

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

2 Ke Cao^{1,2}, Richard Condit^{3,4}, Xiangcheng Mi^{1*}, Lei Chen¹, Haibao Ren¹, Wubing Xu^{1,5},
3 David F. R. P. Burslem⁶, Chunrong Cai⁷, Min Cao^{8,9}, Li-Wan Chang¹⁰, Chengjin Chu¹¹,
4 Fuxin Cui⁷, Hu Du¹², Sisira Ediriweera¹³, C.S.V. Gunatilleke¹⁴, I.U.A.N. Gunatilleke¹⁴,
5 Zhanqing Hao¹⁵, Guangze Jin¹⁶, Jinbo Li⁷, Buhang Li¹¹, Yide Li¹⁷, Yankun Liu¹⁸, Hongwei
6 Ni¹⁹, Michael J. O'Brien²⁰, Xiujuan Qiao²¹, Guochun Shen²², Songyan Tian¹⁸, Xihua Wang²²,
7 Han Xu¹⁷, Yaozhan Xu^{21,9}, Libing Yang⁷, Sandra L. Yap²³, Juyu Lian^{24,9}, Wanhui Ye^{24,9},
8 Mingjian Yu²⁵, Sheng-Hsin Su¹⁰, Chia-Hao Chang-Yang²⁶, Yili Guo²⁷, Xiankun Li²⁸, Fuping
9 Zeng¹¹, Daoguang Zhu⁷, Li Zhu¹, I-Fang Sun²⁷, Keping Ma¹, Jens-Christian Svenning⁵

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 ⁵Center for Biodiversity Dynamics in a Changing World (BIOCHANGE) & Section for
18 Ecoinformatics and Biodiversity, Department of Biology, Aarhus University, Ny

19 Munkegade 114, DK-8000 Aarhus C, Denmark

20 ⁶School of Biological Sciences, University of Aberdeen, Cruickshank Building, St Machar
21 Drive, Aberdeen AB24 3UU, UK

22 ⁷Institute of Natural Resources and Ecology, Heilongjiang Academy of Sciences, Harbin
23 150040

24 ⁸CAS Key Laboratory of Tropical Forest Ecology, Xishuangbanna Tropical Botanical
25 Garden, Chinese Academy of Sciences, Kunming 650223

- 26 ⁹Center of Conservation Biology, Core Botanical Gardens, Chinese Academy of Sciences,
27 Wuhan 430074, China
- 28 ¹⁰Taiwan Forestry Research Institute, 53 Nanhai Road, Taipei 100051
- 29 ¹¹Sun Yat-sen University, Guangzhou 510275
- 30 ¹²Institute of Subtropical Agriculture, Chinese Academy of Sciences, Changsha, Hunan
31 410125
- 32 ¹³Faculty of Applied Sciences, Uva Wellassa University, Badulla 90000, Sri Lanka
- 33 ¹⁴Department of Botany, University of Peradeniya, Peradeniya 20400, Sri Lanka
- 34 ¹⁵School of Ecology and Environment, Northwestern Polytechnical University, Xi'an 710072
- 35 ¹⁶Center for Ecological Research, Northeast Forestry University, Harbin 150040
- 36 ¹⁷Research Institute of Tropical Forestry, Chinese Academy of Forestry, Guangzhou 510520
- 37 ¹⁸Heilongjiang Key Laboratory of Forest Ecology and Forestry Ecological Engineering,
38 Heilongjiang Forestry Engineering and Environment Institute, Harbin 150040
- 39 ¹⁹Heilongjiang Academy of Forestry, Harbin 150081
- 40 ²⁰Área de Biodiversidad y Conservación, Universidad Rey Juan Carlos, c/ Tulipán s/n., E-
41 28933 Móstoles, Spain
- 42 ²¹Key Laboratory of Aquatic Botany and Watershed Ecology, Wuhan Botanical Garden,
43 Chinese Academy of Sciences, 430074
- 44 ²²East China Normal University, Shanghai 200241
- 45 ²³Institute of Biology, University of the Philippines, Diliman, Quezon City, PH 1101,
46 Philippines
- 47 ²⁴South China Botanical Garden, Chinese Academy of Sciences, Guangzhou 510650
- 48 ²⁵College of Life Sciences, Zhejiang University, Hangzhou 310058
- 49 ²⁶National Sun Yat-sen University, Kaohsiung, 80424

50 ²⁷Guangxi Key Laboratory of Plant Conservation and Restoration Ecology in Karst Terrain,
51 Guangxi Institute of Botany, Guangxi Zhuang Autonomous Region and Chinese Academy
52 of Sciences, Guilin, 541006

53 ²⁸Department of Natural Resources and Environmental Studies, National Dong Hwa
54 University, Hualian 97401

55

56

57

58 Correspondence authors: Xiangcheng Mi

59 Email: mixiangcheng@ibcas.ac.cn

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

61 Chinese Academy of Sciences, Beijing 100093;

62

63 **Abstract**

64 The decline in species richness at higher latitudes is among the most fundamental patterns in
65 ecology. Whether changes in species composition across space (beta-diversity) contribute to
66 this gradient of overall species richness (gamma-diversity) remains hotly debated. Previous
67 studies that failed to resolve the issue suffered from a well-known tendency for small samples
68 in areas with high gamma-diversity to have inflated measures of beta-diversity. Here, we
69 provide here a novel analytical test, using beta-diversity metrics that correct the gamma-
70 diversity and sampling biases, to compare beta-diversity and species packing across a
71 latitudinal gradient in tree species richness of 21 large forest plots along a large environmental
72 gradient in East Asia. We demonstrate that after accounting for topography and correcting the
73 gamma-diversity bias, tropical forests still have higher beta-diversity than temperate analogs.
74 This suggests that beta-diversity contributes to the latitudinal species richness gradient as a
75 component of gamma-diversity. Moreover, both niche specialization and niche marginality (a
76 measure of niche spacing along an environmental gradient) also increase towards the equator,
77 after controlling for the effect of topographic heterogeneity. This supports the joint
78 importance of tighter species packing and larger niche space in tropical forests while also
79 demonstrating the importance of local processes in controlling beta-diversity.

80 Key words: Beta-diversity, gamma-diversity, sampling bias, latitude, species packing, niche
81 specialization

82

83 **Introduction**

84 Beta-diversity is the variation of species composition across space, and it is a key element of
85 conservation planning because it indicates whether diversity is concentrated within a few sites
86 or spread across many sites (Koleff *et al.* 2003; Anderson *et al.* 2011; Socolar *et al.* 2016).

