative influence greater than 12.5%, which is the percentage of relative influence by chance (100% divided by eight explanatory variables) in the BRTs were 330 used as predictors in the general additive models (GAM) with SES.FD_Q or SES.PD_Q as response 331 variables and accounting for spatial autocorrelation. The model for $SES.FD_Q$ explained 4.6% of the deviance and suggested a positive relationship with climate variability after the LGM and temperature of the coldest quarter and month (PC2, *Fig. 4*). A negative relationship was shown for precipitation seasonality (PC5).

 Annual precipitation (PC1), vegetation type and the spatial smoothing spline explained 37.3% 336 of the deviance of the SES.PD_Q model. SES.PD_Q increased with increasing precipitation and

- 337 was higher in forests than in non-forest ecosystems (*Fig. 5*). The model of the log relationship 338 r ratio between SES.FD_Q and SES.PD_Q reflected the results of SES.PD_Q with an explained 339 deviance of 30.8% (*Fig. 6*).
- 340 In order to explore the effect of environmental predictors on the general patterns of coupling
- 341 and decoupling we modelled the relationship between SES.FD_Q and SES.PD_Q as an ordered
- 342 categorical variable with three states, to acknowledge that while there is only one way for
- 343 communities to be coupled, decoupling can come in two ways: decoupling with PD > FD, or
- 344 decoupling with FD > PD. When doing so the explained deviance was 10.2% (*Fig. S 6*) with
- 345 annual precipitation (PC1), precipitation seasonality (PC5) and forest or non-forest as the
- 346 variables with the highest power to discriminate the three categories.

 Figure 4: Drivers of the standardized effect size of functional diversity (SES.FDQ). Residuals of SES.FD^Q as a function of A temperature of the coldest quarter and month (PC2), B precipitation seasonality (PC5), and C climate variability after the last glacial maximum. The general additive model (GAM) explained 4.6% of the deviance. The solid line shows the regression obtained from the GAM. The density hexagons show the distribution of the residuals of the model without the explanatory variable of interest. The smooth term of SES.FD^Q can be found in Fig. S 76 A.

 Figure 5: Drivers of standardized effect size of phylogenetic diversity (SES.PDQ). Residuals of SES.PD^Q as a function of A PC1 - annual precipitation, and B vegetation type. The general additive model (GAM) explained 37.3% of the deviance. The solid line shows the regression obtained from the GAM. The density hexagons show the distribution of the residuals of the model without the explanatory variable of interest. The smooth term of SES.PD^Q can be found in Fig. S. 76 B.

363
364

 Figure 6: Drivers of the relationship log ratio between the standardized effect size of functional diversity (SES.FDQ) and phylogenetic diversity (SES.PDQ). Residuals of log(SES.FDQ/SES.PDQ) as a function of A PC1 - annual precipitation, and B vegetation type based on the dominant species. The general additive model (GAM) explained 30.8% of the deviance. The solid line shows the regression obtained from the GAM. The density hexagons show the distribution of the residuals of the model without the explanatory variable of interest. The smooth term of log(SES.FDQ/SES.PDQ) can be found in Fig. S. 76 C.

Discussion

 Plant communities differ in their functional and phylogenetic composition. Here, we modelled the relationship between functional and phylogenetic diversity in plant communities across the globe and made inferences about the drivers of these diversity facets. We showed that values of functional and phylogenetic diversity tend to be decoupled, suggesting global patterns of community assembly are primarily driven by either functional or phylogenetic diversity, less acting together. Functional diversity (FD) was driven by both recent climate conditions, as well as by past climatic events. In line with our initial hypothesis, we found high 379 phylogenetic diversity (PD) in forest communities. The log ratio of FD and PD varied as a function of vegetation type (forest vs. non-forest), and of recent climate conditions, in line with what observed for PD.

 Contrary to our hypothesis, we found a negative but weak relationship between FD and PD at the global scale (*Fig. 2 A*). As PD is often considered to be a proxy for capturing unmeasured patterns of species functional traits, we did expect a positive relationship between FD and 385 \cdot PD³⁹, as postulated also by theoretical studies²⁴. The negative correlation observed at the global scale shows that functional and phylogenetic diversity are more often decoupled than coupled in plant communities, with communities either having high phylogenetic or 388 functional diversity, which is in line with recent results in grassland communities²⁵. Additionally, distribution of traits across phylogenies can vary at small spatial scales, including 390 both trait clustering and overdispersion^{14,19}. This indicates that, contrary to the expected from 391 θ the coupling of FD and PD, closely related species exhibit greater differences in their trait 392 values, while phylogenetically distant species tend to share more similar trait values than 393 expected by chance. It is possible that co-occurring species with similar traits differ in other, not easily measurable traits, e.g., herbivory resistance, which are captured by phylogeny but 395 less so by functional traits. Vice versa, phylogenetically close species tend to vary in their 396 functional traits. This fEunctional clustering could be due to equalizing competitive dynamics 397 in neutrally assembled communities⁴⁰ or because of broader-scale environmental filters. Additionally, when considering lineages' biogeographic histories, phylogenetic clustering could arise due to recent stochastic extinctions or limited dispersal following allopatric 400 speciation⁴¹.

 $|401$ The negative covariation between PD and FD might primarily be explained by -the different 402 impacts of **biotic interactions–competitive exclusion** and environmental filtering across 403 communities^{40,42,43}. In phylogenetically **closely related** clustered communities, competitive 404 exclusion seems to be the main acting mechanism, resulting in the co-existence of species 405 with dissimilar phenotypes and thus, higher FD. In contrast, environmental filtering seems to 406 be the driving process in communities with low FD and high PD. Here, only species with 407 specific phenotypes would be admitted to the community⁴⁴, which however might come from 408 different clades, thus, exhibiting functional convergence but phylogenetic variation. This 409 pattern also suggests that thoese species would differ in features not captured by the traits 410 we used for included in-calculating FD⁴⁵. Since most communities showed decoupling with 411 high FD (53%), competitive exclusion seems to be the strongest driver for global plant 412 community assembly processes. However, we have to consider that trait divergence can also 413 arise from interacting environmental factors that filter the species in a community, in \vert 414 **particular when these factors interact**¹³. In communities with intermediate values of PD, 415 environmental filtering and competitive exclusion seem to be equally important, thus 416 resulting in coupled communities. However, the relative importance of such mechanisms is 417 almost impossible to test as we do not know if species are excluded from a given community 418 due to the environmental conditions, biotic interactions, dispersal limitation, or by the \vert 419 interaction between multiple factors^{13,46}. This results in FD and PD aremay more often 420 become decoupled in communities where geographical, and $-$ or-local drivers differentially $|421$ interact with factors of biotic interactions affecting functional and phylogenetic relationships 422 among co-occurring species.

