

1 **Species packing and the latitudinal gradient in local beta-diversity**

2 Ke Cao^{1,2}, Richard Condit^{3,4}, Xiangcheng Mi^{1*}, Lei Chen¹, Haibao Ren¹, Wubing Xu¹, David
3 F. R. P. Burslem⁵, Chunrong Cai⁶, Min Cao⁷, Li-Wan Chang⁸, Chengjin Chu⁹, Fuxin Cui⁶, Hu
4 Du¹⁰, Sisira Ediriweera¹¹, C.S.V. Gunatilleke¹², I.U.A.N. Gunatilleke¹², Zhanqing Hao¹³,
5 Guangze Jin¹⁴, Jinbo Li⁶, Buhang Li⁹, Yide Li¹⁵, Yankun Liu¹⁶, Hongwei Ni⁶, Michael J.
6 O'Brien¹⁷, Xiujuan Qiao¹⁸, Guochun Shen¹⁹, Songyan Tian¹⁶, Xihua Wang¹⁹, Han Xu¹⁵,
7 Yaozhan Xu¹⁸, Libing Yang⁶, Sandra L. Yap²⁰, Juyu Lian²¹, Wanhui Ye²¹, Mingjian Yu²²,
8 Sheng-Hsin Su⁸, Chia-Hao Chang-Yang²³, Yili Guo²⁴, Xiankun Li²⁴, Fuping Zeng¹⁰,
9 Daoguang Zhu⁶, Li Zhu¹, I-Fang Sun²⁵, Keping Ma^{1*}, Jens-Christian Svenning²⁶

10

11 ¹State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese
12 Academy of Sciences, Beijing 100093

13 ²Key Laboratory of Biodiversity Sciences and Ecological Engineering, Ministry of Education,
14 College of Life Sciences, Beijing Normal University, Beijing 100875

15 ³Morton Arboretum, 4100 Illinois Rte. 53, Lisle, IL 60532, USA

16 ⁴Field Museum of Natural History, 1400 S. Lake Shore Dr., Chicago, IL 60605, USA

17 ⁵School of Biological Sciences, University of Aberdeen, Cruickshank Building, St Machar
18 Drive, Aberdeen AB24 3UU, UK

19 ⁶Institute of Natural Resources and Ecology, Heilongjiang Academy of Sciences, Harbin
20 150040

21 ⁷CAS Key Laboratory of Tropical Forest Ecology, Xishuangbanna Tropical Botanical Garden,
22 Chinese Academy of Sciences, Kunming 650223

23 ⁸Taiwan Forestry Research Institute, 53 Nanhai Road, Taipei 10066

24 ⁹Sun Yat-sen University, Guangzhou 510275

- 25 ¹⁰Institute of Subtropical Agriculture, Chinese Academy of Sciences, Changsha, Hunan
26 410125
- 27 ¹¹Faculty of Applied Sciences, Uva Wellassa University, Badulla 90000, Sri Lanka
- 28 ¹²Department of Botany, University of Peradeniya, Peradeniya 20400, Sri Lanka
- 29 ¹³Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110016
- 30 ¹⁴Center for Ecological Research, Northeast Forestry University, Harbin 150040
- 31 ¹⁵Research Institute of Tropical Forestry, Chinese Academy of Forestry, Guangzhou 510520
- 32 ¹⁶Heilongjiang Forest Engineering and Environment Institute, Harbin 150040
- 33 ¹⁷Área de Biodiversidad y Conservación, Universidad Rey Juan Carlos, c/ Tulipán s/n., E-
34 28933 Móstoles, Spain
- 35 ¹⁸Key Laboratory of Aquatic Botany and Watershed Ecology, Wuhan Botanical Garden,
36 Chinese Academy of Sciences, 430074
- 37 ¹⁹East China Normal University, Shanghai 200241
- 38 ²⁰Institute of Biology, University of the Philippines, Diliman, Quezon City, PH 1101,
39 Philippines
- 40 ²¹South China Botanical Garden, Chinese Academy of Sciences, Guangzhou 510650
- 41 ²²College of Life Sciences, Zhejiang University, Hangzhou 310058
- 42 ²³National Sun Yat-sen University, Kaohsiung, 80424
- 43 ²⁴Guangxi Institute of Botany, Guangxi Zhuang Autonomous Region and Chinese Academy
44 of Sciences, Guilin 541006
- 45 ²⁵Department of Natural Resources and Environmental Studies, National Dong Hwa
46 University, Hualian 97401
- 47 ²⁶Center for Biodiversity Dynamics in a Changing World (BIOCHANGE) & Section for
48 Ecoinformatics and Biodiversity, Department of Biology, Aarhus University, Ny Munkegade
49 114, DK-8000 Aarhus C, Denmark

50 *Correspondence author: Xiangcheng Mi, Keping Ma

51 Email: mixiangcheng@ibcas.ac.cn, kpma@ibcas.ac.cn

52 Address: State Key Laboratory of Vegetation and Environmental Change, Institute of Botany,

53 Chinese Academy of Sciences, Beijing 100093;

54

55 **Abstract**

56 The latitudinal gradient of declining species richness at higher latitudes is among the most
57 fundamental patterns in ecology. However, whether changes in species composition across
58 space (beta-diversity) contribute to this global gradient of species richness remains debated.

59 Previous studies that failed to resolve the issue suffered from a well-known tendency for

60 small samples in high gamma-diversity areas to inflate measures of beta-diversity. We

61 provide here a rigorous test, comparing species-packing and local heterogeneity across a

62 latitudinal gradient in tree species richness in Asia, using beta-diversity metrics that correct

63 the gamma-diversity and sampling bias. Our data include 21 large forest plots across a wide

64 environmental gradient in East Asia. We demonstrate that local beta-diversity increases with

65 topographic heterogeneity, but after accounting for this and correcting the gamma-diversity

66 bias, tropical forests still have higher beta-diversity than temperate, contributing to the

67 latitudinal gradient of species richness. This supports the hypothesis of tighter species packing

68 and larger niche space in tropical forests while demonstrating the importance of local

69 processes in controlling beta-diversity.