87 One factor enhancing beta-diversity should be large niche space, i.e., more species sharing
88 more available niches, perhaps associated with abiotic habitat heterogeneity (MacArthur
89 1972; Brown *et al.* 2013; Brown 2014; Alahuhta *et al.* 2017; Bracewell *et al.* 2018; Pontarp *et*
90 *al.* 2019; Storch and Okie 2019). Another feature elevating beta-diversity would be dense
91 species packing, i.e., many narrow niches result from stable climate and high productivity
92 (Janzen 1967; MacArthur 1972; Brown 2014; Bracewell *et al.* 2018; Pontarp *et al.* 2019;
93 Storch and Okie 2019). Both stable climate and greater productivity would then lead to higher
94 beta-diversity at low latitudes (Gaston 2000; Willig *et al.* 2003; Hillebrand 2004; Pontarp *et*
95 *al.* 2019). On the other hand, if beta-diversity is driven mostly by abiotic heterogeneity, we
96 would not expect a latitudinal gradient in beta-diversity, since the abiotic heterogeneity
97 should not vary with latitude. These alternatives remain unresolved and studies on the causes
98 of the latitudinal gradient in beta-diversity appears to reach opposing conclusions (Lenoir *et*
99 *al.* 2010; Kraft *et al.* 2011; De Cáceres *et al.* 2012; Mori *et al.* 2013; Myers *et al.* 2013; Qian
100 *et al.* 2013; Sreekar *et al.* 2018). Underlying the debate has been controversy about statistical
101 biases in tools for measuring beta-diversity.

102 The bias in beta-diversity metrics arises from a dependence on sample size that interacts with
103 gamma-diversity (Condit *et al.* 2005; Kraft *et al.* 2011; Tuomisto and Ruokolainen 2012;
104 Myers and LaManna 2016), a bias that is easy to illustrate using simple measures of species
105 overlap. Small samples rarely (if ever) capture all local species. Two small samples from two
106 sites that have exactly the same composition will appear to differ by randomly capturing
107 different subsets of the local communities. The fewer the species sampled, the greater this

108 artifactual beta-diversity will appear (Condit *et al.* 2005; Tuomisto and Ruokolainen 2012). A
109 crucial aspect of the sample size bias is the dependence on gamma-diversity it engenders,
110 since small samples underestimate diversity more severely in species-rich sites than in
111 species-poor sites (Condit *et al.* 2005; Kraft *et al.* 2011; Tuomisto and Ruokolainen 2012;
112 Chao *et al.* 2014; Sreekar *et al.* 2018). This bias has led authors to develop metrics that
113 correct beta-diversity for sample size (Condit *et al.* 2005; Chao *et al.* 2014; Cao *et al.* 2021)
114 or tools based on comparisons with null models (Kraft *et al.* 2011; Myers and LaManna
115 2016). Crucial in the sample size bias is the dependence on gamma-diversity it engenders,
116 since larger samples are needed in species-rich sites (Condit *et al.* 2005; Tuomisto and
117 Ruokolainen 2012; Chao *et al.* 2014; Sreekar *et al.* 2018). Once correcting for sample size
118 bias, gamma-diversity dependence should be removed, and it should be straightforward to
119 compare beta-diversity across a gradient of species diversity in order to evaluate the
120 importance of species packing and total niche space.

121 We carry out this comparison using a steep latitudinal gradient in tree species richness, as
122 documented in our census of 3 million trees at 21 sites spanning 50° of latitude in East Asia
123 (Anderson-Teixeira *et al.* 2015; Feng *et al.* 2016). We define beta-diversity within each plot,
124 so it is a measure of how tree species partition local niche space, then we compare the local
125 estimates of beta-diversity across the latitudinal gradient. In a previous simulation study, Cao
126 *et al.* (Cao *et al.* 2021) identified that the corrected beta-Shannon diversity index is highly
127 effective at removing the bias arising from beta-diversity metrics in small samples of high
128 gamma-diversity communities (Cao *et al.* 2021). With this corrected index, we can answer
129 two fundamental questions about variation in beta-diversity and its impact on the overall
130 species richness: 1) Is there a latitudinal gradient in within-plot beta-diversity? 2) Do local
131 environmental heterogeneity, niche marginality (the distance between the species optima
132 relative to the overall mean habitat), and niche specialization contribute to the latitudinal

133 patterns of beta-diversity? By simultaneously testing the importance of local heterogeneity
134 and latitude, we can establish whether species packing and total niche space contributes to
135 higher richness in tropical relative to temperate forests.

136 **Materials and Methods**

137 **Forest dynamic plots** We used data from 21 forest dynamics plots (15-52 ha) that are part of
138 the ForestGEO and Chinese Forest Biodiversity Monitoring Networks (Anderson-Teixeira *et*
139 *al.* 2015; Feng *et al.* 2016) (figure 1a; electronic supplementary material, table S1). All stems
140 with diameter at breast height (DBH) ≥ 1 cm were spatially mapped, tagged, measured and
141 identified to species (Condit 1998). The plots range from tropical rain forest at 2.98° N
142 latitude to boreal forest at 51.82° N latitude (electronic supplementary material, table S1),
143 from sea level to more than 1400 m elevation, and local topographic variation is as low as
144 17.7 m and as high as 298.6 m (figure 1b and electronic supplementary material, table S1).
145 We divided plots into non-overlapping quadrats of different scales (grain sizes) (10 m \times 10 m,
146 20 m \times 20 m, and 50 m \times 50 m) in order to assess the effect of grain size on beta-diversity
147 (De Cáceres *et al.* 2012; Sreekar *et al.* 2018). We define alpha diversity as the quadrat level
148 diversity, and gamma diversity as plot level diversity. In the main results, we present only the
149 results at grain size of 20m \times 20m, and details of results at grain size of 10m \times 10m and at
150 grain size of 50m \times 50 m could be found in electronic supplementary materials (Table S2,
151 Figure S2).