423 We found no clear spatial patterns of functional and phylogenetic diversity, as vegetation $|424$ plots with coupleding and decoupleding ef -FD and PD were observed in geographical 425 proximityly close plant communities, indicating that local-scale factors dominate community 426 assembly are the drivers of diversity within specific regions (*Fig 2 B*). Previous studies have 427 reported geographical patterns of functional diversity based on climatic conditions, such as 428 precipitation gradients⁴⁷. Similarly, phylogenetic diversity can differ along latitudinal 429 gradients, decreasing polewards^{48,49}. Studies on the global distribution of PD showed striking $|$ 430 differences across that many different ecoregions or biomes are able to exhibit high values of 431 **phylogenetic diversity**^{50,51}. This leads to regional diversity patterns which do not translate into global patterns, as the broader scale environmental conditions are unable to reflect local 433 geographical ecological conditions conditions are likely to be blurred by broader 434 environmental conditions at the global scale. However, considering the relationship between functional and phylogenetic diversity as a three-level categorical variable ("Decoupling with higher PD", "Coupling", "Decoupling with higher FD") we were able to show that large-scale environmental factor do play a role (*Fig. S 6*). This suggests that even though we are not able 438 to explain the full range of possible combinations of FD and PD, broader patterns can be explained.

440 We were able to reveal some tendencies between $SES.FD_Q$ and environmental conditions, $|441$ but not to show that SES.FD_Q is strongly driven by those conditions at the global scale (*Fig. 4*). In particular, functional diversity was not well explained by current climatic conditions and climate variability after the Last Glacial Maximum (LGM). This is in line with studies suggesting 444 that the functional composition of local communities depends mostly on local factors, such 445 as land use history, soil properties and microclimatic conditions^{23,52}. However, $-a$ fine classification of vegetation types, as it was done in a recent Europe-wide analysis on climate-447 trait relationship⁵³, could have possibly increased the explanatory power of our model.

448 Phylogenetic diversity (SES.PD_Q) was consistently higher in forests compared to non-forest ecosystems, which points to the complex evolutionary structure of the different layers of forest communities (*Fig. 5*). Forests are normally characterized by the presence of different structural layers, with woody and non-woody species occupying different layers. Interestingly, this stratification was connected to increased phylogenetic diversity but not to higher functional diversity. We interpret this pattern as the result of the evolutionary history of trees, which significantly differs from that of the understory vegetation. Many tree species belong to families that are mostly woody, meaning they are more phylogenetically distant to other plant families which contributes to the high phylogenetic diversity found in forest 457 ecosystems^{30–32}. This is particularly true for conifers, which represent a clade of woody 458 species separating from today's angiosperms as early as 300 Mya¹⁸, and now most commonly found in forests. Furthermore, ferns and lycopods, which are typical components of the herb layer in temperate forests and typically occur as epiphytes in tropical forests, represent very distinct evolutionary histories compared to trees, contributing to the increased phylogenetic 462 diversity distance between co-occurring species that we observed in forests^{54,55}. This resulted

 in higher PD in forests where those lineages were present. Additionally, more stable microclimatic conditions under a closed canopy could have led to more favorable conditions 465 for different species across distinct families^{56,57}. Overall, our findings suggest that while forest 466 ecosystems display high PD, the functional diversity of plant species within these 467 ecosystemsin forests may be more-limited by the due to convergence in functional traits across different layers.

 Our work represents a first contribution to understanding the relationship between functional and phylogenetic diversity at the global scale, but it does not come without limitations. Even if sPlot is the biggest, harmonized database of global vegetation plots, the coverage is uneven across Earth´s biomes and vegetation types, which may bias our results. Yet, when using an environmentally balanced subset of the data, where data from the temperate zone are downsampled in favour of data from the tropics, we observed an even 475 stronger negative relationship between FD and PD. This suggests that tropical plant communities contribute disproportionately to this pattern. Furthermore, the data contained in sPlot were collected using different sampling protocols and approaches, for instance focusing on woody species only or using plots of various shapes and sizes. While we partially overcome this problem by including predictors related to plot record characteristics (see methods) and by calculating standardized effect sizes, it remains unknown how these biases influence the correlation between FD and PD. As species abundance data is not well standardized in sPlot, the use of presence-absence data was the robust choice, which might limit the comparison to other studies on functional and phylogenetic diversity. Also, the selection of functional traits might influence the observed relationship between functional and phylogenetic diversity, especially given that we used only three traits to calculate FD. We 486 note, however, that our results were robust to the selection of individual traits used, either 487 individually or jointly, used-when calculating FD, which did not -indicating that the specific 488 trait chosen to calculate FD did not significantly impact the relationship between FD and PD (*Fig. S 78, Tab. S 1*). The polytomies included in the constructed phylogeny might lead to a 490 possible underestimation of PD, which we accounted for by calculating standardized effect size of PD. Additionally, we found the same negative pattern when we considered functional dispersion and mean pairwise distance (*Fig. S 1 E)* as proxy for FD and PD, where the latter is \pm known to show different dispersion patterns than FD_Q⁵⁹. However, when including PD as an

 explanatory variable for future studies, it is important to consider the relationship between traits and phylogeny and the potential non-linearity of trait evolution. Additionally, our analysis revealed that none of the potential traits exhibited a strong phylogenetic signal in all 497 families considered in this study (*Fig. S* $\frac{28}{6}$ *B*). Moreover, it appeared that certain families 498 tend to possess more conserved traits compared to others. This is in line with other findings 499 that evolutionary conservation can be associated with specific traits and lineages³⁷, but this 500 is not a commonly observed pattern. Consequently, depending on the sampled community and plant species, different patterns may emerge in the relationship between FD and PD. While both plant characteristics and evolutionary history are playing a crucial role in community assembly processes the underlying interacting mechanisms of biotic and abiotic 504 factors remain unclear.