70

71 **Main Text**

72 Beta-diversity is the spatial organization of local (alpha-) diversity at larger scales, and it is

73 arguably more important to conservation than local diversity¹⁻³. Conserving species richness,

74 for example, must consider whether diversity is concentrated within sites or spread across

75 many sites¹. Are observed gradients in species richness around the world caused by
76 differences in beta-diversity⁴⁻⁷? For example, is the well-known latitudinal gradient in species
77 richness associated with beta-diversity, in other words, do tropical communities have more
78 habitat heterogeneity, larger niche space or narrower niches than temperate communities?
79 These questions continue to be debated, with researchers reaching opposite conclusions⁸⁻¹³.
80 Underlying the debate has been controversy about statistical biases in tools for measuring
81 beta-diversity^{12,14-16}.
82 The bias arising in beta-diversity metrics is a dependence on sample size that interacts with
83 overall species richness (gamma-diversity)^{12,14-16}. It is easy to illustrate using simple
84 measures of species overlap. Small samples never capture all local species, and it follows that
85 two small samples will appear to differ by randomly capturing a different set of local species,
86 causing an increase in species overlap with the fraction of species sampled^{14,16}. As a result,
87 high local species richness will artificially inflate beta-diversity¹². This bias has led to metrics
88 that correct for sample size^{14,17,18} or tools based on comparisons with null models^{12,15}.
89 Crucial in the sample size bias is the dependence on gamma-diversity it engenders, since
90 bigger samples are needed in richer communities^{14,16,17}. Once correcting for sample size bias,
91 gamma-diversity dependence should be removed, and it should be straightforward to compare
92 beta-diversity across a gradient of species diversity in order to judge the importance of local
93 species packing.
94 We carry out this comparison using the steep latitudinal gradient in tree species richness as
95 documented in our census of 3 million trees at 21 sites spanning 50° of latitude in East Asia
96 (Fig. 1 and Extended Data Table 1)^{19,20}. In a simulation study¹⁸, we tested several metrics of
97 beta-diversity, including a null model approach plus sample size correction methods designed
98 by Chao *et al.*¹⁷. We identified the corrected beta Shannon entropy and similar metrics as
99 highly effective at removing dependence on gamma-diversity and sample size¹⁸. These

100 indices thus allow us to answer two fundamental questions about the source of local species
101 richness: 1) Is there a latitudinal gradient in beta-diversity revealed by the corrected beta
102 Shannon entropy? 2) Do local environmental heterogeneity, niche specialization (the ratio of
103 the narrowness of available habitat of a plot to that of a species) and marginality (the distance
104 between the species optimum relative to the mean habitat of a plot) contribute to the
105 latitudinal patterns of local beta-diversity? By testing simultaneously the importance of local
106 heterogeneity and latitude we can establish whether species-packing contributes to higher
107 richness in tropical relative to temperate forests^{21,22}.

108

109 Gamma-diversity declined by more than forty-fold between tropical and temperate latitudes,
110 from 818 species at Pasoh to 18 at Daxinganling (Extended Data Table 1). Local beta-
111 diversity also declined with latitude, and this pattern was stronger at small scales (Fig. 2a).
112 We found positive correlations between local topographic heterogeneity and beta-diversity
113 (Fig. 2b). Further, beta-diversity was correlated with both latitude and topographic
114 heterogeneity in multiple linear regression models, but the relative effect size varied as scale
115 changed (Fig. 2c). Specifically, the effect of adjusted latitude decreased, whereas the effect of
116 topographic heterogeneity increased at larger scales.

117 Both community-level niche specialization (species-level niche specialization weighted by
118 relative species abundance) and niche marginality (species-level niche marginality weighted
119 by relative species abundance) decreased from tropical to temperate forests after controlling
120 local topographic heterogeneity, suggesting narrower niche width and larger niche space in
121 tropical forests (Figs. 3a-3d). Moreover, niche specialization and niche marginality were
122 positively correlated with each other across scales (Extended Data Figs. 2g-2i). Meanwhile,
123 they were both well predicted by local topographic heterogeneity across scales (Extended
124 Data Figs. 2a-2f). Furthermore, multiple linear regression models revealed that the effect sizes

125 of topographic heterogeneity were much larger than those of adjusted latitude across scales,

126 although their effect sizes were scale-dependent (Figs. 3b and 3d).

127

128 Our results confirm that local beta-diversity increases from boreal toward tropical forests of
129 Asia after accounting for local topographic heterogeneity. Previous studies demonstrating this
130 pattern^{3,5,21} have been questioned due to the bias of inflated beta-diversity at high gamma-
131 diversity regions^{12,15}. We found that the gradient persisted, however, even after removing the
132 gamma-diversity bias and controlling for local topographic heterogeneity. This suggests that
133 local beta-diversity contributes to the latitudinal gradient in species richness.

134 Given higher species turnover with topography and greater niche specialization and
135 marginality at the same scales at lower latitude, there must be tighter species packing and
136 larger niche space in tropical relative to temperate forests^{4,7,21,23,24}. This hypothesis has been
137 floated for decades, attributed to higher and more stable productivity in the tropics: a larger
138 niche space enables more species to persist at low abundance and allows species to specialize
139 on narrower subsets of the resources available^{7,22-25}. Since topographic heterogeneity did not
140 vary with latitude (Extended Data Fig. 3), it appears that local topographic heterogeneity does
141 not contribute to the latitudinal gradient in local beta-diversity, in line with previous findings
142 of Ricklefs and He²⁶ and Chu et al.²⁷.

143 We also conclude that local beta-diversity is driven largely by local processes—specifically,
144 topographic heterogeneity and the niche differentiation it fosters (Figs. 2 and 3). This may
145 seem an unsurprising result, but the role of local ecological processes has been questioned
146 given the broad latitudinal gradient of gamma-diversity^{4,12}. We suggest that the effect of local
147 processes has been obscured by gamma-diversity dependence in previous studies¹⁵.

148 Moreover, our large samples over 55 degrees of latitude provide comparable measures of
149 niche differentiation, topographic heterogeneity, and beta-diversity, well beyond what was

150 available in early studies^{28,29}. Our results could be refined by considering the influence of
151 additional factors that contribute to local environmental heterogeneity and niche
152 differentiation, such as soil types and soil nutrients³⁰, because we expect these additional
153 local factors to contribute to beta-diversity. In addition, it is necessary to examine these
154 metrics of beta-diversity that incorporate gamma-diversity and sample size corrections in
155 other taxa and regions. Gamma-diversity dependence is also associated with other attributes
156 of ecosystem such as species abundance distribution³¹ and should be examined in other
157 systems.

158 We found that a latitudinal gradient in local beta-diversity contributes to the broad latitudinal
159 pattern of species richness after separately controlling for gamma-diversity and local
160 topographic heterogeneity. The results suggest tighter species packing and larger niche space
161 in tropical forests^{4,22,23}, but also confirmed environmental heterogeneity as a determinant of
162 beta-diversity. Our findings may help resolve recent debates on the contribution of local beta-
163 diversity to latitudinal gradient of species richness.

164

165 **Materials and Methods**

166 **Forest dynamic plots** We used data from 21 forest dynamics plots that are part of the
167 ForestGEO and Chinese Forest Biodiversity Monitoring Networks^{19,20} (Fig. 1a and Extended
168 Data Table 1). All stems with diameter at breast height (DBH) ≥ 1 cm were spatially mapped,
169 tagged, measured and identified to species³². The plots range from tropical rain forest at 2.98°
170 N latitude to boreal forest at 51.82° N latitude (Extended Data Table 1). Plots vary from sea
171 level to more than 1400 m elevation, and within-plot elevation range is as low as 17.7 m and
172 as high as 298.6 m (Extended Data Table 1 and Fig. 1b).