152 Plot latitudes were adjusted for mean elevation: adding 100 km of latitude per 100-m increase
153 in elevation. Local environmental heterogeneity was quantified in terms of topography, which
154 was the only environmental factor consistently available across all plots. Specifically, we used
155 the ratio of surface area to planimetric as a metric of topographic heterogeneity, calculating at
156 grain sizes of 10 m \times 10 m, 20 m \times 20 m, and 50 m \times 50 m, which provided a useful measure
157 of the range and roughness of the overall plot, based on digital elevation models (DEMs)

158 (Jenness 2004; Brown *et al.* 2013). Local habitat and species niches were defined using six
159 topographic factors as environmental variables: mean elevation, convexity, slope, aspect,
160 topographical wetness index (TWI) and altitude above channel (ACH) (Legendre *et al.* 2009;
161 Kanagaraj *et al.* 2011; PUNCHI-MANAGE *et al.* 2013).

162 **Measurement of beta-diversity** To remove gamma-diversity dependence caused by sample-
163 size bias of beta-diversity metrics, we used the correction method designed for Shannon
164 diversity index based on the relationship between cumulative diversity and sample size (Chao
165 *et al.* 2013). The beta-Shannon diversity index measures the heterogeneity of pooled
166 communities, and is calculated as the effective number of compositionally distinct and
167 equally abundant communities (Jost 2007; Tuomisto 2010):

$$168 \quad {}^1D_\alpha = \exp\left(-\frac{1}{N}\sum_{i=1}^S p_{i1}\log p_{i1} - \frac{1}{N}\sum_{i=1}^S p_{i2}\log p_{i2} - \dots - \frac{1}{N}\sum_{i=1}^S p_{iN}\log p_{iN}\right) \quad (1)$$

$$169 \quad {}^1D_\gamma = \exp\left[-\sum_{i=1}^S \frac{1}{N}(p_{i1} + p_{i2} + \dots + p_{iN})\log(p_{i1} + p_{i2} + \dots + p_{iN})\right] \quad (2)$$

$$170 \quad {}^1D_\beta = \frac{{}^1D_\gamma}{{}^1D_\alpha}$$

171 (3)

172 where ${}^1D_\alpha$, ${}^1D_\beta$ and ${}^1D_\gamma$ are alpha-, beta-, and gamma-Shannon diversity, respectively;
173 p_i is the proportional abundance of species i ; S and N are the total number of species and the
174 total number of local communities (or plots), respectively, in the pooled communities. Alpha-
175 and gamma-Shannon diversity are mathematically independent (i.e., gamma-diversity does
176 not contain information of alpha-diversity) (Jost 2007). Beta-Shannon diversity weights all
177 species by their abundance. We then used a sample-size dependence correction method to
178 reduce the bias in beta-Shannon diversity for comparing beta-diversity among regions (Chao
179 *et al.* 2013; Chao *et al.* 2014). As in a species accumulation curve, the expected cumulative
180 alpha- or gamma-diversity was depicted as a function of sample size, while sample

181 completeness was estimated from community structures of samples (Chao *et al.* 2013; Chao *et*
182 *al.* 2014). Beta-diversity was then estimated from asymptotically approximated alpha- and
183 gamma-diversity based on the diversity-sample size curve. Details of undersampling
184 correction method for the beta-Shannon diversity can be found in the electronic
185 supplementary material S1. Simulation work conducted by Cao *et al.* (2021) confirmed that β -
186 metrics that incorporate an undersampling correction method were more effective at removing
187 dependence on gamma-diversity and inferring casual mechanisms compared to other
188 uncorrected beta-diversity metrics or null models (Cao *et al.* 2021).

189 **Community-level niche differentiation**

190 Niche differentiation was described using attributes of specialization and marginality. Niche
191 specialization was defined as $SD(\text{available habitat})/SD(\text{habitat used})$, in which $SD(\text{available}$
192 $\text{habitat})$ represented the standard deviation of environmental conditions for a community and
193 $SD(\text{habitat used})$ represented the standard deviation of environmental conditions occupied by
194 a species (illustrated in figure 2). Niche marginality was defined as the distance between a
195 species' optimum and the mean environmental conditions within the plot (figure 2) (Hirzel *et*
196 *al.* 2002; Devictor *et al.* 2010). Both specialization and marginality were calculated from
197 multivariate measures of habitat, known as ecological niche factor analysis (Hirzel *et al.*
198 2002). To better meet the assumption of normality of residual in regression model and
199 approximate the linear relationship between niche specialization and explanatory variables
200 (Supplementary material, figure S1a, 1c, 1e), the log- and Box-Cox transformations (Box and
201 Cox 1964) were applied for niche specialization across grain sizes (Supplementary material,
202 figure S1b, 1d, 1f). Based on the precise mapping of all individuals in these plots, the
203 community-level niche marginality and specialization were respectively quantified as species-
204 level niche marginality and specialization weighted by relative species abundance. Higher
205 community-level niche specialization indicates the fine partitioning of available niche space,

206 while higher community-level niche marginality indicates a larger deviation from mean
207 environmental conditions of a community, and thus suggesting a larger niche space.
208 Topographic variables are typically strongly correlated with the variation in resources such as
209 water availability and soil conditions (Wright 2002; Fortunel *et al.* 2018), thus can capture
210 potentially important axes of niche differentiation. Aspect was computed as $\sin(\text{aspect})$ and
211 $\cos(\text{aspect})$, and other topographic variables were Box-Cox transformed before being
212 included into analyses (Box and Cox 1964).

213 **Statistical analysis** To examine the significance of latitudinal gradients in local beta-
214 diversity, niche specialization and niche marginality, we first modeled beta-diversity,
215 community-level niche specialization and niche marginality against topographic heterogeneity
216 and adjusted latitude separately using simple linear regression models. Subsequently, to
217 determine the relative effect sizes of adjusted latitude and topography, we performed multiple
218 linear regression models with beta-diversity, niche specialization, and niche marginality as
219 response variables, respectively, and all variables were scaled using $(x - \text{mean}(x))/SD(x)$
220 before being included.

221 All statistical analyses were performed with R software, version 3.6.4 (R Core Team 2019).
222 The corrected beta-Shannon diversity was calculated using R package 'entropart' and 'vegan'
223 (Marcon and Hérault 2015; Oksanen *et al.* 2018). The topographic variables were computed
224 using the 'RSAGA' package (Brenning 2008) and the SAGA GIS software (Conrad *et al.* 2015).
225 Ecological niche factor analysis was implemented to calculate niche metrics using R package
226 'adehabitatHS' (Calenge 2006).

227

228 **Results**

229 Gamma-diversity declined by more than forty-fold from tropical to temperate latitudes, from
230 818 species at Pasoh to 18 at Daxinganling (electronic supplementary material, table S1).