505 Our findings on the relationship of $SES.FD_Q$ and $SES.PD_Q$, imply that ecological communities can exhibit a wide range of combinations of functional and phylogenetic diversity. The general 507 decoupling, even with negative correlation of FD and PD found in our study $\frac{1}{2}$ implyimplies a 508 dominant signal of competitive exclusion in plant communities. This highlights that for an effective conservation of biodiversity we need to consider both functional and phylogenetic diversity, as both seems to drive community assembly and may reflect also the adaption possibilities of the community to climate changes. However, future research is needed, especially in areas where we were able to detect communities with both high FD and PD values, to understand which regional conditions leads to those diversity hotspots. Achieving a better understanding of the diverse and context-dependent nature of FD and PD will help 515 us shed light to better understand on and protect the intricate dynamics and complexities of ecological communities.

Methods

Species community data

520 The vegetation plot database sPlot²⁸ [\(www.idiv.de/splot\)](http://www.idiv.de/splot) is a harmonized collection of national- and regional-scale vegetation-plot datasets. sPlot provides geo-referenced information on the presence and abundance of all vascular plants co-occurring in a sampling area, i.e., vegetation plot. The database version sPlot 3.0 holds a total number of 1,977,637 vegetation plot records from 160 datasets collected between 1873 and 2019, across six continents and most biomes, including 76,912 vascular plant species (for version 2.1, see ref. 28). The size of a plot varies according to the type of vegetation being sampled; plot size 527 anged from 1 m² in grasslands to 250,000 m² in forest ecosystems. The vegetation type of a plot was classified as forest and non-forest based on tree layer cover and the growth form of 529 dominant species²⁸. Vegetation plot records were included in the study if the cumulative coverage of species for which both trait and phylogenetic information was available accounted for at least 50% of the relative vegetation cover in that plot (see below).

532 In addition, we used sPlotOpen³⁸, which is an environmentally balanced, open-access subset of sPlot, as a benchmark of our results, both when testing for the effect of trait selection when calculating functional diversity, and for the effect of uneven coverage of sPlot data across the Earth`s biomes.

Functional diversity

537 Plant functional traits were available from the gap-filled version of the TRY 5.0 database $60-63$. 538 We calculated functional diversity as Rao's quadratic entropy (FD_Q) as well as functional dispersion (FDis) for all vegetation plots in sPlot 3.0. The calculation of Rao's quadratic 540 entropy⁶⁴ is based on a Gower distance matrix calculated for the species present in each vegetation plot. FDis was computed from the uncorrected species-species distance matrix 542 with the function *dbFD* from the R-package *FD*^{65,66}. We based this calculation on three functional traits selected to cover most of the variation within plant traits and to represent different axes in the plant economic spectrum, i.e. belowground and resource strategy of acquisition or conservation (specific root length, specific leaf area) and reproduction strategy 546 of quality or quantity (plant height) $36,67$. To evaluate the influence of trait selection on the

547 relationship of functional and phylogenetic diversity, we calculated FD_Q on eight functional traits (specific leaf area, specific root length, seed mass, plant height, leaf phosphorus and nitrogen content, leaf dry matter content, chromosome number), both taken individually and jointly. We did this additional analysis based on the sPlotOpen subset only, since calculating standardized effect sizes (see below) of FD calculated on eight traits in all plots was computationally unfeasible, even using our High Performance Cluster. Additionally, considering all eight traits for the complete dataset would have led to a loss of approximately 2000 species (~10% of species considered in this study, see below) due to missing data in the TRY database.

 Functional traits can be conserved ion the phylogeny. This was tested with two evolutionary models, i.e., Blomberg`s *K* and Pagel`s *λ*, where the latter is known to be more robust against 558 incomplete resolved phylogenies or suboptimal branch lengths^{16,17}. Pagel's Λ and Blomberg's *K* were calculated using the function *phylosig* from the R-package *picante*⁶⁸. In contrast to other tests for phylogenetic signals both models can be used to compare phylogenetic signals 561 across different phylogenies¹⁶, which needs to be done as a global plant phylogeny is simply too large for an appropriate calculation of phylogenetic signals. Therefore, the phylogenetic signal for each trait was calculated within each family. All eight functional traits showed either no or low phylogenetic signals for Pagel`s ʎ and Blomberg`s *K* (*Fig. S 7 8 B & C*). Therefore, we assume that there is also no phylogenetic signal across angiosperms for the considered traits.

Phylogenetic diversity

 For all species present in sPlot, a phylogenetic tree was built using the function *phylo.maker* 568 from the R-package *V.PhyloMaker⁶⁹*. The phylogenetic backbone of the package is the combination of GenBank taxa with a backbone provided by the Open Tree of Life, version 9.1 570 (GBOTB), for seed plants⁷⁰ and the clade of pteridophytes⁷¹. Missing genera were inserted to the half point of the family tree. This approach was evaluated by ref. 72, who showed that phylogenetic indices based on the calculated tree were highly correlated with indices based on the "PhytoPhylo megaphylogeny" (updated phylogenetic tree from ref. 71). Species that could not be inserted by the *phylo.maker* were bound to the half of the terminal level of a sister species if only one species was available in this genus, or to the most recent ancestor (MRCA) if the genus included more than one species. This additional binding was done with 577 the *bind.node* function from the R-package *phytools*⁷³.

 The computed phylogenetic tree for sPlot contained 160 families with 68,052 of 76,912 species (88%) present within the database. Additional 3,802 species were included, with 3,348 being bound to the node of the most recent ancestor (MRCA) of already present sister species and 454 species to the half of the terminal level on the family node. The final phylogenetic tree contained 71,854 species on 32,395 nodes. A total of 31,727 species in the phylogeny also had traits in the TRY database. Of this subset, 322 species (approx. 1%) were bound to the half of the terminal level on the family node and 2766 (approx. 9%) to the MRCA. Vegetation plot records were only included in the analysis if both trait and phylogenetic information was available for at least 50% of the total relative cover of the species in that plot. In total, 1,781,836 out of 1,977,637 plot records remained.

588 Phylogenetic diversity was calculated as Rao's quadratic entropy (PD_Q) which amounts to the mean nearest taxon distance for presence-absence data. We used the function *raoD* from the 590 R-package *picante⁶⁸*, which is based on the cophenetic distance of all *n* species in the phylogeny, pruned to contain only the species in that plot. To account for the non-linearity of 592 evolutionary histories, we also calculated PD_Q based on the square root-transformed 593 cophenetic distance⁷⁴. Additionally we calculated mean pairwise distance (MPD), to be compared with functional dispersion, as MPD could show opposite dispersion patterns than 595 \cdot PD_Q⁵⁹. Only species with both trait information and known phylogeny were used to calculate functional and phylogenetic diversity.