173

174 **Measurement of beta-diversity** To circumvent gamma-diversity dependence caused by
175 sample-size bias of beta-diversity metrics, we used a correction method designed for beta
176 Shannon entropy based on the relationship between cumulative diversity curve and sample
177 size³³. The beta Shannon entropy measures the heterogeneity of pooled communities, and is
178 calculated as the effective number of compositionally distinct and equally abundant
179 communities^{34,35}. As the beta Shannon entropy incorporates species abundance, it could
180 weight common or rare species more by changing the diversity order q ³⁴. Here we chose
181 diversity of order $q = 1$ for weighting all species by their abundance, without favoring either
182 common or rare species. Additionally, observed species diversity in a sample is known to be a
183 biased estimate of true species diversity, and is highly sensitive to the area surveyed, the
184 number of individuals counted, and the regional species pool size³⁶. We thus used a sample-
185 size dependence correction method to produce accurate, low-bias estimates of the beta
186 Shannon entropy for comparing beta-diversity among regions^{17,33}. In this approach, similar to
187 a species accumulation curve, the expected cumulative alpha- or gamma-diversity is
188 analytically depicted as a function of sample size, while sample completeness is estimated
189 from community structures of samples^{17,33}. Beta-diversity can then be estimated from the
190 predicted alpha- and gamma-diversity under hypothetical complete sampling based on the
191 diversity-sample size curve. For a comparison, we also used a pairwise dissimilarity metric –
192 the Jaccard-Chao index (Extended Data Fig. 1), which corrects undersampling bias by
193 estimating the effect of undetected shared species³⁷. Our simulations confirmed that β -
194 metrics that incorporate an undersampling correction method are more effective at removing
195 dependence on gamma-diversity and sample size, compared with other conventional beta-
196 diversity metrics¹⁸.

197 **Local topographic heterogeneity, community-level niche differentiation** Local
198 topographic heterogeneity was quantified by the surface to planimetric area ratio²⁸. Niche

199 differentiation was described using attributes of specialization and marginality. Niche
200 specialization was defined as the ratio of the standard deviation of available habitat for a
201 community to that used by a species, and marginality was defined as the ecological distance
202 between a species optimum and the mean habitat within the plot^{38,39}. Specialization and
203 marginality were calculated for each species with species composition data and six
204 topographic factors: mean elevation, convexity, slope, aspect, topographical wetness index
205 (TWI) and altitude above channel (ACH) - across spatial scales⁴⁰⁻⁴². Aspect was computed as
206 $\sin(\text{aspect})$ and $\cos(\text{aspect})$, and other topographic variables were Box-Cox transformed
207 before being included into analysis⁴³. We then calculated the mean community-level niche
208 specialization and marginality across all species occurring in at least ten subplots, weighting
209 by species abundance.

210 **Statistical analysis** To examine the significance of latitudinal gradients in explaining local
211 beta-diversity, niche specialization and niche marginality, we first modeled beta-diversity,
212 community-level niche specialization and niche marginality against topographic heterogeneity
213 and adjusted latitude (an upward shift of 100 m approximately equals to a poleward shift of
214 100 km) separately using simple linear regression models. Subsequently, to determine the
215 relative effect sizes of adjusted latitude and topography, we performed multiple linear
216 regression models with beta-diversity, niche specialization and marginality as response
217 variables respectively, and all variables were standardized by $(x-x')/SD(x)$ before being
218 included. To achieve normality of niche specialization (Extended Data Fig. 4a), the log- and
219 Box-Cox transformation⁴³ were employed (Extended Data Figs. 4b and 4c). Finally, the Box-
220 Cox transformed niche specialization were used in analyses, and for comparison, it was min-
221 max normalized into the range between [0, 1] using $((x-\min(x))/(\max(x)-\min(x)))$. In total, we
222 conducted all the analyses across three spatial scales by dividing plots into quadrats of
223 different grain sizes (10 m × 10 m, 20 m × 20 m and 50 m × 50 m).

224 All statistical analyses were performed with R software, version 3.6.4 ⁴⁴. The corrected
225 Shannon entropy index was calculated using R package 'entropart' ⁴⁵. The topographic
226 variables were computed using 'RSAGA' package ⁴⁶ and SAGA GIS ⁴⁷. Ecological niche
227 factor analysis (ENFA) was implemented to calculate niche metrics using R package
228 'adehabitatHS' ⁴⁸.

229 **Data availability**

230 The data supporting Figure 1-3 have been deposited in the Dryad Digital Repository
231 (<https://datadryad.org/stash/share/6bhhuxg5b3637cgOSzPVQzdyAPh9vy5hf29DCglp6hs>).
232 Full census data are available upon reasonable request from the ForestGEO data portal,
233 <http://ctfs.si.edu/datarequest/>.

234 **Code availability**

235 The code used for data analysis have been deposited in the Dryad Digital Repository
236 (<https://datadryad.org/stash/share/6bhhuxg5b3637cgOSzPVQzdyAPh9vy5hf29DCglp6hs>).

237

238

239 **References:**

- 240 1. Socolar, J. B., Gilroy, J. J., Kunin, W. E. & Edwards, D. P. How Should Beta-
241 Diversity Inform Biodiversity Conservation? *Trends Ecol Evol* **31**, 67-80, (2016).
- 242 2. Anderson, M. J. *et al.* Navigating the multiple meanings of beta diversity: a roadmap
243 for the practicing ecologist. *Ecol. Lett.* **14**, 19-28, (2011).
- 244 3. Koleff, P., Lennon, J. J. & Gaston, K. J. Are there latitudinal gradients in species
245 turnover? *Global Ecol. Biogeogr.* **12**, 483-498, (2003).
- 246 4. Gaston, K. J. Global patterns in biodiversity. *Nature* **405**, 220-227, (2000).
- 247 5. Willig, M. R., Kaufman, D. M. & Stevens, R. D. Latitudinal gradients of biodiversity:
248 pattern, process, scale, and synthesis. *Annu. Rev. Ecol. Evol. Syst.*, 273-309, (2003).