231 Beta-diversity measured by the corrected beta-Shannon diversity also declined with latitude,
232 although this pattern was not significant (figure 3a). However, the corrected beta-Shannon
233 diversity was significantly correlated with latitude (e.g., 20m × 20m, *standardized effect size*
234 = -0.39 , $p = 0.033$) in multiple regression models, after controlling for the effect of local
235 topographic heterogeneity (electronic supplementary material, figure S2c). We also found that
236 beta-diversity was positively correlated with community-level niche specialization, niche
237 marginality and local topographic heterogeneity (figures 3b-3d, electronic supplementary
238 material, figure S3). We obtained similar results across three grain sizes although the effect
239 size of topographic heterogeneity and latitude varied with grain sizes (electronic
240 supplementary material, Figs. S2, S3).

241 Various predictors of beta-diversity were also associated with latitude. Both community-level
242 niche specialization and niche marginality significantly decreased from tropical to temperate
243 forests at some grain sizes (figures 4a, 4c, S6a, S6c). However, topographic heterogeneity did
244 not have a significant relationship with latitude (electronic supplementary material, figure
245 S5). Both niche specialization and niche marginality were positively correlated with each
246 other (electronic supplementary material, figures. S4g-4i), and both were also positively
247 associated with local topographic heterogeneity (figures 4b, 4d, electronic supplementary
248 material, figures. S4a-4f). Multiple linear regression models confirmed these results, showing
249 that specialization and marginality both significantly declined with latitude after controlling
250 for topographic heterogeneity at most grain sizes. In the multiple regression models, the effect
251 sizes of topographic heterogeneity were larger than those of adjusted latitude in predicting
252 specialization and marginality (electronic supplementary material, Table S3, figures S6b and
253 6d).

254

255 **Discussion**

256 Whether beta-diversity contributes to the latitudinal diversity gradient has been intensely
257 debated in recent years, largely because of the bias in beta-diversity metrics in small samples
258 of high gamma-diversity communities (Condit *et al.* 2005; Kraft *et al.* 2011; Tuomisto and
259 Ruokolainen 2012; Qian *et al.* 2013; Myers and LaManna 2016; Sreekar *et al.* 2018). To
260 move this debate forward, we first examined the latitudinal gradient in beta-diversity by
261 removing the gamma-diversity and sample size bias with a correction for undersampling
262 (Chao *et al.* 2013; Chao *et al.* 2014), while also accounting for the effect of topographic
263 heterogeneity statistically. Our results showed that beta-diversity increased from high to lower
264 latitudes, in lines with a number of previous studies also finding higher beta-diversity in the
265 tropics (Koleff *et al.* 2003; Willig *et al.* 2003; Vazquez and Stevens 2004; Myers *et al.* 2013).
266 This supports the hypothesis that beta-diversity contributes to the latitudinal gradient in
267 species richness. Since topographic heterogeneity did not systematically vary with latitude, it
268 appears that local topographic heterogeneity does not contribute to the latitudinal gradient in
269 beta-diversity, in line with previous findings (Alstad *et al.* 2016; Chu *et al.* 2019).
270 High beta diversity in the tropics reveals higher species turnover at lower latitudes, meaning
271 tighter species packing and expanded niche space in tropical relative to temperate forests
272 (Ricklefs and Schluter 1993; Gaston 2000; Vazquez and Stevens 2004; Brown 2014; Pontarp
273 *et al.* 2019). These hypotheses have been investigated for decades, with dense species-
274 packing in large niche space attributed to stable climate and higher productivity in the tropics
275 (MacArthur 1965; Ricklefs and Schluter 1993; Evans *et al.* 2005; Brown 2014; Pontarp *et al.*
276 2019). We found increasing niche marginality and specialization towards lower latitudes,
277 supporting this hypothesis. Perhaps larger niche space enables more species to utilize more
278 variable resources, while higher niche specialization allows species to specialize on narrower
279 subsets of the resources available (MacArthur 1965; Ricklefs and Schluter 1993; Evans *et al.*
280 2005; Brown 2014; Pontarp *et al.* 2019). These consequently reduce niche overlap and

281 competition between co-occurring species and facilitates species coexistence (Arellano *et al.*
282 2017). Tighter species packing and larger niche space in the tropics could be related to other
283 mechanisms as well, such as higher diversification rate (Fine 2015) and stronger conspecific
284 negative density dependence (Fine *et al.* 2004; Umaña *et al.* 2017) at lower latitudes.

285 We also conclude that beta-diversity at extent of 15-52 ha is largely driven largely by local
286 processes—specifically, topographic heterogeneity and the niche differentiation it fosters.
287 However, topographic heterogeneity did not contribute to the latitudinal gradient in beta-
288 diversity (figures 3 and 4). This may seem an unsurprising result, but the roles of local
289 ecological processes have been questioned given the broad latitudinal gradient of gamma-
290 diversity (Gaston 2000; Kraft *et al.* 2011). We suggest that the effect of local processes have
291 been obscured by the biases in beta-diversity metrics of small samples from high gamma-
292 diversity communities in previous studies (Myers and LaManna 2016). Moreover, our large
293 samples over 55 degrees of latitude provide comparable measures of niche differentiation,
294 topographic heterogeneity, and beta-diversity, well beyond what was available in early studies
295 (Brown *et al.* 2013; Shen *et al.* 2013). Our results could be refined by considering the
296 influence of additional factors that contribute to local environmental heterogeneity and niche
297 differentiation, such as soil types and soil nutrients (Baldeck *et al.* 2013), which could also
298 contribute to beta-diversity. The biases in beta-diversity metrics in small sample from high
299 gamma-diversity communities are also associated with other attributes of communities such as
300 the species abundance distributions (Chao and Jost 2012), and tests of the alternative
301 techniques in other systems are warranted.

302 In conclusion, our results support that a latitudinal gradient in beta-diversity contributes to the
303 latitudinal gradient in tree species richness after separately controlling for local topographic
304 heterogeneity and the bias in beta-diversity metrics in small samples of high gamma-diversity
305 areas. Our results further suggest tighter species packing and larger niche space in tropical

306 forests (MacArthur 1965; Ricklefs and Schluter 1993; Gaston 2000), but also confirmed
307 environmental heterogeneity as a determinant of beta-diversity. Our findings help resolve the
308 ongoing debates on the contribution of local beta-diversity to latitudinal gradient of species
309 richness.