Standardized effect size

 The species richness of the vegetation plot records ranged from one to 412 species (*Fig. S 89*). 599 Functional and phylogenetic diversity indices are known to depend on species richness^{75–77}. Especially for functional diversity, a higher number of species in a community is more likely 601 to return higher functional diversity values than communities with fewer species⁷⁶. We controlled for species richness by calculating the standardized effect size of each diversity 603 index for every vegetation plot record⁷⁸, fixing the number of species of the plot record and drawing species randomly, which is equivalent to shuffling traits across species. As species do not equally occur across the globe, we calculated our null expectations based on biome-

 specific species pools accounting for the frequency of species in the plot records in each biome. However, to see if the patterns also hold true for broader species pools we used the \vert 608 following hierarchical approach with t here four stages of defined species pools. For the simplest species pool, we calculated our null expectations based on all species present in the whole sPlot database, so we allowed each species to occur everywhere in the world. For a more geographically constrained approach we calculated the null expectations based on $\left| 612 \right|$ species pools within 16 phytogeographical units³⁷ (stage 2) and ten predefined biomes (stage $\begin{bmatrix} 613 & 3 \end{bmatrix}$ in response to global climate variation^{28,79}, namely: alpine, boreal zone, dry mid-latitudes, dry tropics and subtropics, polar and subpolar zone, subtropics with winter rain, subtropics with year-round rain, temperate mid-latitudes, tropics with summer rain, and tropics with year-round rain. The third-fourth and most complex null model was based on the species pool within each biome, additionally sampling the species weighted by their frequency in the plot records within each biome. This means a species that occurred more frequently within a biome was randomly drawn more often to recalculate the null diversity index, compared to a species occurring less often. For each of the **three-four** null models, we calculated the mean and standard deviation of the distribution of null functional and phylogenetic indices across 499 draws. Vegetation plots only containing one species or for which trait and phylogenetic information was not available were excluded from functional or phylogenetic diversity calculations. Standardized effect sizes (SES) were obtained by subtracting the mean index of the randomized data from the observed index and dividing the result by the standard deviation of the index of the randomized data.

Definition of coupling and decoupling

 To measure the percentage of coupled and decoupled communities a confidence interval was defined. We randomly drew one million values from a uniform distribution, defined between the minimum and maximum of observed standardized effect sizes of Rao´s quadratic entropy 631 based on functional traits (SES.FD $_{\text{Q}}$) as explanatory variable. We created a correlated response variable by adding an error from a normal distribution, obtained from the mean and the 633 standard deviation of the observed SES.FD₀. We fitted a linear model and extracted the 634 intercept and the confidence interval. Communities with an observed value of SES.FD_Q were considered coupled if the standardized effect sizes of Rao´s quadratic entropy based on 636 phylogenetic distance (SES.PD_Q) fell within this interval. **Based on this, we defined three** categories of community patterns, i.e. "Decoupling with higher FD than PD", "Coupling" and "Decoupling with lower FD than PD". This variable was later used as an ordered categorical 639 response.

640 Additionally, we calculated the log ratio between $SES.FD_Q$ and $SES.PD_Q$ as 641 log(SES.FD $_Q$ /SES.PD_Q) after scaling the values between 0.001 and 1. Positive and negative</sub> 642 values define the deviation with higher and lower SES.FD_Q than SES.PD_Q, respectively, from a perfect coupled community.

Explanatory variables

 Current climate conditions (1981-2010) were represented by the 19 bioclimatic variables 646 from CHELSA v.2.1^{80,81}. A principal component analyseis (PCA) was performed to reduce data dimensionality. In the following analyses, we only used the first five PCA axes, collectively accounting for 92.3% of explained variation. We interpreted the axes based on the highest loadings of the corresponding climate variable as follows: annual precipitation for PC1; mean daily air temperature of the coldest quarter and mean daily minimum air temperature of the coldest month for PC2; annual air temperature range for PC3; isothermality for PC4; and precipitation seasonality for PC5 (*Tab. S 2*, *Fig. S 910*).

 Mean air temperature variability after the Last Glacial Maximum (LGM) was derived from the open-access StableClim v1.1. dataset, containing estimates from 21,000 years ago at 2.5° 655 spatial resolution⁸². Climate variability represents rapid global warming during the last 656 deglaciation during the Bølling-Allerød transition⁸³ on land and sea. The mean temperature variability between 21,000 B.P. and 100 A.D. was used as indices for the climate variability after the LGM.

 All climate variables were extracted for each plot with the *extract* function from the R-660 package raster⁸⁴.

 Not all vegetation plot records were complete in terms of the sampled functional groups. Records from tropical forest plots often contained either only tree data, or tree and shrub data. As the exclusion of those plots would have substantially reduced the spatial coverage of our model, we added the nominal predictor variable called 'plants recorded' to our models to partially control for this source of bias as in ref. 35. The variable 'plants recorded' has four values: all vascular plants, only dominant species, all woody plants, only trees. Additionally, we used the vegetation type (forest vs. non-forest) from the vegetation plot database sPlot as predictor variable.

 In total, we prepared eight explanatory variables, five related to the current climate conditions, one to past climate variability, and two to plot record characteristics.

Statistical modelling

 A generalised additive model (GAM) was used to model the relationship between functional and phylogenetic diversity, either expressed as observed Rao`s quadratic entropy (for phylogenetic diversity also after a square root transformation of the distance matrix), or as standardized effect size of Rao`s quadratic entropy, functional dispersion and mean pairwise distance. A GAM is a generalised linear model in which the linear response can depend on unknown smooth functions of the explanatory variables. To account for the spatial structure of the data, the spatial coordinates were included as smooth spherical splines. All GAMs included a basis penalty smoother spline on the sphere (bs = "sos"), applied to the geographic coordinates of every plot, thus taking spatial autocorrelation into account. The explanatory variable was included as linear predictors without any smooth function. The model was 682 performed using the function *gam* from the R-package *mgcv*⁸⁵⁻⁹⁰, defined as following:

683 gam(SES.FD_a ~ SES.PD_a + s(Longitude, Latitude, bs = "sos"), family = "gaussian", method = "REML")

685 SES.FD₀ is the standardized effect size of Rao's quadratic entropy based on the three selected 686 functional plant traits and SES.PD₀ is the standardized effect size of Rao's quadratic entropy based on the phylogenetic distances of species present in the community. This step was done 688 for the complete dataset and for the sPlotOpen subset, for which we considered theing eight 689 traits, both -individually and jointly, for calculating standardized effect size of FD.