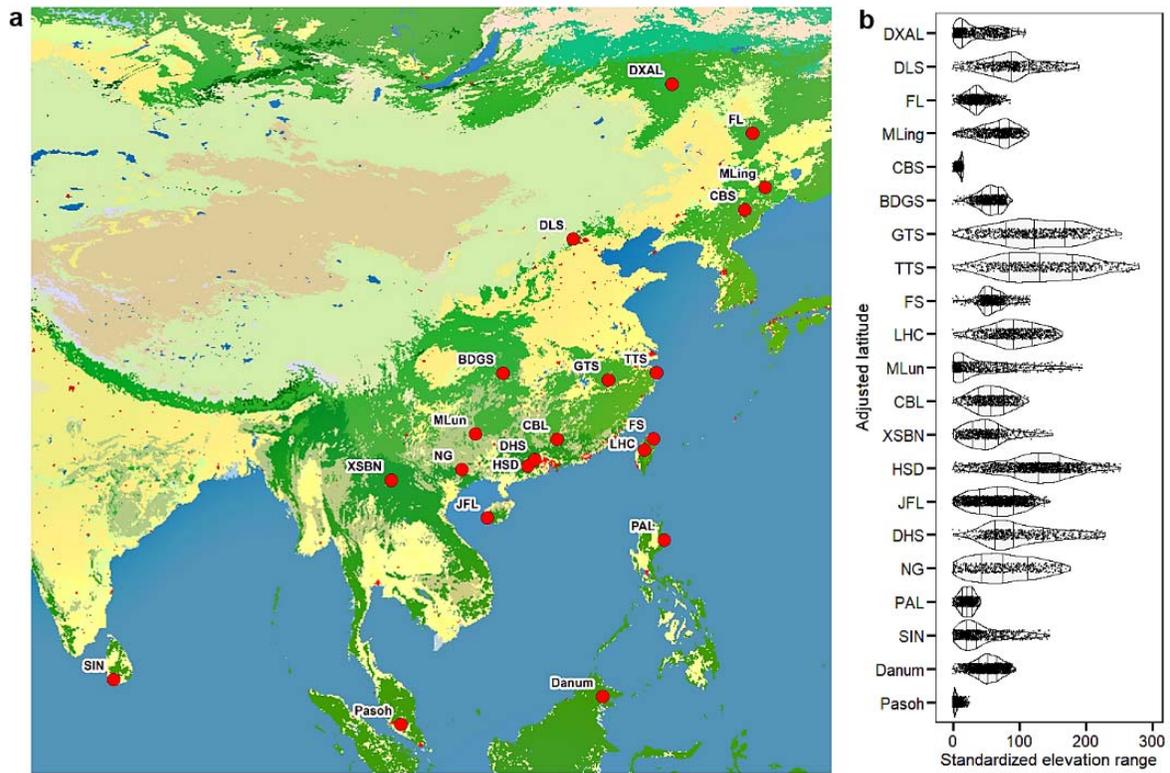
- 249 6. Hillebrand, H. On the generality of the latitudinal diversity gradient. *Am Nat* **163**, 192-
250 211, (2004).
- 251 7. Pontarp, M. *et al.* The Latitudinal Diversity Gradient: Novel Understanding through
252 Mechanistic Eco-evolutionary Models. *Trends Ecol. Evol.* **34**, 211-223, (2019).
- 253 8. Lenoir, J. *et al.* Cross-scale analysis of the region effect on vascular plant species
254 diversity in southern and northern European mountain ranges. *PLoS One* **5**, e15734,
255 (2010).
- 256 9. Mori, A. S. *et al.* Community assembly processes shape an altitudinal gradient of
257 forest biodiversity. *Global Ecol. Biogeogr.* **22**, 878-888, (2013).
- 258 10. Qian, H., Chen, S., Mao, L. & Ouyang, Z. Drivers of β -diversity along latitudinal
259 gradients revisited. *Global Ecol. Biogeogr.* **22**, 659-670, (2013).
- 260 11. Myers, J. A. *et al.* Beta-diversity in temperate and tropical forests reflects dissimilar
261 mechanisms of community assembly. *Ecol. Lett.* **16**, 151-157, (2013).
- 262 12. Kraft, N. J. *et al.* Disentangling the drivers of beta diversity along latitudinal and
263 elevational gradients. *Science* **333**, 1755-1758, (2011).
- 264 13. De Cáceres, M. *et al.* The variation of tree beta diversity across a global network of
265 forest plots. *Global Ecol. Biogeogr.* **21**, 1191-1202, (2012).
- 266 14. Condit, R., Perez, R., Lao, S., Aguilar, S. & Somoza, A. Geographic ranges and b-
267 diversity: discovering how many tree species there are where. *Biologiske Skrifter* **55**,
268 57-71, (2005).
- 269 15. Myers, J. A. & LaManna, J. A. The promise and pitfalls of β -diversity in ecology and
270 conservation. *J. Veg. Sci.* **27**, 1081-1083, (2016).
- 271 16. Tuomisto, H. & Ruokolainen, K. Comment on "Disentangling the drivers of beta
272 diversity along latitudinal and elevational gradients". *Science* **335**, 1573; author reply
273 1573, (2012).

- 274 17. Chao, A. *et al.* Rarefaction and extrapolation with Hill numbers: a framework for
275 sampling and estimation in species diversity studies. *Ecol. Monogr.* **84**, 45-67, (2014).
- 276 18. Cao, K. *et al.* Comparing the effectiveness of abundance-based β -diversity metrics in
277 correcting γ -diversity dependence. *Global Ecol. Biogeogr.*, Under review, (2020).
- 278 19. Anderson-Teixeira, K. J. *et al.* CTFS-ForestGEO: a worldwide network monitoring
279 forests in an era of global change. *Glob Chang Biol* **21**, 528-549, (2015).
- 280 20. Feng, G. *et al.* CForBio: a network monitoring Chinese forest biodiversity. *Sci. Bull.*
281 **61**, 1163-1170, (2016).
- 282 21. Vazquez, D. P. & Stevens, R. D. The latitudinal gradient in niche breadth: concepts
283 and evidence. *Am Nat* **164**, E1-19, (2004).
- 284 22. MacArthur, R. H. Patterns of Species Diversity. *Biol. Rev.* **40**, 510-533, (1965).
- 285 23. Ricklefs, R. & Schluter, D. in *Species diversity in ecological communities: historical*
286 *and geographical perspectives* (eds RE Ricklefs & D Schluter) 350-359 (University
287 of Chicago Press, 1993).
- 288 24. Brown, J. H. Why are there so many species in the tropics? *J. Biogeogr.* **41**, 8-22,
289 (2014).
- 290 25. Evans, K. L., Warren, P. H. & Gaston, K. J. Species-energy relationships at the
291 macroecological scale: a review of the mechanisms. *Biol. Rev.* **80**, 1-25, (2005).
- 292 26. Ricklefs, R. E. & He, F. Region effects influence local tree species diversity.
293 *Proceedings of the National Academy of Sciences* **113**, 674-679, (2016).
- 294 27. Chu, C. *et al.* Direct and indirect effects of climate on richness drive the latitudinal
295 diversity gradient in forest trees. *Ecol. Lett.* **22**, 245-255, (2019).
- 296 28. Brown, C. *et al.* Multispecies coexistence of trees in tropical forests: spatial signals of
297 topographic niche differentiation increase with environmental heterogeneity. *Proc*
298 *Biol Sci* **280**, 20130502, (2013).