310

311 **Data availability** The data supporting Figure 1-4 and code for data analyses are available from
312 the Dryad Digital Repository: <https://doi.org/10.5061/dryad.tht76hdww>. Full census data are
313 available upon reasonable request from the data portal of ForestGEO
314 (<http://ctfs.si.edu/datarequest/>) and CForBio (Chinese Forest Biodiversity Monitoring
315 Networks (<http://www.cfbiodiv.org>)).

316 **Author contributions** K.C., R.C., X.M., K.M. and J.C.S. designed research, K.C. and X.M.
317 compiled and analysed data; K.C., R.C., X.M., K.M. and J.C.S. wrote the draft with
318 substantial input from L.C., W.X., D.F.R.P.B. and M.J.B.. Many authors contributed to data
319 collection of forest censuses and all authors contributed to revisions of the manuscript.

320 **Competing interest** The authors declare no competing financial interests.

321 **Funding** This work was financially supported by Strategic Priority Research Program of the
322 Chinese Academy of Sciences (XDB310300) and National Natural Science Foundation of
323 China (NSFC 31770478). Data collection was funded by many organizations, principally,
324 NSFC 31470490, 31470487, 41475123, 31570426, 31570432, 31570486, 31622014,
325 31660130, 31670441, 31670628, 31700356, 31760141, 31870404, and 32061123003, the
326 Southeast Asia Rain Forest Research Programme (SEARRP), National Key Basic Research
327 Program of China (Grant No. 2014CB954100), SEARRP partners especially Yayasan Sabah,
328 HSBC Malaysia, financial project of Heilongjiang Province (XKLY2018ZR01), National Key
329 R&D Program of China (2016YFC1201102 and 2016YFC0502405), the Central Public-
330 interest Scientific Institution Basal Research Fund (CAFYBB2017ZE001), CTFS Forest GEO

331 for funding for Sinharaja forest plot, the Taiwan Forestry Bureau (92-00-2-06 and
332 tfbm960226), the Taiwan Forestry Research Institute (93AS-2.4.2-FI-G1, 94AS-11.1.2-FI-
333 G1, and 97AS-7.1.1.F1-G1), and the Ministry of Science and Technology of Taiwan (NSC92-
334 3114-B002-009) for funding the Fushan and Lienhuachih plots, Scientific Research Funds of
335 Heilongjiang Provincial Research Institutes (CZKYF2021B006). JCS considers this work a
336 contribution to his VILLUM Investigator project “Biodiversity Dynamics in a Changing
337 World” funded by VILLUM FONDEN (grant 16549).

338 **Acknowledgements** We thank Dingliang Xing, Tak Fung, Fangliang He and Gabriel
339 Arellano for comments on earlier draft. We thank Alex Karolus for leading the census in
340 Danum Valley forest plot, and we are grateful to Mike Bernados and Bill McDonald for
341 species identifications, to Fangliang He, Stuart Davies and Shameema Esufali for advice and
342 training, to Qianjiangyuan National Park, Fushan Research Center, Lienhuachih Research
343 Center and Sri Lankan Forest Department for logistical support and the hundreds of field-
344 workers and students who measured and mapped the trees analyzed in this study.

345

346

347 **References**

- 348 1. Socolar J.B., Gilroy J.J., Kunin W.E., Edwards D.P. 2016 How should beta-diversity
349 inform biodiversity conservation? *Trends Ecol Evol* **31**(1), 67-80.
350 (doi:10.1016/j.tree.2015.11.005).
- 351 2. Koleff P., Lennon J.J., Gaston K.J. 2003 Are there latitudinal gradients in species turnover?
352 *Global Ecol Biogeogr* **12**(6), 483-498. (doi:10.1046/j.1466-822X.2003.00056.x).
- 353 3. Anderson M.J., Crist T.O., Chase J.M., Vellend M., Inouye B.D., Freestone A.L., Sanders
354 N.J., Cornell H.V., Comita L.S., Davies K.F., et al. 2011 Navigating the multiple meanings of
355 beta diversity: a roadmap for the practicing ecologist. *Ecol Lett* **14**(1), 19-28.
356 (doi:10.1111/j.1461-0248.2010.01552.x).

- 357 4. Alahuhta J., Kosten S., Akasaka M., Auderset D., Azzella M.M., Bolpagni R., Bove C.P.,
358 Chambers P.A., Chappuis E., Clayton J., et al. 2017 Global variation in the beta diversity of
359 lake macrophytes is driven by environmental heterogeneity rather than latitude. *J Biogeogr*
360 **44**(8), 1758-1769. (doi:10.1111/jbi.12978).
- 361 5. Brown J.H. 2014 Why are there so many species in the tropics? *J Biogeogr* **41**(1), 8-22.
362 (doi:10.1111/jbi.12228).
- 363 6. Brown C., Burslem D.F., Illian J.B., Bao L., Brockelman W., Cao M., Chang L.W.,
364 Dattaraja H.S., Davies S., Gunatilleke C.V., et al. 2013 Multispecies coexistence of trees in
365 tropical forests: spatial signals of topographic niche differentiation increase with environmental
366 heterogeneity. *P Roy Soc B-Biol Sci* **280**(1764), 20130502. (doi:10.1098/rspb.2013.0502).
- 367 7. Bracewell S.A., Clark G.F., Johnston E.L. 2018 Habitat complexity effects on diversity
368 and abundance differ with latitude: an experimental study over 20 degrees. *Ecology* **99**(9),
369 1964-1974. (doi:10.1002/ecy.2408).
- 370 8. MacArthur R. 1972 *Geographical ecology*, Princeton University Press.
- 371 9. Pontarp M., Bunnefeld L., Cabral J.S., Etienne R.S., Fritz S.A., Gillespie R., Graham C.H.,
372 Hagen O., Hartig F., Huang S., et al. 2019 The Latitudinal Diversity Gradient: Novel
373 Understanding through Mechanistic Eco-evolutionary Models. *Trends Ecol Evol* **34**(3), 211-
374 223. (doi:10.1016/j.tree.2018.11.009).
- 375 10. Storch D., Okie J.G. 2019 The carrying capacity for species richness. *Global Ecol Biogeogr*
376 **28**(10), 1519-1532. (doi:<https://doi.org/10.1111/geb.12987>).
- 377 11. Janzen D.H. 1967 Why Mountain Passes are Higher in the Tropics. *Am Nat* **101**(919), 233-
378 249. (doi:10.1086/282487).
- 379 12. Gaston K.J. 2000 Global patterns in biodiversity. *Nature* **405**(6783), 220-227.
380 (doi:10.1038/35012228).