 To model the relationship between either functional or phylogenetic diversity and the set of the eight explanatory variables described above, we used a two-step approach. In the first step, we used Boosted Regression Trees to select relevant explanatory variables and quantify their relative influence. In the second step, we fitted GAMs using functional, phylogenetic diversity or their log ratio as response variables, and the predictors selected in the first step as explanatory variables. We did this because fitting a full GAM algorithm with all predictors would lead to convergence issues, due to the huge number of data points.

 Boosted regression trees (BRTs) are a machine-learning technique used in regression and classification having few prior assumptions and being robust against overfitting and collinearity. They are known to uncover nonlinear relationships as well as interactions among predictors. The parameters of the BRT were set as follows: a tree complexity of five and a bag fraction of 0.5. The learning rate was set to 0.01 with a maximum number of 20,000 trees. 702 The BRTs were calculated using the *gbm.step* routine from the *dismo* package⁹¹. An explanatory variable was considered relevant in the model if its relative influence was greater than 12.5%, which is the expected influence of a variable if all the eight predictors had an equal relative importance.

 The variables that were considered as relevant from the BRTs were then used in a second set 707 of GAMs, having as response variable either functional diversity (SES.FD_Q), phylogenetic 708 diversity (SES.PD_Q) or their log ratio, and as explanatory variables those that turned out to be relevant in the corresponding BRT. Additionally, we fitted a GAM with the ordered categorical response of coupling and decoupling against the environmental predictors, which were selected by the BRTs for functional and phylogenetic diversity. As the three categories were not equally represented, we sampled 10,000 communities for each category and repeated the GAM 100 times, besides run the same model on the complete (unbalanced) dataset. The $|714$ spatial coordinates were included as smooth spherical splines in the all model as explained above. As not all vegetation plot entries in sPlot are classified as forest / non-forest the number of observations for the environmental models was 1,497,238.

 The prediction of each explanatory variable was performed using the *prediction* function from 718 the R-package *marginaleffects*⁹² by predicting the explanatory variable based on the sequence between the minimum and maximum of the variable in the original data and the GAM model. The plotted regressions were obtained by extracting the residuals from a GAM without the explanatory variable of interest.

- 722 For plotting, Ffunctional and phylogenetic variables were averaged plotted as mean for each
- 723 grid cell with a size of 863.8 km². The spatial smoother within the GAM was plotted at the
- 724 same resolution based on the following model (example based on SES.FD_a):
- 725 gam($SES.FD_Q \sim 1 + s(Longitude, Latitude, bs = "sos"), family = "gaussian", method = "REML")$
- 726 All analyses were performed in R 4.1.3 93 .

Main references

 1. O'Connor, B., Bojinski, S., Röösli, C. & Schaepman, M. E. Monitoring global changes in biodiversity and climate essential as ecological crisis intensifies. *Ecological Informatics* **55**, (2020).

 2. Anwar, M. R., Liu, D. L., Macadam, I. & Kelly, G. Adapting agriculture to climate change: a review. *Theoretical and Applied Climatology* **113**, 225–245 (2013).

 3. Benevolenza, M. A. & DeRigne, L. The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature. *Journal of Human Behavior in the Social Environment* **29**, 266–281 (2019).

 4. Fahad, S. *et al. Climate Change and Plants: Biodiversity, Growth and Interactions*. (CRC Press, 2021).

 5. Corlett, R. T. & Westcott, D. A. Will plant movements keep up with climate change? *Trends in Ecology & Evolution* **28**, 482–488 (2013).

 6. Cavender-Bares, J., Kozak, K. H., Fine, P. V. A. & Kembel, S. W. The merging of community ecology and phylogenetic biology. *Ecology Letters* **12**, 693–715 (2009).

- 7. Götzenberger, L. *et al.* Ecological assembly rules in plant communities—approaches, patterns and prospects. *Biological Reviews* **87**, 111–127 (2012).
- 8. Rieseberg, L. H., Wood, T. E. & Baack, E. J. The nature of plant species. *Nature* **440**, 524–527 (2006).

 9. Verdú, M. & Pausas, J. G. Fire drives phylogenetic clustering in Mediterranean Basin woody plant communities. *Journal of Ecology* **95**, 1316–1323 (2007).

 10. Ackerly, D. D., Schwilk, D. W. & Webb, C. O. Niche Evolution and Adaptive Radiation: Testing the Order of Trait Divergence. *Ecology* **87**, S50–S61 (2006).

 11. Pillar, V. D., Duarte, L. da S., Sosinski, E. E. & Joner, F. Discriminating trait-convergence and trait-divergence assembly patterns in ecological community gradients. *Journal of Vegetation Science* **20**, 334–348 (2009).

 12. Pillar, V. D., Sabatini, F. M., Jandt, U., Camiz, S. & Bruelheide, H. Revealing the functional traits linked to hidden environmental factors in community assembly. *Journal of Vegetation Science* **32**, e12976 (2021).

 13. Pillar, V. D. Trait divergence in plant community assembly is generated by environmental factor interactions. Preprint at https://doi.org/10.5281/zenodo.10929621 (2024).

 14. Ackerly, D. Conservatism and diversification of plant functional traits: Evolutionary rates versus phylogenetic signal. *PNAS* **106**, 19699–19706 (2009).

 15. Ávila-Lovera, E., Winter, K. & Goldsmith, G. R. Evidence for phylogenetic signal and correlated evolution in plant–water relation traits. *New Phytologist* **237**, 392–407 (2023).

 16. Münkemüller, T. *et al.* How to measure and test phylogenetic signal. *Methods in Ecology and Evolution* **3**, 743–756 (2012).

 17. Molina-Venegas, R. & Rodríguez, M. Á. Revisiting phylogenetic signal; strong or negligible impacts of polytomies and branch length information? *BMC Evolutionary Biology* **17**, (2017).