- 299 29. Shen, G. *et al.* Quantifying effects of habitat heterogeneity and other clustering
300 processes on spatial distributions of tree species. *Ecology* **94**, 2436-2443, (2013).
- 301 30. Baldeck, C. A. *et al.* Soil resources and topography shape local tree community
302 structure in tropical forests. **280**, 20122532, (2013).
- 303 31. Chao, A. & Jost, L. Coverage-based rarefaction and extrapolation: standardizing
304 samples by completeness rather than size. *Ecology* **93**, 2533-2547, (2012).
- 305 32. Condit, R. *Tropical forest census plots: Methods and results from Barro Colorado*
306 *Island, Panama and comparison with other plots.* (Springer, 1998).
- 307 33. Chao, A., Wang, Y. T., Jost, L. & Warton, D. Entropy and the species accumulation
308 curve: a novel entropy estimator via discovery rates of new species. *Methods Ecol.*
309 *Evol.* **4**, 1091-1100, (2013).
- 310 34. Jost, L. Partitioning diversity into independent alpha and beta components. *Ecology* **88**,
311 2427-2439, (2007).
- 312 35. Tuomisto, H. A diversity of beta diversities: straightening up a concept gone awry.
313 Part 1. Defining beta diversity as a function of alpha and gamma diversity. *Ecography*
314 **33**, 2-22, (2010).
- 315 36. Gotelli, N. J. & Colwell, R. K. Quantifying biodiversity: procedures and pitfalls in the
316 measurement and comparison of species richness. *Ecol. Lett.* **4**, 379-391, (2001).
- 317 37. Chao, A., Chazdon, R. L., Colwell, R. K. & Shen, T. J. Abundance-based similarity
318 indices and their estimation when there are unseen species in samples. *Biometrics* **62**,
319 361-371, (2006).
- 320 38. Hirzel, A. H., Hausser, J., Chessel, D. & Perrin, N. Ecological-Niche Factor Analysis:
321 How to Compute Habitat-Suitability Maps without Absence Data? *Ecology* **83**, 2027-
322 2036, (2002).

- 323 39. Devictor, V. *et al.* Defining and measuring ecological specialization. *J. Appl. Ecol.* **47**,
324 15-25, (2010).
- 325 40. Legendre, P. *et al.* Partitioning beta diversity in a subtropical broad-leaved forest of
326 China. *Ecology* **90**, 663-674, (2009).
- 327 41. Kanagaraj, R., Wiegand, T., Comita, L. S. & Huth, A. Tropical tree species
328 assemblages in topographical habitats change in time and with life stage. *J. Ecol.* **99**,
329 1441-1452, (2011).
- 330 42. Punchi-Manage, R. *et al.* Effects of topography on structuring local species
331 assemblages in a Sri Lankan mixed dipterocarp forest. *J. Ecol.* **101**, 149-160, (2013).
- 332 43. Box, G. E. P. & Cox, D. R. An Analysis of Transformations. *J. R. Stat. Soc. B.* **26**,
333 211-252, (1964).
- 334 44. R Core Team. *R: A language and environment for statistical computing.* , <
335 <https://www.R-project.org/>> (2019).
- 336 45. Marcon, E. & Hérault, B. entropart: An R package to measure and partition diversity.
337 *J. Stat. Softw.* **67**, 1-26, (2015).
- 338 46. Brenning, A. Statistical geocomputing combining R and SAGA: The example of
339 landslide susceptibility analysis with generalized additive models. *Hamburger*
340 *Beiträge zur Physischen Geographie und Landschaftsökologie* **19**, 410, (2008).
- 341 47. Conrad, O. *et al.* System for Automated Geoscientific Analyses (SAGA) v. 2.1.4.
342 *Geoscientific Model Development* **8**, 1991-2007, (2015).
- 343 48. Calenge, C. The package “adehabitat” for the R software: A tool for the analysis of
344 space and habitat use by animals. *Ecol. Model.* **197**, 516-519, (2006).
- 345
- 346

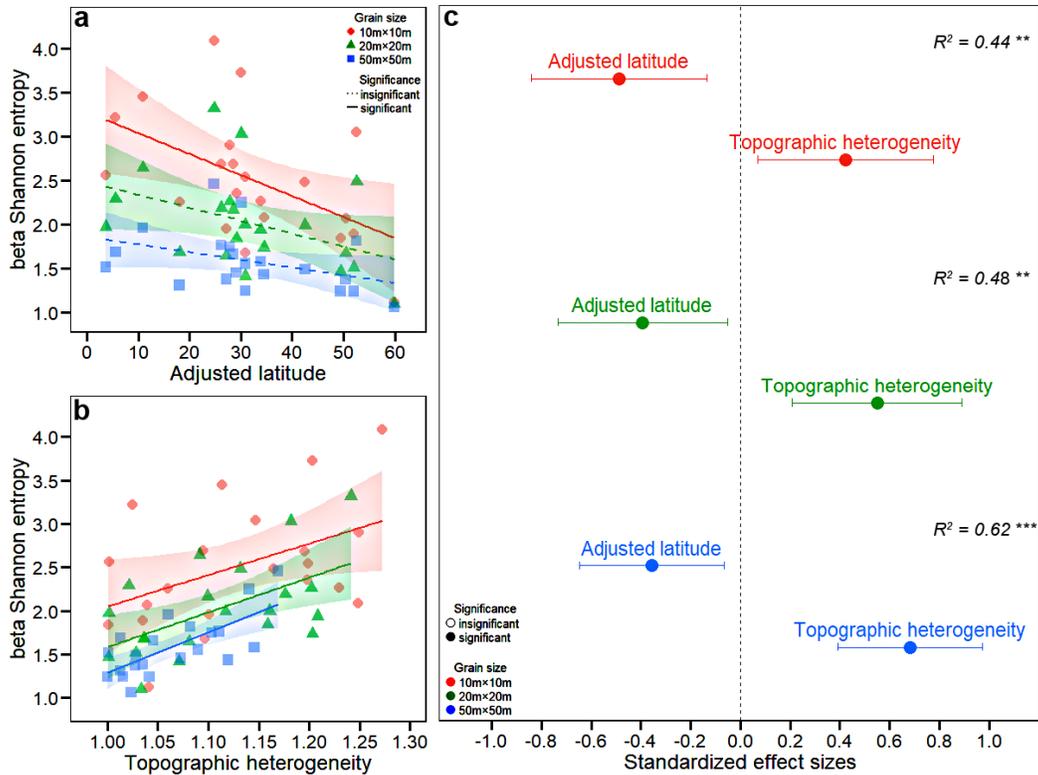
347



348

349 **Figure 1 | The spatial distribution of forest dynamic plots (a, full plot names were listed**
350 **in Extended Data Table 1) and the elevation range of each plot along latitude (b). Panel b**
351 shows the latitudinal pattern of elevation range, which was transformed by subtracting the
352 minimum elevation of each plot. Latitude was adjusted with mean elevation (an upward shift
353 of 100 m equal to a poleward shift of 100 km). The width of each violin plot reflects
354 probability density distribution of mean elevation for 20 m × 20 m subplots in each forest
355 dynamics plot.

