

1 **Contrasting adaptation and optimization of stomatal traits across**
2 **communities at continental-scale**

3 **Running title:** Stomatal trait distributions

4

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15

16 **Abstract**

17 The maximum stomatal conductance (g), a major anatomical constraint on plant productivity,
18 is a function of the stomatal area fraction (f) and stomatal space-use efficiency (e). However, f
19 and g have been considered as equivalents, with e rarely considered, and their adaptation to
20 the environment and their regulation of ecosystem productivity are unclear. Here, we analyzed
21 the community-weighted mean, variance, skewness, and kurtosis of stomatal traits from
22 tropical to cold-temperature forests. The variance of g and f was higher for arid sites,
23 indicating greater functional niche differentiation, whereas that for e was lower, indicating
24 convergence in efficiency. Besides, when other stomatal trait distributions remained
25 unchanged, increasing kurtosis but decreasing skewness of g would improve ecosystem
26 productivity, and f showed the opposite patterns. These findings highlight how the relative
27 importance and equivalence of inter-related traits can differ at community scale.

28

29 **Keywords:** stomata; community-weighted method; community, adaptation; ecosystem
30 productivity.

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32

33 **Introduction**

34 Stomata are micropores on the leaf surface that regulate the exchange of water vapor and CO₂
35 between plants and the atmosphere (Edwards et al., 1998; Hetherington and Woodward, 2003).
36 Indeed, the evolution of stomata was necessary for plants to colonize terrestrial ecosystems
37 and the diversification of stomatal traits enables plants to inhabit a wide range of
38 environments (Haworth et al., 2011; Raven, 2002). The numbers of stomatal pores, and their
39 area and depth determine the maximum stomatal conductance (g), which represent an
40 anatomical constraint on the maximum rates of diffusion of carbon and water, and thereby
41 their fluxes in given environments. Indeed, given that there is a close relationship between g
42 and field-measured stomatal conductance (McElwain et al., 2016; Murray et al., 2019;
43 Xiong and Flexas, 2020), and g has been used to predict water vapor and CO₂ fluxes
44 (Franks and Beerling, 2009; McElwain et al., 2016; Sack and Buckley, 2016). In turn, g can be
45 considered a product of the fraction of leaf epidermal space that is allocated to the stomata
46 (the stomatal area fraction; f) and the stomatal space-use efficiency (e), which is a function of
47 stomatal size (see Methods). The f is more properly an index of the combined costs associated
48 with the construction, operation and maintenance of the stomata, but it is often taken as a
49 proxy for g (Holland and Richardson, 2009; Liu et al., 2018; Sack et al., 2003), especially as g
50 and f are theoretically and empirically correlated with each other (de Boer et al., 2016;
51 Franks and Beerling, 2009). Yet the relative importance and the equivalence of these traits have
52 not been tested at a large scale.

53 The importance of g and its determinants is especially critical for the understanding of
54 the adaptation of diverse species of communities across gradients of aridity. A rich literature

55 shows contrasting trait values enables co-occurring species to exploit different resources, or
56 the same resources on contrasting spatial or temporal scales (Gross et al., 2017; Hooper, 1998;
57 Hooper et al., 2005), resulting in species-variation in tolerances of scarcity, e.g., drought
58 (Grossiord, 2020), as well as facilitation (Callaway, 1995) and “selection effects”, i.e.,
59 differential contribution to the community-weighted trait values (Loreau, 2000). Indeed, traits
60 that contribute to resource partitioning, such as root stratification (Schwendenmann et al.,
61 2015) or differential stomatal regulation (West et al., 2012) can contribute not only to the
62 mechanisms by which plants tolerate drought but also can improve species-specific soil
63 moisture status by reducing competition for water among species. As a composite stomatal
64 trait, g is coordinated with other plant hydraulic traits (Sack et al., 2003). Generally, a higher g
65 should benefit species under selection for high productivity or competition (Sack and Buckley,
66 2016; Taylor et al., 2012), and thus, in communities with high water availability, we expected
67 narrower functional niche differentiation of g than in communities of drier regions. Indeed,
68 because plants can tolerate drought by maintaining low rates of water uptake and productivity
69 as soils dry, i.e., “tolerance” and/or by achieving their growth primarily when water is
70 available, i.e., “avoidance” (Grubb, 1998; Hetherington and Woodward, 2003), we
71 hypothesized that g values, which influence water uptake and productivity, would tend to be
72 more variable in communities of drier regions. Notably, as g depends on f and e , where g is a
73 proxy for the benefit of assimilated carbon, and f represents the cost of stomatal construction,
74 maintenance and spatial allocation (de Boer et al., 2016), therefore e , which is g/f , is a
75 benefit-cost ratio, i.e., the maximum amount of CO_2 that can diffuse through a unit of
76 stomatal area per unit time. We thus hypothesized that that variability of e within communities

77 would be strongly constrained under water scarcity.