- 18. Melzer, R., Wang, Y.-Q. & Theißen, G. The naked and the dead: The ABCs of gymnosperm reproduction and the origin of the angiosperm flower. *Seminars in Cell & Developmental Biology* **21**, 118–128 (2010).
- 19. Cavender-Bares, J., Ackerly, D. D., Baum, D. A. & Bazzaz, F. A. Phylogenetic overdispersion in Floridian oak communities. *The American Naturalist* **163**, 823–843 (2004).
- 20. Cadotte, M., Albert, C. H. & Walker, S. C. The ecology of differences: assessing community assembly with trait and evolutionary distances. *Ecology Letters* **16**, 1234–1244 (2013).
- 21. Srivastava, D. S., Cadotte, M. W., MacDonald, A. A. M., Marushia, R. G. & Mirotchnick, N. Phylogenetic diversity and the functioning of ecosystems. *Ecology Letters* **15**, 637–648 (2012).
- 22. Webb, C. O. Exploring the Phylogenetic Structure of Ecological Communities: An Example for Rain Forest Trees. *The American Naturalist* **156**, 145–155 (2000).
- 23. Flynn, D. F. B., Mirotchnick, N., Jain, M., Palmer, M. I. & Naeem, S. Functional and phylogenetic diversity as predictors of biodiversity–ecosystem-function relationships. *Ecology* **92**,
- 1573–1581 (2011).
- 24. Tucker, C. M., Davies, T. J., Cadotte, M. W. & Pearse, W. D. On the relationship between phylogenetic diversity and trait diversity. *Ecology* **99**, 1473–1479 (2018).
- 25. Martin Večeřa *et al.* Decoupled phylogenetic and functional diversity in European grasslands. *Preslia* **95**, 413–445 (2023).
- 26. Prinzing, A. *et al.* Less lineages more trait variation: phylogenetically clustered plant communities are functionally more diverse. *Ecology Letters* **11**, 809–819 (2008).
- 27. Kluge, J. & Kessler, M. Phylogenetic diversity, trait diversity and niches: species assembly of ferns along a tropical elevational gradient. *Journal of Biogeography* **38**, 394–405 (2011).
- 28. Bruelheide, H. *et al.* sPlot A new tool for global vegetation analyses. *Journal of Vegetation Science* **30**, 161–186 (2019).
- 29. Castagneyrol, B., Jactel, H., Vacher, C., Brockerhoff, E. G. & Koricheva, J. Effects of plant phylogenetic diversity on herbivory depend on herbivore specialization. *Journal of Applied Ecology* **51**, 134–141 (2014).
- 30. Qian, H., Hao, Z. & Zhang, J. Phylogenetic structure and phylogenetic diversity of angiosperm assemblages in forests along an elevational gradient in Changbaishan, China. *Journal of Plant Ecology* **7**, 154–165 (2014).
- 31. Honorio Coronado, E. N. *et al.* Phylogenetic diversity of Amazonian tree communities. *Diversity and Distributions* **21**, 1295–1307 (2015).
- 32. Mastrogianni, A., Kallimanis, A. S., Chytrý, M. & Tsiripidis, I. Phylogenetic diversity patterns in forests of a putative refugial area in Greece: A community level analysis. *Forest Ecology and Management* **446**, 226–237 (2019).
- 33. Klimeš, A., Šímová, I., Zizka, A., Antonelli, A. & Herben, T. The ecological drivers of growth form evolution in flowering plants. *Journal of Ecology* **110**, 1525–1536 (2022).
- 34. Chai, Y. *et al.* Patterns of taxonomic, phylogenetic diversity during a long-term succession of forest on the Loess Plateau, China: insights into assembly process. *Scientific Reports* **6**, (2016).

35. Díaz, S. *et al.* The global spectrum of plant form and function. *Nature* **529**, 167–171 (2016).

- 36. Weigelt, A. *et al.* An integrated framework of plant form and function: the belowground perspective. *New Phytologist* **232**, 42–59 (2021).
- 37. Carta, A., Peruzzi, L. & Ramírez-Barahona, S. A global phylogenetic regionalization of vascular plants reveals a deep split between Gondwanan and Laurasian biotas. *New Phytologist* **233**, 1494– 1504 (2022).
- 38. Sabatini, F. M. *et al.* sPlotOpen An environmentally balanced, open-access, global dataset of vegetation plots. *Global Ecology and Biogeography* **30**, 1740–1764 (2021).
- 39. Reich, P. B. *et al.* The Evolution of Plant Functional Variation: Traits, Spectra, and Strategies. *International Journal of Plant Sciences* **164**, 143–164 (2003).
- 40. Mayfield, M. M. & Levine, J. M. Opposing effects of competitive exclusion on the phylogenetic structure of communities. *Ecology Letters* **13**, 1085–1093 (2010).
- 41. Pigot, A. L. & Etienne, R. S. A new dynamic null model for phylogenetic community structure. *Ecology Letters* **18**, 153–163 (2015).
- 42. Godoy, O., Kraft, N. J. B. & Levine, J. M. Phylogenetic relatedness and the determinants of competitive outcomes. *Ecology Letters* **17**, 836–844 (2014).
- 43. Kraft, N. J. B., Godoy, O. & Levine, J. M. Plant functional traits and the multidimensional nature of species coexistence. *Proceedings of the National Academy of Sciences* **112**, 797–802 (2015).
- 44. de Bello, F. *et al. Handbook of Trait-Based Ecology: From Theory to R Tools*. (Cambridge University Press, Cambridge, 2021).
- 45. Owen, N. R., Gumbs, R., Gray, C. L. & Faith, D. P. Global conservation of phylogenetic diversity captures more than just functional diversity. *Nat Commun* **10**, 859 (2019).
- 46. Kraft, N. J. B. *et al.* Community assembly, coexistence and the environmental filtering metaphor. *Functional Ecology* **29**, 592–599 (2015).
- 47. Zuo, X. *et al.* Functional diversity response to geographic and experimental precipitation gradients varies with plant community type. *Functional Ecology* **35**, 2119–2132 (2021).
- 48. Massante, J. C. *et al.* Contrasting latitudinal patterns in phylogenetic diversity between woody and herbaceous communities. *Scientific Reports* **9**, 6443 (2019).
- 49. Cai, H. *et al.* Geographical patterns in phylogenetic diversity of Chinese woody plants and its application for conservation planning. *Diversity and Distributions* **27**, 179–194 (2021).
- 50. Tietje, M. *et al.* Global hotspots of plant phylogenetic diversity. *New Phytologist* **240**, 1636– 1646 (2023).
- 51. Qian, H., Zhang, J. & Jiang, M. Global patterns of taxonomic and phylogenetic diversity of flowering plants: Biodiversity hotspots and coldspots. *Plant Diversity* **45**, 265–271 (2023).
- 52. De Pauw, K. *et al.* Taxonomic, phylogenetic and functional diversity of understorey plants respond differently to environmental conditions in European forest edges. *Journal of Ecology* **109**, 2629–2648 (2021).
- 53. Kambach, S. *et al.* Climate-trait relationships exhibit strong habitat specificity in plant communities across Europe. *Nature Communications* **14**, 712 (2023).
- 54. Pryer, K. M. *et al.* Horsetails and ferns are a monophyletic group and the closest living relatives to seed plants. *Nature* **409**, 618–622 (2001).
- 55. Rothfels, C. J. *et al.* The evolutionary history of ferns inferred from 25 low-copy nuclear genes. *American Journal of Botany* **102**, 1089–1107 (2015).
- 56. De Frenne, P. *et al.* Forest microclimates and climate change: Importance, drivers and future research agenda. *Global Change Biology* **27**, 2279–2297 (2021).
- 57. Kovács, B., Tinya, F. & Ódor, P. Stand structural drivers of microclimate in mature temperate mixed forests. *Agricultural and Forest Meteorology* **234–235**, 11–21 (2017).
- 58. Swenson, N. Phylogenetic Resolution and Quantifying the Phylogenetic Diversity and Dispersion of Communities. *PloS one* **4**, e4390 (2009).
- 59. Sessa, E. B. *et al.* Community assembly of the ferns of Florida. *American Journal of Botany* **105**, 549–564 (2018).