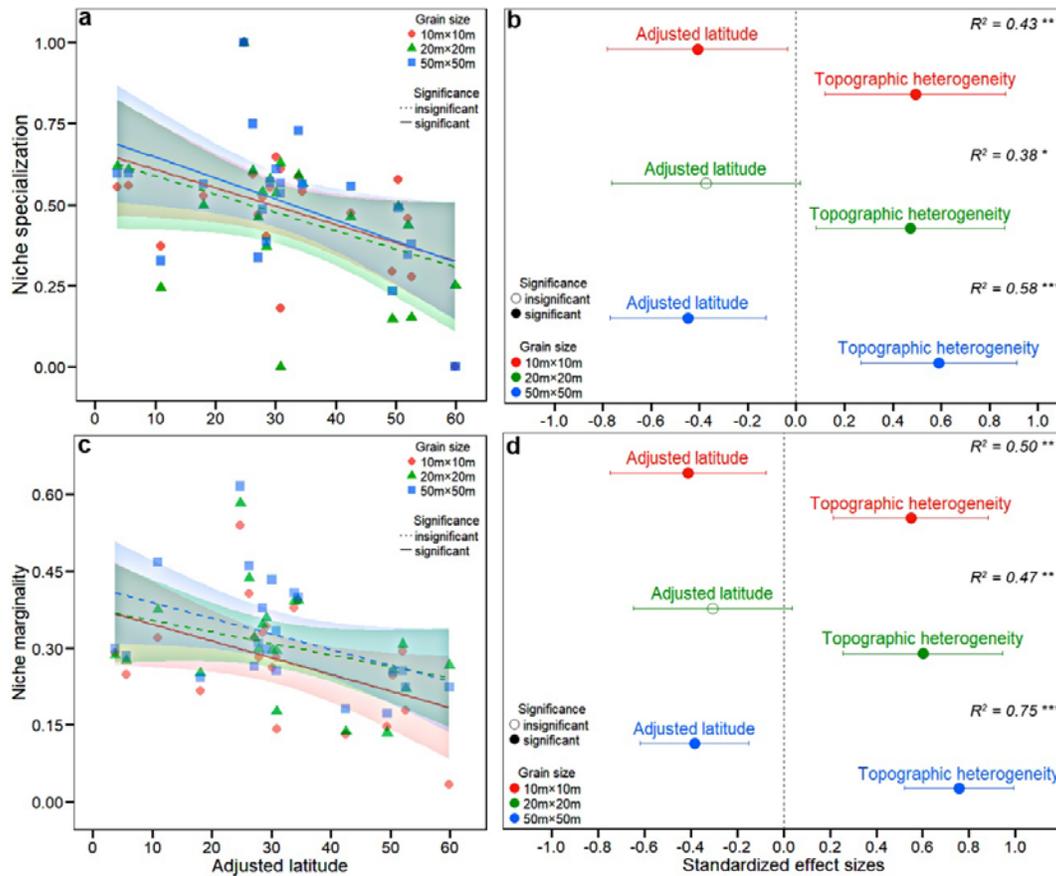
356



357

358 **Figure 2 | The relationship of beta-diversity (corrected beta Shannon entropy) with**
 359 **adjusted latitude and local topographic heterogeneity across grain sizes.** In each panel,
 360 different colours of points and lines represent grain sizes. In panel a and b, solid and dashed
 361 lines indicate significant and insignificant linear correlations (significance level, $\alpha = 0.05$),
 362 respectively. The shaded areas represent the 95% confidence interval of the predictions. The
 363 results of these linear regression models for beta-diversity across scales in panel a and b were
 364 listed in Extended Data Table 2. In panel c, points represent the standardized effect sizes of
 365 explanatory variables, and solid circles represent the standardized effect sizes of variables
 366 being significantly different from zero. The significance level of the total *R-square* are $\alpha <$
 367 0.001, ‘***’; $\alpha < 0.01$, ‘**’; $\alpha < 0.05$ ‘*’.

368



369

370 **Figure 3 | The relationships of community-level niche specialization (a and b) and**
 371 **marginality (c and d) with adjusted latitude and local topographic heterogeneity across**
 372 **grain sizes.** In each panel, different colours of points and lines represent grain sizes. In panel
 373 a and c, solid and dashed lines indicate significant and insignificant linear correlations ($\alpha =$
 374 0.05), respectively. The shaded areas represent the 95% confidence interval of the predictions.
 375 The results of these linear regression models for niche specialization and marginality in panel
 376 a and c were listed in Extended Data Table 3. In panel b and d, points represent the
 377 standardized effect sizes of explanatory variables, and solid and hollow circles represent the
 378 standardized effect sizes of variables being significantly and insignificantly different from
 379 zero. The significance level of the total *R-square* are $\alpha < 0.001$, ‘***’; $\alpha < 0.01$, ‘**’; $\alpha < 0.05$
 380 ‘*’.

381

382

383 **Acknowledgements** We thank Dingliang Xing, Tak Fung and Fangliang He for comments on
384 earlier draft. The data analyses reported in this study were financially supported by Strategic
385 Priority Research Program of the Chinese Academy of Sciences (XDB310300) and National
386 Natural Science Foundation of China (NSFC 31770478). Data collection was funded by many
387 organizations, principally, NSFC 31470490, 31470487, 41475123, 31570426, 31570432,
388 31570486, 31622014, 31660130, 31670441, 31670628, 31700356, 31760141, and 31870404,
389 the Southeast Asia Rain Forest Research Programme (SEARRP), National Key Basic
390 Research Program of China (Grant No. 2014CB954100), SEARRP partners especially
391 Yayasan Sabah, HSBC Malaysia, financial project of Heilongjiang Province
392 (XKLY2018ZR01), National Key R&D Program of China (2016YFC1201102 and
393 2016YFC0502405), the Central Public-interest Scientific Institution Basal Research Fund
394 (CAFYBB2017ZE001), Taiwan Forestry Research Institute grant under the project 97 AS-
395 7.1.1.F1-G1 and the Forestry Bureau of Taiwan (No. tfbm960226), CTFS Forest GEO for
396 funding for Sinharaja forest plot, the Taiwan Forestry Bureau, the Taiwan Forestry Research
397 Institute and the Ministry of Science and Technology of Taiwan for funding the census of
398 Fushan forest plot. We thank Alex Karolus for leading the census in Danum Valley forest
399 plot, and we are grateful to Mike Bernados and Bill McDonald for species identifications, to
400 Fangliang He, Stuart Davies and Shameema Esufali for advice and training, to Qianjiangyuan
401 National Park, Fushan Research Center and Sri Lankan Forest Department for logistical
402 support and the hundreds of field-workers who measured and mapped the trees analyzed in
403 this study.

404

405 **Author contributions**

406 KC, RC, XM, KM and JCS designed research, KC and XM compiled and analysed data; KC,
407 RC, XM, KM and JCS wrote drift with substantial input from LC, WX, DFRPB and MJB.

408 Many authors contributed to data collection of forest censuses and all authors contributed to
409 revisions of the manuscript.

410

411 **Competing interest**

412 The authors declare no competing financial interests.

413

414

415

416 Extended data

417

418

Extended Data Table 1. | Basic information of 21 forest dynamic plots.