- 381 13. Willig M.R., Kaufman D.M., Stevens R.D. 2003 Latitudinal gradients of biodiversity:
382 pattern, process, scale, and synthesis. *Annu Rev Ecol Evol Syst*, 273-309.
383 (doi:10.1146/annurev.ecolsys.34.012103.144032).
- 384 14. Hillebrand H. 2004 On the generality of the latitudinal diversity gradient. *Am Nat* **163**(2),
385 192-211. (doi:10.1086/381004).
- 386 15. Lenoir J., Gegout J.C., Guisan A., Vittoz P., Wohlgemuth T., Zimmermann N.E., Dullinger
387 S., Pauli H., Willner W., Grytnes J.A., et al. 2010 Cross-scale analysis of the region effect on
388 vascular plant species diversity in southern and northern European mountain ranges. *PLoS One*
389 **5**(12), e15734. (doi:10.1371/journal.pone.0015734).
- 390 16. Mori A.S., Shiono T., Koide D., Kitagawa R., Ota A.T., Mizumachi E. 2013 Community
391 assembly processes shape an altitudinal gradient of forest biodiversity. *Global Ecol Biogeogr*
392 **22**(7), 878-888. (doi:10.1111/geb.12058).
- 393 17. Qian H., Chen S., Mao L., Ouyang Z. 2013 Drivers of β -diversity along latitudinal
394 gradients revisited. *Global Ecol Biogeogr* **22**(6), 659-670. (doi:10.1111/geb.12020).
- 395 18. Myers J.A., Chase J.M., Jimenez I., Jorgensen P.M., Araujo-Murakami A., Paniagua-
396 Zambrana N., Seidel R. 2013 Beta-diversity in temperate and tropical forests reflects dissimilar
397 mechanisms of community assembly. *Ecol Lett* **16**(2), 151-157. (doi:10.1111/ele.12021).
- 398 19. De Cáceres M., Legendre P., Valencia R., Cao M., Chang L.-W., Chuyong G., Condit R.,
399 Hao Z., Hsieh C.-F., Hubbell S., et al. 2012 The variation of tree beta diversity across a global
400 network of forest plots. *Global Ecol Biogeogr* **21**(12), 1191-1202. (doi:10.1111/j.1466-
401 8238.2012.00770.x).
- 402 20. Kraft N.J.B., Comita L.S., Chase J.M., Sanders N.J., Swenson N.G., Crist T.O., Stegen J.C.,
403 Vellend M., Boyle B., Anderson M.J., et al. 2011 Disentangling the drivers of β diversity along
404 latitudinal and elevational gradients. *Science* **333**(6050), 1755-1758.
405 (doi:10.1126/science.1208584).

- 406 21. Sreekar R., Katabuchi M., Nakamura A., Corlett R.T., Slik J.W.F., Fletcher C., He F.,
407 Weiblen G.D., Shen G., Xu H., et al. 2018 Spatial scale changes the relationship between beta
408 diversity, species richness and latitude. *Royal Society Open Science* **5**(9), 181168.
409 (doi:10.1098/rsos.181168).
- 410 22. Condit R., Perez R., Lao S., Aguilar S., Somoza A. 2005 Geographic ranges and b-diversity:
411 discovering how many tree species there are where. *Biologiske Skrifter* **55**, 57-71.
- 412 23. Myers J.A., LaManna J.A. 2016 The promise and pitfalls of β -diversity in ecology and
413 conservation. *J Veg Sci* **27**(6), 1081-1083. (doi:10.1111/jvs.12482).
- 414 24. Tuomisto H., Ruokolainen K. 2012 Comment on "Disentangling the drivers of β diversity
415 along latitudinal and elevational gradients". *Science* **335**(6076), 1573.
416 (doi:10.1126/science.1216393).
- 417 25. Chao A., Gotelli N.J., Hsieh T.C., Sander E.L., Ma K.H., Colwell R.K., Ellison A.M. 2014
418 Rarefaction and extrapolation with Hill numbers: a framework for sampling and estimation in
419 species diversity studies. *Ecol Monogr* **84**(1), 45-67. (doi:10.1890/13-0133.1).
- 420 26. Cao K., Svenning J.-C., Yan C., Zhang J., Ma K., Mi X. 2021 Undersampling correction
421 methods to control γ -dependence for comparing β -diversity between regions. *BioRxiv*, doi:
422 10.1101/2021.1101.1124.427952.
- 423 27. Anderson-Teixeira K.J., Davies S.J., Bennett A.C., Gonzalez-Akre E.B., Muller-Landau
424 H.C., Wright S.J., Abu Salim K., Almeyda Zambrano A.M., Alonso A., Baltzer J.L., et al. 2015
425 CTFS-ForestGEO: a worldwide network monitoring forests in an era of global change. *Glob
426 Chang Biol* **21**(2), 528-549. (doi:10.1111/gcb.12712).
- 427 28. Feng G., Mi X., Yan H., Li F.Y., Svenning J.-C., Ma K. 2016 CForBio: a network
428 monitoring Chinese forest biodiversity. *Sci Bull* **61**(15), 1163-1170. (doi:10.1007/s11434-016-
429 1132-9).