78 Stomatal traits may be a model for plant traits that are important in determining
79 ecosystem functions, as this role of traits has become a priority topic in ecological research
80 (Reichstein et al., 2014). The effect of species' traits aggregated at ecosystem scale is typically
81 quantified using to the mass ratio hypothesis or the niche complementarity hypothesis.
82 According to the mass ratio hypothesis the extent to which the trait of a given species affects
83 ecosystem properties depends on its relative contribution to the total community biomass
84 (Garnier et al., 2004), and many studies found correlations between ecosystem functions and
85 community-weighted mean (CWM) values of plant traits (Garnier et al., 2004; Griffin-Nolan
86 et al., 2018; MuscarellaandUriarte, 2016). According to the niche complementarity hypothesis,
87 resource niches may be used more completely when a community is functionally more
88 diverse (SchumacherandRoscher, 2009), and many studies reported that ecosystem function
89 can be predicted by niche complementarity of traits, as quantified using community-weighted
90 variance, skewness, or kurtosis of trait values (Gross et al., 2017; Le Bagousse-Pinguet et al.,
91 2017; Liu et al., 2020; Mensah et al., 2020; Zhang et al., 2019). Indeed, the global vegetation
92 models predict ecosystem production based on the mean values of traits. It is still a missing
93 picture that how trait distributions influence the prediction. Although stomatal traits are
94 expected to influence ecosystem productivity given their essential role in controlling leaf
95 water and CO₂ fluxes (HetheringtonandWoodward, 2003; Wang et al., 2015), no studies have
96 tested the relative importance of the distributions of stomatal traits (including
97 community-weighted mean, variance, skewness, and kurtosis) in predicting ecosystem
98 productivity across communities. We hypothesized a strong importance of these community

99 distribution metrics for g and potentially for its components, f and e , for regulating ecosystem
100 productivity at community scale.

101 We analyzed the community-weighted mean, variance, skewness, and kurtosis and
102 relationships among these statistical moments, for g , f and e for 800 plant species from nine
103 sites along a climatic gradient. We hypothesized that the community-weighted variance in g
104 would increase with aridity, due to variability of f , rather than e . We also hypothesized that
105 functional niche differentiation of g would be stronger for communities at higher aridity, and
106 tested whether trait assembly of stomata followed the general assembly rule for maximization
107 of trait diversity previously reported for drylands globally using specific leaf area and
108 maximum plant height (Gross et al., 2017). We also hypothesized that stomatal distributions
109 would predict differences in productivity across ecosystems.

110

111 **Results**

112 **Relationships between stomatal trait moments and climate**

113 Stomatal traits were closely related to temperature, precipitation, and climatic aridity
114 (Fig. 1). Overall, the relationships of community-weighted trait means and variances with
115 climate variables were stronger than those of community-weighted skewness and kurtosis,
116 and the aridity index was a stronger predictor of stomatal traits than temperature and
117 precipitation. The community-weighted means and variances of g and f were strongly
118 positively associated with climatic aridity whereas those of e were negatively associated with
119 climatic aridity (Fig. 2).

120 The correlations between community-weighted variance and kurtosis were also tested

121 (Fig. S1). For g and f , the community-weighted variance and kurtosis were negatively
122 correlated; such correlations were not observed with e . At drier sites, g generally showed
123 larger variance with lower kurtosis, whereas communities of wetter sites generally had
124 smaller variance with a wide range of kurtosis.

125

126 **Skewness-kurtosis relationships (SKR) and random expectations**

127 In most cases, the distributions of stomatal traits differed substantially from normality (Fig. 3).
128 The community-weighted skewness² and kurtosis of these three stomatal traits were strongly
129 positively related. The skewness and kurtosis values generated by the null model were located
130 within the constraint triangle imposed by the inequality $\text{Kurtosis} \geq \text{Skewness}^2 + 1$. The
131 observed empirical skewness-kurtosis relationships (SKR) for g deviated strongly from the
132 predictions of the two null models, with the slopes (β) were higher and intercepts (α) lower
133 than would be expected by chance, based on Monte Carlo analyses (Table S6). The observed
134 kurtosis values for both g and f were significantly closer than expected by chance to the lower
135 boundary of the mathematical constraint triangle. In other words, after controlling for the
136 degree of skewness of g and f , observed kurtosis within communities was minimal.
137 Skewness-kurtosis relationships for e did not differ statistically from those generated by the
138 two null models; thus, the D of e was not smaller than expected (Fig. 3).