Plot name	Area (ha)	Latitude (°N)	Longitude (°E)	Mean elevation (m)	Elevation range (m)	Gamma- diversity	Number of stems
Pasoh	50	2.98	102.31	80	24	818	335400
Danum Valley	50	5.1	117.69	54.1	101.12	642	234916
Sinharaja	25	6.4	80.4	499.5	151	239	250131
Palanan	16	17.04	122.38	111	55	415	66000
Jianfengling	60	18.73	108.9	932	150.4	290	439676
Xishuangbanna	20	21.6	101.57	765.1	159.87	467	95834
Nonggang	15	22.42	106.95	260	190	223	67870
Heishiding	50	22.7	111.99	568.8	263	236	264391
Dinghushan	20	23.17	112.52	339	240	195	71617
Lienhuachih	25	23.91	120.88	765.4	178	144	153268
Chebaling	20	24.72	114.22	488	131	222	86517
Fushan	25	24.76	121.56	675.3	133	110	114500
Mulun	25	25.13	108	547	208.8	254	144679
Gutianshan	24	29.25	118.12	580.6	268.6	159	140700
Badagongshan	25	29.77	110.09	1414	101	241	186556
Tiantongshan	20	29.81	121.79	447.25	298.63	152	115536
Donglingshan	20	40	115.43	1395	219.3	53	52136
Changbaishan	25	42.22	128.53	801.5	17.7	52	38902
Muling	25	43.95	130.07	719.5	123	57	63877
Fenglin	30	48.08	129.12	439	66	46	94920
Daxinganling	25	51.82	122.98	896.7	115.3	18	126532

419

420 **Extended Data Table 2. | The results of simple linear regression models for beta-diversity across scales in Figure 2a and 2b.**

Explanatory variables	Grain size	Coefficients	Standard error	t-value	p-value	R-square
	10m x 10m	-0.024	0.01	-2.59	0.02	0.26
Adjusted	20m x 20m	-0.015	0.01	-2.01	0.06	0.18
latitude	50m x 50m	-0.0087	0.01	-1.86	0.08	0.15
	10m x 10m	3.62	1.65	2.19	0.04	0.20
Topographic	20m x 20m	4.00	1.33	3.02	0.007	0.32
heterogeneity	50m x 50m	4.63	1.08	4.28	<0.001	0.49

421

422

423 **Extended Data Table 3. The results of simple regression models for niche specialization and marginality against adjusted latitude in**
424 **Figure 3a and 3c.**

Response variables	Grain size	Coefficients	Standard error	t-value	p-value	R-square
Niche specialization	10m × 10m	-0.0057	0.0027	-2.10	0.049	0.19
	20m × 20m	-0.0056	0.0030	-1.88	0.076	0.16
	50m × 50m	-0.0065	0.0027	-2.38	0.028	0.23
Niche marginality	10m × 10m	-0.0033	0.0015	-2.15	0.044	0.20
	20m × 20m	-0.0022	0.0014	-1.55	0.14	0.11
	50m × 50m	-0.0031	0.0015	-2.04	0.013	0.055

425

426

427

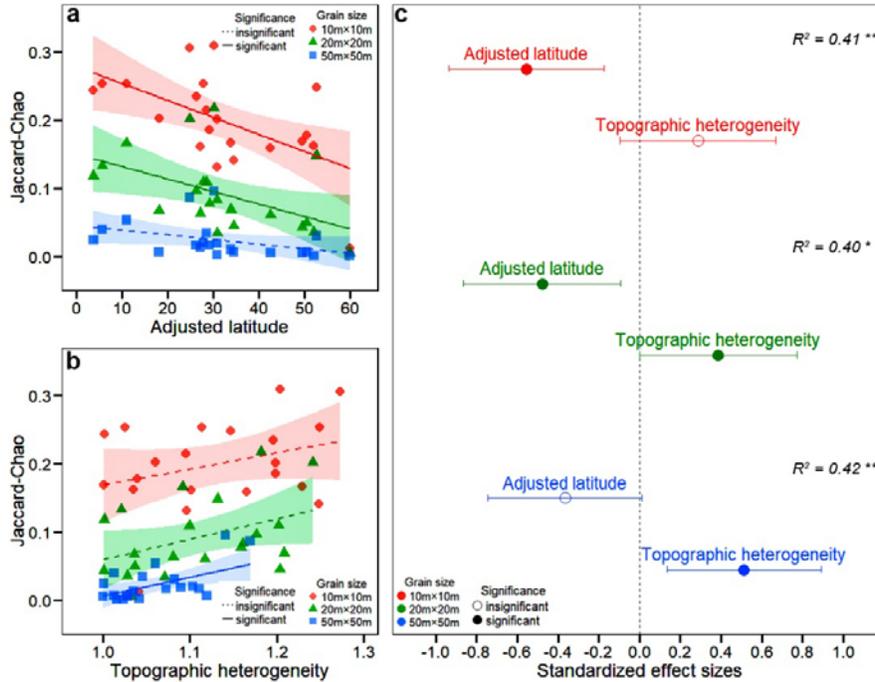
428 **Extended Data Table 4. | The results of the simple regression models for beta-diversity measured by the Jaccard-Chao index in**
429 **Extended Data Figure 1a and 1b.**

Explanatory variables	Grain size	Coefficients	Standard error	t-value	p-value	R-square
	10m x 10m	-0.0025	0.001	-3.03	0.0068	0.33
Adjusted	20m x 20m	-0.0018	0.001	-2.49	0.022	0.25
latitude	50m x 50m	-0.00068	0.0003	-1.86	0.078	0.15
	10m x 10m	0.24	0.16	1.45	0.16	0.10
Topographic	20m x 20m	0.30	0.15	1.95	0.066	0.17
heterogeneity	50m x 50m	0.27	0.10	2.74	0.013	0.28

430

431

432



433

434

435

Extended Data Figure 1 | The linear relationship of beta-diversity (measured by the Jaccard-Chao index) with adjusted latitude (a) and

436

local topographic heterogeneity (b) across grain sizes. In each panel, different colours of points and lines represent grain sizes. In panel a and

437

b, solid and dashed lines indicate significant and insignificant linear correlations (significance level, $\alpha = 0.05$), respectively. The shaded areas

438

represent the 95% confidence interval of the predictions. In panel c, points represent the standardized effect sizes of explanatory variables, and

439

solid and hollow circles represent variables with values significantly and insignificantly different from zero, respectively. The output of these linear

440

regression models in panel a and b were listed in Extended Data Table 4. The total R -square and significance level ($\alpha < 0.001$, ****; $\alpha < 0.01$, ***;