- 430 29. Condit R. 1998 *Tropical forest census plots: Methods and results from Barro Colorado*
431 *Island, Panama and comparison with other plots*. Berlin, Springer.
- 432 30. Jenness J.S. 2004 Calculating landscape surface area from digital elevation models. *Wildl*
433 *Soc Bull* **32**(3), 829-839. (doi:10.2193/0091-7648(2004)032[0829:CLSAFD]2.0.CO;2).
- 434 31. Legendre P., Mi X., Ren H., Ma K., Yu M., Sun I.F., He F. 2009 Partitioning beta diversity
435 in a subtropical broad-leaved forest of China. *Ecology* **90**(3), 663-674. (doi:10.1890/07-1880.1).
- 436 32. Kanagaraj R., Wiegand T., Comita L.S., Huth A. 2011 Tropical tree species assemblages
437 in topographical habitats change in time and with life stage. *J Ecol* **99**(6), 1441-1452.
438 (doi:10.1111/j.1365-2745.2011.01878.x).
- 439 33. Punchi-Manage R., Getzin S., Wiegand T., Kanagaraj R., Savitri Gunatilleke C.V., Nimal
440 Gunatilleke I.A.U., Wiegand K., Huth A., Zuidema P. 2013 Effects of topography on
441 structuring local species assemblages in a Sri Lankan mixed dipterocarp forest. *J Ecol* **101**(1),
442 149-160. (doi:10.1111/1365-2745.12017).
- 443 34. Chao A., Wang Y.T., Jost L. 2013 Entropy and the species accumulation curve: a novel
444 entropy estimator via discovery rates of new species. *Methods Ecol Evol* **4**(11), 1091-1100.
445 (doi:10.1111/2041-210x.12108).
- 446 35. Jost L. 2007 Partitioning diversity into independent alpha and beta components. *Ecology*
447 **88**(10), 2427-2439. (doi:10.1890/06-1736.1).
- 448 36. Tuomisto H. 2010 A diversity of beta diversities: straightening up a concept gone awry.
449 Part 1. Defining beta diversity as a function of alpha and gamma diversity. *Ecography* **33**(1),
450 2-22. (doi:10.1111/j.1600-0587.2009.05880.x).
- 451 37. Hirzel A.H., Hausser J., Chessel D., Perrin N. 2002 Ecological-Niche Factor Analysis:
452 How to Compute Habitat-Suitability Maps without Absence Data? *Ecology* **83**(7), 2027-2036.
453 (doi:10.1890/0012-9658(2002)083[2027:Enfaht]2.0.Co;2).

- 454 38. Devictor V., Clavel J., Julliard R., Lavergne S., Mouillot D., Thuiller W., Venail P.,
455 Villéger S., Mouquet N. 2010 Defining and measuring ecological specialization. *J Appl Ecol*
456 **47**(1), 15-25. (doi:10.1111/j.1365-2664.2009.01744.x).
- 457 39. Box G.E.P., Cox D.R. 1964 An Analysis of Transformations. *J R Stat Soc B* **26**(2), 211-
458 252. (doi:10.1111/j.2517-6161.1964.tb00553.x).
- 459 40. Wright J.S. 2002 Plant diversity in tropical forests: a review of mechanisms of species
460 coexistence. *Oecologia* **130**(1), 1-14. (doi:10.1007/s004420100809).
- 461 41. Fortunel C., Lasky J.R., Uriarte M., Valencia R., Wright S.J., Garwood N.C., Kraft N.J.B.
462 2018 Topography and neighborhood crowding can interact to shape species growth and
463 distribution in a diverse Amazonian forest. *Ecology* **99**(10), 2272-2283. (doi:10.1002/ecy.2441).
- 464 42. R Core Team. 2019 R: A language and environment for statistical computing. . (R
465 Foundation for Statistical Computing, Vienna, Austria, URL: <https://www.R-project.org/>).
- 466 43. Marcon E., Hérault B. 2015 entropart: An R package to measure and partition diversity. *J*
467 *Stat Softw* **67**(1), 1-26. (doi:10.18637/jss.v067.i08).
- 468 44. Oksanen J., Blanchet F.G., Friendly M., Kindt R., Legendre P., McGlinn D., Minchin P.R.,
469 O'Hara R.B., Simpson G.L., Solymos P., et al. 2018 vegan: community ecology package. R
470 package version 2.5-1. (<https://CRAN.R-project.org/package=vegan>).
- 471 45. Brenning A. 2008 Statistical geocomputing combining R and SAGA: The example of
472 landslide susceptibility analysis with generalized additive models. *Hamburger Beiträge zur*
473 *Physischen Geographie und Landschaftsökologie* **19**(23-32), 410.
- 474 46. Conrad O., Bechtel B., Bock M., Dietrich H., Fischer E., Gerlitz L., Wehberg J., Wichmann
475 V., Böhner J. 2015 System for Automated Geoscientific Analyses (SAGA) v. 2.1.4.
476 *Geoscientific Model Development* **8**(7), 1991-2007. (doi:10.5194/gmd-8-1991-2015).

- 477 47. Calenge C. 2006 The package “adehabitat” for the R software: A tool for the analysis of
478 space and habitat use by animals. *Ecol Model* **197**(3-4), 516-519.
479 (doi:10.1016/j.ecolmodel.2006.03.017).
- 480 48. Vazquez D.P., Stevens R.D. 2004 The latitudinal gradient in niche breadth: concepts and
481 evidence. *Am Nat* **164**(1), E1-19. (doi:10.1086/421445).
- 482 49. Chu C., Lutz J.A., Král K., Vrška T., Yin X., Myers J.A., Abiem I., Alonso A., Bourg N.,
483 Burslem D.F.R.P., et al. 2019 Direct and indirect effects of climate on richness drive the
484 latitudinal diversity gradient in forest trees. *Ecol Lett* **22**(2), 245-255. (doi:10.1111/ele.13175).
- 485 50. Alstad A.O., Damschen E.I., Givnish T.J., Harrington J.A., Leach M.K., Rogers D.A.,
486 Waller D.M. 2016 The pace of plant community change is accelerating in remnant prairies. *Sci*
487 *Adv* **2**(2), e1500975. (doi:10.1126/sciadv.1500975).
- 488 51. Ricklefs R., Schluter D. 1993 Species diversity: regional and historical influences. In
489 *Species diversity in ecological communities: historical and geographical perspectives* (eds.
490 Ricklefs R., Schluter D.), pp. 350-359, University of Chicago Press.
- 491 52. Evans K.L., Greenwood J.J., Gaston K.J. 2005 Dissecting the species-energy relationship.
492 *Proc Biol Sci* **272**(1577), 2155-2163. (doi:10.1098/rspb.2005.3209).
- 493 53. MacArthur R.H. 1965 Patterns of Species Diversity. *Biol Rev* **40**(4), 510-533.
494 (doi:10.1111/j.1469-185X.1965.tb00815.x).
- 495 54. Arellano G., Umaña M.N., Macía M.J., Loza M.I., Fuentes A., Cala V., Jørgensen P.M.
496 2017 The role of niche overlap, environmental heterogeneity, landscape roughness and
497 productivity in shaping species abundance distributions along the Amazon–Andes gradient.
498 *Global Ecology and Biogeography* **26**(2), 191-202.
- 499 55. Fine P.V.A. 2015 Ecological and Evolutionary Drivers of Geographic Variation in Species
500 Diversity. *Annu Rev Ecol Evol Syst* **46**(1), 369-392. (doi:10.1146/annurev-ecolsys-112414-
501 054102).