Data availability

 The vegetation-plot raw data contained in the sPlot database are available upon request by submitting a project proposal to sPlot's Steering Committee. The proposals should follow the Governance and Data Property Rules of the sPlot Working Group available on the sPlot website (www.idiv.de/splot).

Code availability

 All R scripts used for this study can be found in our GitHub repository at [https://github.com/georghaehn/Haehn-et-al-2023-FD-PD-coupling.](https://github.com/georghaehn/Haehn-et-al-2023-FD-PD-coupling)

Method references

 16. Münkemüller, T. *et al.* How to measure and test phylogenetic signal. *Methods in Ecology and Evolution* **3**, 743–756 (2012).

 17. Molina-Venegas, R. & Rodríguez, M. Á. Revisiting phylogenetic signal; strong or negligible impacts of polytomies and branch length information? *BMC Evolutionary Biology* **17**, (2017).

 28. Bruelheide, H. *et al.* sPlot – A new tool for global vegetation analyses. *Journal of Vegetation Science* **30**, 161–186 (2019).

 37. Carta, A., Peruzzi, L. & Ramírez-Barahona, S. A global phylogenetic regionalization of vascular plants reveals a deep split between Gondwanan and Laurasian biotas. *New Phytologist* **233**, 1494– 1504 (2022).

 38. Sabatini, F. M. *et al.* sPlotOpen – An environmentally balanced, open-access, global dataset of vegetation plots. *Global Ecology and Biogeography* **30**, 1740–1764 (2021).

 60. Kattge, J. *et al.* TRY plant trait database – enhanced coverage and open access. *Global Change Biology* **26**, 119–188 (2020).

 61. Shan, H. *et al.* Gap Filling in the Plant Kingdom: Trait Prediction Using Hierarchical Probabilistic Matrix Factorization. Preprint at https://doi.org/10.48550/arXiv.1206.6439 (2012).

 62. Fazayeli, F., Banerjee, A., Kattge, J., Schrodt, F. & Reich, P. B. Uncertainty Quantified Matrix Completion Using Bayesian Hierarchical Matrix Factorization. in *2014 13th International Conference on Machine Learning and Applications* 312–317 (2014). doi:10.1109/ICMLA.2014.56.

 63. Schrodt, F. *et al.* BHPMF – a hierarchical Bayesian approach to gap-filling and trait prediction for macroecology and functional biogeography. *Global Ecology and Biogeography* **24**, 1510–1521 (2015).

 64. Rao, C. R. Diversity and dissimilarity coefficients: A unified approach. *Theoretical Population Biology* **21**, 24–43 (1982).

890 65. Laliberté, E. & Legendre, P. A distance-based framework for measuring functional diversity from multiple traits. *Ecology* **91**, 299–305 (2010).

 66. Laliberté, E., Legendre, P. & Shipley, B. FD: Measuring functional diversity from multiple traits, and other tools for functional ecology. *R package version* **1**, 0–12 (2014).

 67. Walker, A. P., McCormack, M. L., Messier, J., Myers-Smith, I. H. & Wullschleger, S. D. Trait covariance: the functional warp of plant diversity? *New Phytologist* **216**, 976–980 (2017).

68. Kembel, S. W. *et al.* picante: Integrating Phylogenies and Ecology. (2020).

 69. Jin, Y. & Qian, H. V.PhyloMaker: an R package that can generate very large phylogenies for vascular plants. *Ecography* **42**, 1353–1359 (2019).

 70. Smith, S. A. & Brown, J. W. Constructing a broadly inclusive seed plant phylogeny. *American Journal of Botany* **105**, 302–314 (2018).

 71. Zanne, A. E. *et al.* Three keys to the radiation of angiosperms into freezing environments. *Nature* **506**, 89–92 (2014).