139 Although the skewness-kurtosis relationships of g and f cannot be explained by chance,
140 the D of g and f was also influenced by climate. Specifically, drier communities had lower D
141 values for g and f , while for e the D values showed no climatic trends (Fig. 4).

142

143 **Stomatal trait moments and ecosystem productivity**

144 The distributions of stomatal traits regulated ecosystem productivity (Fig. 5). The amount of
145 variance in ecosystem productivity explained by community-weighted skewness and kurtosis
146 was greater than that explained by community-weighted mean and variance.

147 Community-weighted skewness and kurtosis of g and f played different roles in optimizing
148 ecosystem productivity: If the other independent variables were fixed, increasing the
149 skewness of f but decreasing that of g , and increasing the kurtosis of g but decreasing that of f
150 would improve ecosystem productivity (Fig. 6). Further, ecosystem productivity increased
151 across communities positively with the mean of e .

152 Overall stomatal traits explained up to 66% of the total variation observed in ecosystem
153 productivity, which was greater than that explained by the distributions of stomatal traits
154 generated by the two null models (Fig. S2).

155

156 **Discussion**

157 **Maximum stomatal conductance (g) increases with climatic aridity at continental scale**

158 The linkage of g with low water availability has remained controversial. Indeed, plants
159 may adapt to dry conditions with a low g that may enable sustained low rates of gas exchange
160 under extended periods of lower water supply, with increased CO₂ gain relative to water loss,
161 i.e., higher water use efficiency (Franks et al., 2015). However, some studies have proposed a
162 higher g and stomatal conductance can confer an advantage for plants in arid climates,
163 enabling greater rates of photosynthesis in the shorter “pulses” when water is available
164 (Grubb, 1998; Scoffoni et al., 2011; Wang et al., 2017), and thus “avoiding” drought with

165 opportunistic rapid growth during short periods of water availability. One of the major novel
166 findings of this study was that the community-weighted mean value of g was positively
167 related to climatic aridity across the continent, and thus that pulse-driven “avoidance” is the
168 dominant trend for adaptation of communities with low water availability. Our findings
169 extend to continental scale the hypothesis that plants and communities adapted to arid
170 climates would generally maintain a low stomatal conductance, but given their high
171 maximum stomatal conductance, can sharply increase stomatal conductance during pulses of
172 rainfall availability to maximize growth (Grubb, 1998). This hypothesis is also consistent with
173 reports that species with higher g tend to show greater sensitivity to changes in the external
174 environment (Haworth et al., 2018; Siddiq et al., 2017).

175

176 **Greater functional niche differentiation of g under higher climatic aridity**

177 Environmental stress can restrict the variance of trait values, leading to convergence in
178 the distribution of trait values among coexisting species (Kraft et al., 2008). Yet, for
179 communities across a continental scale aridity gradient, the community-weighted variance of
180 g increased with climatic aridity. Notably, this difference for g would be expected due to the
181 ability of plants to close stomata; species with a high g are not obliged to maintain high
182 stomatal conductance during stressful periods, as species with large stomatal pores areas can
183 sharply reduce stomatal conductance and thus transpiration rates. The distance between
184 observed kurtosis and minimum kurtosis (D) for g was lower than that generated by two null
185 models (Table S1), consistent with a general assembly rule that trait diversity of g is
186 maximized within forest plant communities, as previously demonstrated for global drylands in

187 analyses of specific leaf area and maximum height (Gross et al., 2017). Further, the D values
188 of g was lower for drier communities, suggesting that this assembly rule applies more
189 strongly with increasing aridity. Similarly to root stratification (Oram et al., 2018), diversity in
190 g and associated stomatal regulation strategies might improve species-specific soil moisture
191 status (West et al., 2012) and increase species partitioning water resources in space and/or
192 time, thus increasing overall water utilization (Naeem et al., 1994). We observed a negative
193 relationship between community-weighted variance and kurtosis of g (Fig. S1); communities
194 characterized by low variance and low kurtosis values were only observed in the wetter
195 regions, indicating that community assembly process of g was more strictly constrained under
196 lower water availability. The strong patterns linking the stomatal traits of communities with
197 climate at continental scale highlights the importance of these traits across the background of
198 other structural and physiological adaptations to aridity, including specialized xylem anatomy,
199 plant allometry, rooting strategy, dormancy and the ability to recover after dieback (Grossiord,
200 2020).