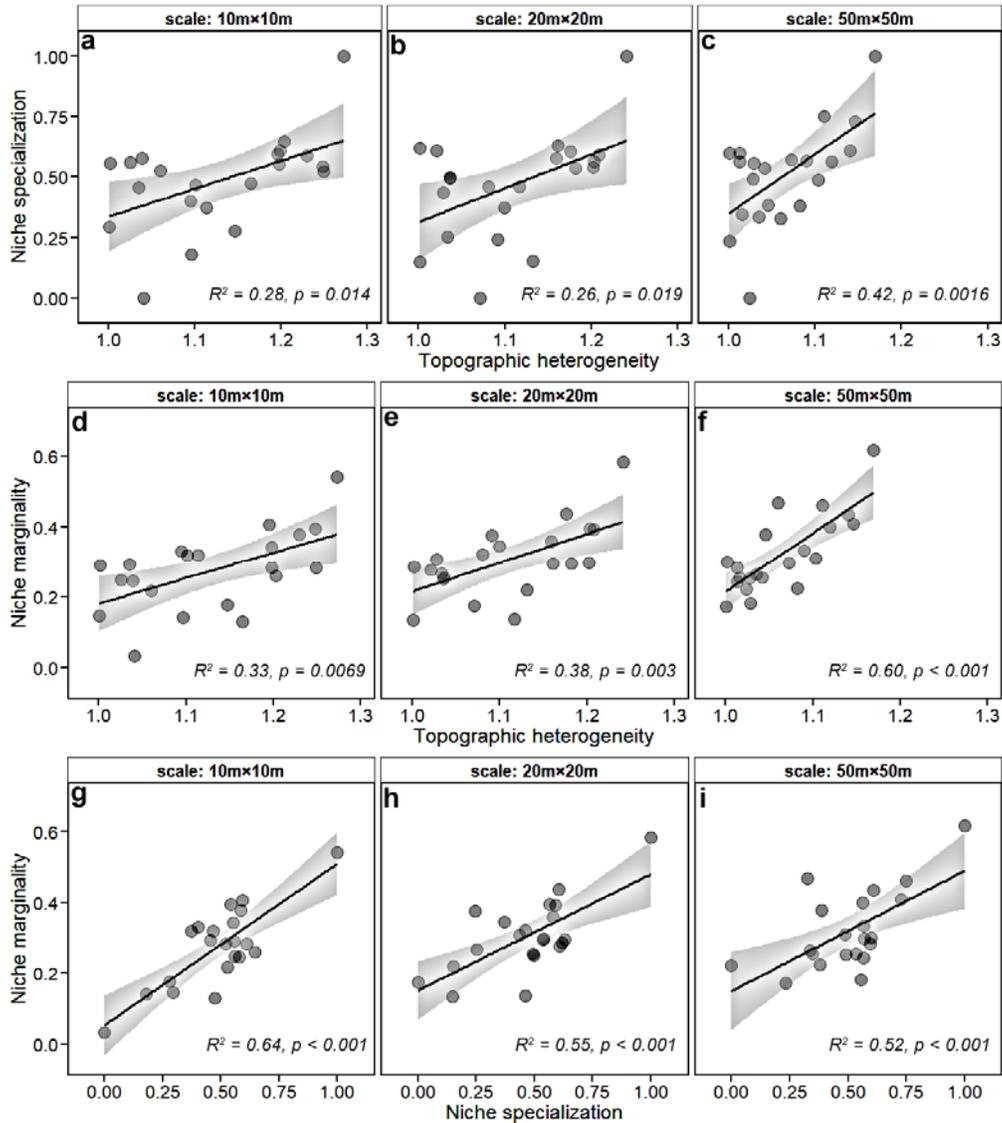
441

$\alpha < 0.05$ **) were annotated at the top-right corner for each multiple linear model in panel c.

442

443

444



445

446 **Extended Data Figure 2 | The linear relationships between topographic heterogeneity, community-level niche specialization and niche**
447 **marginality across grain sizes** (a, d and g: 10 m × 10 m; b, e and h: 20 m × 20 m; c, f and i: 50 m × 50 m). The niche specialization was
448 transformed into normality using a Box-Cox transformation, and then was rescaled to the range in [0, 1] with the min-max normalization.
449 Topographic heterogeneity was quantified as surface: Planimetric area ratio. The *R-square* and *p-value* were shown in each panel for simple
450 linear regression models.

451

452

453

454

455

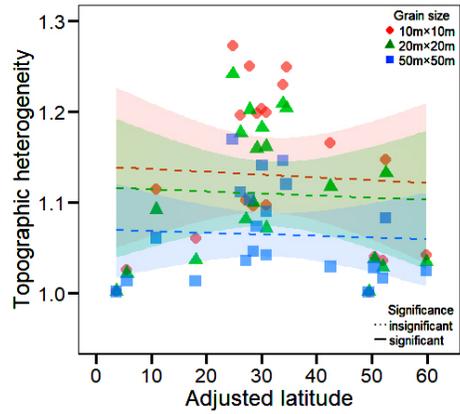
456

457

458

459

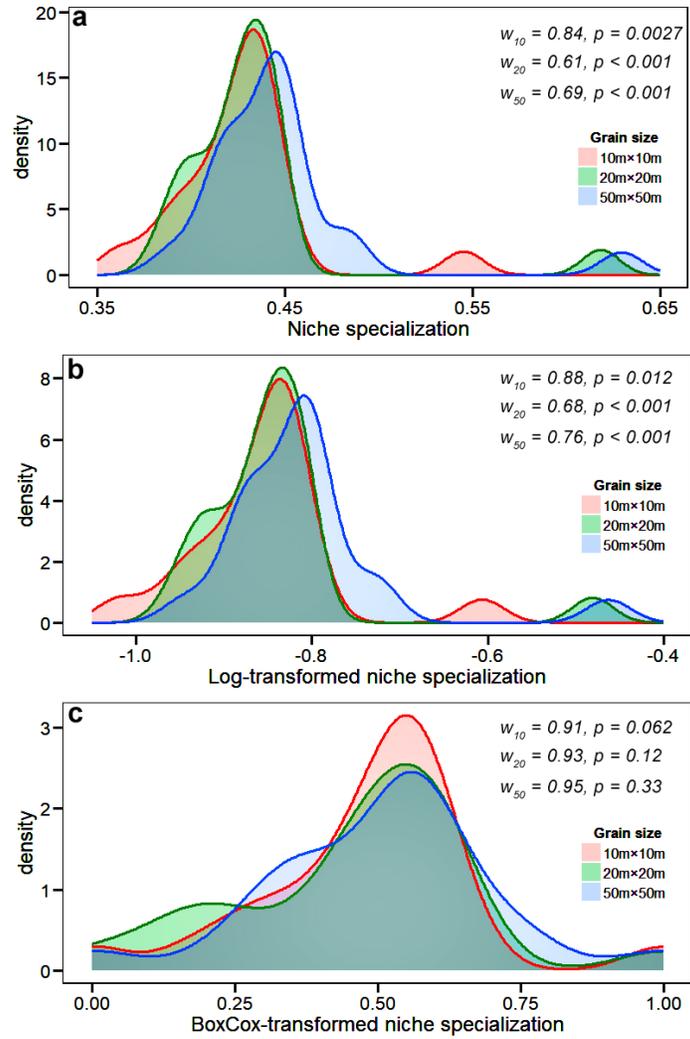
460
461
462



463
464
465
466
467

Extended Data Figure 3 | The linear relationship between topographic heterogeneity (quantified by the surface to planimetric area ratio) and adjusted latitude across grain sizes (10 m x 10 m, 20 m x 20 m and 50 m x 50 m). Dashed lines indicate insignificant linear correlations (significance level, $\alpha = 0.05$), and different colours of points and lines represent grain sizes.

468



469

470

Extended Data Figure 4 | The Shapiro-Wilk test of normality for the observed (a), log-transformed (b), and Box-Cox transformed (c)

471

niche specialization. In each panel, the kernel density curves with different colours showed the probability distribution of niche specialization

472

across grain sizes. The value of the Shapiro-Wilk statistic (w) and p -value across grain sizes were annotated at the top-right corner in each panel.

473

W_{10} , W_{20} and W_{50} were values of the Shapiro-Wilk statistic at scales of 10 m × 10 m, 20 m × 20 m and 50 m × 50 m.

474

475

476