- 72. Qian, H. & Jin, Y. An updated megaphylogeny of plants, a tool for generating plant phylogenies and an analysis of phylogenetic community structure. *Journal of Plant Ecology* **9**, 233– 239 (2016).
- 73. Revell, L. J. phytools: Phylogenetic Tools for Comparative Biology (and Other Things). (2023).
- 74. Letten, A. D. & Cornwell, W. K. Trees, branches and (square) roots: why evolutionary relatedness is not linearly related to functional distance. *Methods in Ecology and Evolution* **6**, 439– 444 (2015).
- 75. de Bello, F., Carmona, C. P., Lepš, J., Szava-Kovats, R. & Pärtel, M. Functional diversity through the mean trait dissimilarity: resolving shortcomings with existing paradigms and algorithms. *Oecologia* **180**, 933–940 (2016).
- 76. Petchey, O. L. & Gaston, K. J. Extinction and the loss of functional diversity. *Proceedings of the Royal Society of London. Series B: Biological Sciences* **269**, 1721–1727 (2002).
- 77. Cadotte, M. W. *et al.* Phylogenetic diversity metrics for ecological communities: integrating species richness, abundance and evolutionary history. *Ecology Letters* **13**, 96–105 (2010).
- 78. Gotelli, N. J. & McCabe, D. J. Species Co-Occurrence: A Meta-Analysis of J. M. Diamond's Assembly Rules Model. *Ecology* **83**, 2091–2096 (2002).
- 79. Schultz, J. *The Ecozones of the World. The Ecological Division of the Geosphere*. *The Ecozones of the World: The Ecological Divisions of the Geosphere* 252 (2005). doi:10.1007/3-540-28527-X.
- 80. Karger, D. N. *et al.* Climatologies at high resolution for the earth's land surface areas. *Scientific Data* **4**, 170122 (2017).
- 81. Karger, D. N. *et al.* Data from: Climatologies at high resolution for the earth's land surface areas. 7266827510 bytes Dryad https://doi.org/10.5061/DRYAD.KD1D4 (2018).
- 82. Brown, S. C., Wigley, T. M. L., Otto-Bliesner, B. L. & Fordham, D. A. StableClim, continuous projections of climate stability from 21000 BP to 2100 CE at multiple spatial scales. *Sci Data* **7**, 335 (2020).
- 928 83. Renssen, H. & Isarin, R. F. B. The two major warming phases of the last deglaciation at ~14.7 and ∼11.5 ka cal BP in Europe: climate reconstructions and AGCM experiments. *Global and Planetary Change* **30**, 117–153 (2001).
- 84. Hijmans, R. J. *Raster: Geographic Data Analysis and Modeling*. (2023).
- 85. Wood, S. mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation. (2023).
- 86. Wood, S. N. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B)* **73**, 3–36 (2011).
- 87. Wood, S. N. Stable and efficient multiple smoothing parameter estimation for generalized additive models. *Journal of the American Statistical Association* **99**, 673–686 (2004).
- 88. Wood, S. N. *Generalized Additive Models: An Introduction with R*. (Chapman and Hall/CRC, 2017).
- 89. Wood, S. N. Thin-plate regression splines. *Journal of the Royal Statistical Society (B)* **65**, 95– 114 (2003).
- 90. Wood, S. N., Pya, N. & Säfken, B. Smoothing Parameter and Model Selection for General Smooth Models. *Journal of the American Statistical Association* **111**, 1548–1563 (2016).
- 91. Hijmans, R. J., Phillips, S., Leathwick, J. & Elith, J. *Dismo: Species Distribution Modeling*. (2022).
- 92. Arel-Bundock, V. *Marginaleffects: Predictions, Comparisons, Slopes, Marginal Means, and Hypothesis Tests*. (2023).
- 93. R Core Team. *R: A Language and Environment for Statistical Computing*. (R Foundation for Statistical Computing, Vienna, Austria, 2022).

Acknowledgements

 The authors are thankful for the efforts of thousands of vegetation scientists sampling and digitalizing vegetation data and making them available in regional, national, or international databases. We appreciate the support of the German Research Foundation for funding sPlot as one of the iDiv research platforms (DFG FZT 118, 202548816). The scientific results have (in part) been computed at the High-Performance Computing (HPC) Cluster EVE, a joint effort of both the Helmholtz Centre for Environmental Research - UFZ (http://www.ufz.de/) and the German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig [\(http://www.idiv-biodiversity.de/\)](http://www.idiv-biodiversity.de/). We would like to thank the administration and support staff of EVE who keep the system running and support us with our scientific computing needs: Thomas Schnicke, Ben Langenberg, Guido Schramm, Toni Harzendorf, Tom Strempel and Lisa Schurack from the UFZ, and Christian Krause from iDiv. F.M.S. gratefully acknowledges financial support from the Rita Levi Montalcini (2019) programme, funded by the Italian Ministry of University and Research (MUR). J.-C.S. considers this work a contribution to Center for Ecological Dynamics in a Novel Biosphere (ECONOVO), funded by Danish National Research Foundation (grant DNRF173) and his VILLUM Investigator project "Biodiversity Dynamics in a Changing World", funded by VILLUM FONDEN (grant 16549). V.D.P. received support from Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq, Brazil, grant 313315/2022-1). I.B. and J.A.C. were funded by the Basque Government (IT1487-22). A.D.B was supported by the Knut and Alice Wallenberg Foundation (WAF KAW 2019.0202) and the Swedish Foundation for Strategic Research (FFL21-0194). A.G.-de-M. has been supported by National Forestry and Wildlife Service (SERFOR) of Peru (AUT-IFL-2023-017) and

 Fundación Universitaria San Pablo-CEU, grants GNRI 2023 and GNRI 2024. A.Č was supported by Slovenain Research and Innovation Agency (P1-0236). We thank three anonymous reviewers for constructive comments that helped to improve our manuscript.

Author contributions

- G.J.A.H, F.M.S. and H.B. conceived the idea. G.J.A.H. performed the analysis with substantial input from F.M.S, G.D. and H.B. G.J.A.H. drafted the first version of the manuscript with support by F.M.S, G.D., M.S. and H.B. E.A.-D., I.A., M.B., E.B., I.B., A.D.B., G.B., Z.B.-D., J.A.C., A.Č., M.C., R.Ć., A.L.G, M.D.S., Jü.D., J.D, M.E.-S., M.F., A.G.-d.-M., E.G., H.G., V.G., S.H., M.H., B.H., J.H., U.J., F.J., A.J.-B., J.K., M.K., L.K., H.K., F.K., J.L., J.E.M., L.M., A.N., J.N., A.P.-H., O.P., V.D.P., G.R., E.R., B.S., M.Sch., U.S., S.S., F.S., U.Š., B.S., M.S., Z.S., B.St., J.-C.S., C.T., Z.T., A.C.V., C.V., D.W, De.W., H.-F.W., T.W., and G.Z. provided parts of the data. All co-authors edited the
- manuscript and provided suggestions on how to improve the analyses.
- The authors declare no competing interests.
- Supplementary Information is available for this paper at: Suppl. S1 & S2.
- Correspondence and request for materials should be addressed to Georg J. A. Hähn
- (georg.haehn@idiv.de).