201

202 **Limited variability of stomatal space-use efficiency (e) under water scarcity**

203 Stomatal space-use efficiency (e) was first defined in this study, and, by contrast with g
204 and f , community-weighted mean values of e were not statistically constrained by climatic
205 aridity, supporting theory that this efficiency should be generally maximized
206 (Franks and Beerling, 2009). For g and f , the overall negative correlation community-weighted
207 mean trait values with aridity was consistent with the expected trends based on adaptation
208 (Garnier and Navas, 2012; Garnier et al., 2004; Grime, 1998). Likewise, given that

209 community-weighted mean values of e were highly conservative, the narrow
210 community-weighted variance of e would reflect adaptation in which co-occurring species
211 tend to converge in e to a narrow range of optimal values. Our results supported the
212 hypothesis that the variability of e was especially strongly constrained under arid climates,
213 consistent with the expectation of greater cost-effectiveness of investment in stomata under
214 lower water availability than under high water availability, where selection would likely be
215 weaker.

216

217 **Coordinated adaptation of g and f across a climatic gradient**

218 For both g and f , the community-weighted mean and variance increased with the climatic
219 aridity, whereas D decreased, and the trait diversity was maximized. Thus, the distributions of
220 g and f were synchronous in adapting to the environment. Given that g is determined as the
221 product of f and e , and that variation in g was primarily caused by f rather than e , it is clear
222 that the shifts in stomatal area fraction are more typical for the adaptation and assembly of g
223 than shifts in e , which remains constrained. As e is inversely proportional to stomatal size (see
224 Supplementary Note 1 for detailed information), its constraint is consistent with previous
225 studies reporting that stomatal size is less variable than stomatal density or f (Beaulieu et al.,
226 2008; Jordan et al., 2015; Xiong and Flexas, 2020).

227

228 **Contrasting roles of g and f in optimizing ecosystem productivity**

229 Selection for higher g (the benefit) involves a trade-off to minimize f (the cost) (de Boer et al.,
230 2016), and such cost-benefit relationship is also involved in how stomatal traits regulate

231 ecosystem productivity. Decreasing the skewness of g and increasing the skewness of f meant
232 that species with high g and/or low f values were more dominant within communities; thus,
233 the optimization of stomata on ecosystem productivity was economical through decreasing the
234 skewness of g and increasing the skewness of f . A previous study also argued that high
235 kurtosis in leaf traits indicated strong trait optimization (Umaña et al., 2021). Here, the high
236 kurtosis of g meant that co-occurring species of g were convergent toward an optimal value.
237 Nevertheless, the high kurtosis and lower skewness of g coupled with lower kurtosis and
238 higher skewness of f would result in improved e , i.e., the benefit-cost ratio (de Boer et al.,
239 2016), which was positively correlated with ecosystem productivity. Therefore, contrasting
240 regulations of g and f on ecosystem productivity were associated with stomatal cost-benefit
241 relationship.

242

243 **Materials and Methods**

244 **Study sites and climate data**

245 Nine study sites were selected along the 3700-km north–south transect of China
246 (NSTEC), which were designated as Huzhong, Liangshui, Changbai, Dongling, Taiyue,
247 Shennongjia, Jiulian, Dinghu, and Jianfengling. The nine study sites extend from 18.7 °N to
248 51.8 °N latitude, and represent examples of most of the forest types in the northern
249 hemisphere, including cold-temperate coniferous forest, temperate deciduous forest,
250 subtropical evergreen forest, and tropical rain forest (He et al., 2019). Along the NSTEC
251 transect, the mean annual temperature (MAT) ranges from –3.67 to 23.2 °C, and mean annual
252 precipitation (MAP) from 472 to 2266 mm (He et al., 2020). Soil types range from

253 cold-temperate brown soils with high organic matter content to tropical red soils with low
254 organic matter content.

255

256 **Sample collection and analysis**

257 The field survey was conducted in July–August 2013, the peak period of growth for all
258 species. Sampling plots were located within well-protected national nature reserves with
259 relatively continuous vegetation, which is representative of the given forests. Three or four
260 experimental plots (30 m × 40 m) located least 100 m apart were established in each site.
261 Geographical information (latitude, longitude, and altitude), plant species composition, and
262 community structure were recorded for each plot. The number, height, diameter at breast
263 height (DBH) of trees, basal stem diameter of shrubs, and aboveground live-biomass of all
264 herbs were measured (He et al., 2018).