- 502 56. Umaña M.N., Mi X., Cao M., Enquist B.J., Hao Z., Howe R., Iida Y., Johnson D., Lin L.,
503 Liu X., et al. 2017 The role of functional uniqueness and spatial aggregation in explaining rarity
504 in trees. *Global Ecol Biogeogr* **26**(7), 777-786. (doi:10.1111/geb.12583).
- 505 57. Fine P.V.A., Mesones I., Coley P.D. 2004 Herbivores Promote Habitat Specialization by
506 Trees in Amazonian Forests. *Science* **305**(5684), 663-665. (doi:10.1126/science.1098982).
- 507 58. Shen G., He F., Waagepetersen R., Sun I.F., Hao Z., Chen Z.S., Yu M. 2013 Quantifying
508 effects of habitat heterogeneity and other clustering processes on spatial distributions of tree
509 species. *Ecology* **94**(11), 2436-2443. (doi:10.1890/12-1983.1).
- 510 59. Baldeck C.A., Harms K.E., Yavitt J.B., John R., Turner B.L., Valencia R., Navarrete H.,
511 Davies S.J., Chuyong G.B., Kenfack D., et al. 2013 Soil resources and topography shape local
512 tree community structure in tropical forests. *Proc R Soc B* **280**(1753), 20122532.
513 (doi:10.1098/rspb.2012.2532).
- 514 60. Chao A., Jost L. 2012 Coverage-based rarefaction and extrapolation: standardizing samples
515 by completeness rather than size. *Ecology* **93**(12), 2533-2547. (doi:10.1890/11-1952.1).
- 516
517

518

519 **Figure 1. The spatial distribution of forest dynamics plots (a), and their elevational**
520 **ranges (b).** Panel (b) shows the latitudinal pattern of elevation range, which was transformed
521 by subtracting the minimum elevation of each plot. The width of each violin plot reflects
522 probability density distribution of mean elevation for 20 m × 20 m subplots in each forest
523 dynamics plot. Full plot names are listed in electronic supplementary material, table S1.

524

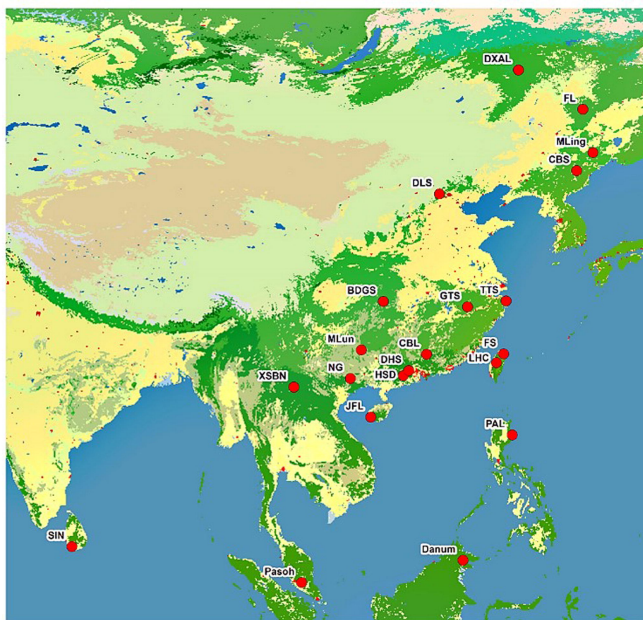
525 **Figure 2.** Illustration of niche specialization and marginality of *Euonymus oblongifolius* and
526 *Symplocos stellaris* in the Gutianshan forest dynamics plot (600 m × 400 m). a. Red solid points
527 represent the spatial distribution of *E. oblongifolius*, and blue circles represent the spatial
528 distribution of *S. stellaris*. b. Illustration of niche specialization and marginality of *E.*
529 *oblongifolius* and *S. stellaris* in two-dimensional niche space based on mean elevation and
530 convexity of distributed 20 m × 20 m quadrats. Niche marginality is the distance from the mean
531 habitat of the focal species to the mean habitat of community habitats. μ_E , μ_S and μ_G represent
532 centroids of environmental conditions for *E. oblongifolius*, *S. stellaris* and the entire
533 community, and distances M_E and M_S are niche marginalities of two species. Likewise, niche
534 specialization is ratio of the entire habitat range of a community to habitat range of the focal
535 species. π_E , π_S and π_G stand for the distributional range of for *E. oblongifolius*, *S. stellaris* and
536 the entire community in two-dimensional niche space respectively, the ratio of π_G/π_E and π_G/π_S
537 are niche specialization of two species. Grey points indicate the topographic variation of the
538 entire community, red squares show higher niche specialization and marginality of *E.*
539 *oblongifolius*, whereas blue triangles indicate lower specialization and marginality of *S.*
540 *stellaris*. c. Hypothetical relationships between beta-diversity and niche. Higher community-
541 level niche specialization indicates the fine partitioning of available niche space, while higher
542 community-level niche marginality suggests a larger niche space. Therefore, higher

543 specialization and marginality lead to a higher beta-diversity (left), while lower specialization
544 and marginality lead to a lower beta-diversity (right).

545
546 **Figure 3. Relationships of beta-diversity (measured corrected beta-Shannon diversity)**
547 **with adjusted latitude (a), and local topographic heterogeneity (b), community-level**
548 **niche specialization (c), and niche marginality (d) at grain size of 20 m × 20 m.** In each
549 panel, different colours of points and lines represent grain sizes. In panels a and b, solid and
550 dashed lines indicate significant and insignificant linear correlations (significance level, $\alpha =$
551 0.05), respectively, and the shaded areas represent the 95% confidence intervals of the
552 predictions (electronic supplementary material, table S2). Full plot names in (a) are listed in
553 electronic supplementary material, table S1. Community-level niche specialization was Box-
554 Cox transformed in (c).

555
556 **Figure 4. The relationships of community-level niche specialization (a and b) and**
557 **marginality (c and d) with adjusted latitude and local topographic heterogeneity at grain**
558 **size of 20 m × 20 m.** Community-level niche specialization was Box-Cox transformed. In
559 each panel, R^2 and p -value of the linear regression models was shown at each panel, and
560 shaded areas represent the 95% confidence intervals of the predictions (electronic
561 supplementary material, table S4).

562

a**b**