265 Leaves were collected from trees, shrubs, and herbs within the plots. For each species,
266 more than 20 mature leaves were collected from the top of the canopy of four healthy
267 individuals and mixed as a composite sample. The leaves were collected from trees using
268 long-handle shears or handpicked by climbing the trees. About half of the leaves were placed
269 in sealed plastic bags, immediately stored in a box with ice, and others were used to measure
270 leaf morphological traits (Li et al., 2018).

271 After sampling, leaf size was measured using a scanner (Cano Scan LIDE 100, Japan)
272 and Photoshop CS software (Adobe, United States). These leaves were subsequently dried to
273 constant mass in an oven before measuring leaf dry mass, and specific leaf area as the ratio of
274 leaf area to leaf dry mass. Eight to ten leaves from the pooled sample were cut into small

275 pieces (1.0×0.5 cm) along the main vein and were fixed in 75% alcohol: formalin: glacial
276 acetic acid: glycerin (90:5:5:5).

277 Stomatal traits were imaged using a scanning electron microscope (S-3400N, Hitachi,
278 Japan), using the same leaf samples as previously studied for stomatal density, size and
279 stomatal area fraction (Liu et al., 2018). Three small pieces were selected from the pooled
280 sample, and each replicate was photographed twice on the lower surface at different positions.
281 Given our use of scanning electron microscopy and investigation of a large number of species
282 across communities, the labor and expense did not allow measurements of the upper
283 epidermis, and we focused on the lower epidermis (Liu et al., 2019). The herbaceous species
284 in closed forests typically have more stomata on their adaxial surfaces, whereas trees and
285 shrubs tend to have few or no stomata on the adaxial surface (Muir, 2015; Muir, 2018). Thus,
286 sampling only the lower epidermis results in some uncertainty, but the community level
287 findings are expected to be robust.

288 The number of stomata in each photograph was recorded, and stomatal density (SD) was
289 calculated as the number of stomata per unit area (Liu et al., 2018). In each photograph, five
290 typical stomata were selected to measure stomatal length (SL), stomatal pore length (PL), and
291 stomatal width (SW) by using MIPS (Optical Instrument Co., Ltd., Chongqing, China). We
292 used the above stomatal traits to calculate f and g (Franks and Farquhar, 2001).

$$f = \frac{\pi}{4} \cdot SD \cdot SW \cdot SL$$
$$g = SD \cdot \left(\frac{D_w}{v} \right) \cdot \frac{a_{\max}}{l + 0.5 \cdot (\pi \cdot a_{\max})^{0.5}}$$

293 where D_w is the diffusivity of water in air, v is the molar volume of water vapor, a_{\max} is the
294 maximum pore area (estimated as the area of the ellipse with major axis PL and minor axis

295 0.5PL), and l is the depth of the stomatal pore, which was approximated as guard cell width.

296 We then calculated e as the ratio of g to f . Notably, e depends inversely on stomatal size,

297 because smaller stomata, having shorter depths, are more efficient for transport for a given

298 pore area (Franks and Farquhar, 2006); the mathematical relationships of e to stomatal size is

299 presented in Supplementary Note 1.

300

301 **Stomatal trait moments of plant communities**

302 To scale up traits to the community scale, and given that stomatal traits were normalized by

303 leaf area, we used the total leaf area of each species in the plot to weight species trait values,

304 and then calculated the distributions of stomatal traits. The total leaf biomass of each

305 individual tree and shrub was calculated using species-specific allometric regressions based

306 on measured values of height, diameter at breast height (DBH) or basal stem diameter, and

307 then the leaf biomass of each species within plots was calculated. Species-specific allometric

308 regressions were obtained from the Chinese Ecosystem Research Network (Wang et al., 2015).

309 The leaf biomass of herbs was measured using the harvest method. The total leaf area of each

310 species was calculated as the product of total leaf biomass and specific leaf area.

311 Community-weighted mean, variance, skewness, and kurtosis were calculated as follows

312 (Gross et al., 2017; Wiczyński et al., 2019):

$$\begin{aligned}\text{Mean} &= \sum_1^n p_i \text{Trait}_i \\ \text{Variance} &= \sum_1^n p_i (\text{Trait}_i - \text{Mean})^2 \\ \text{Skewness} &= \sum_1^n \frac{p_i (\text{Trait}_i - \text{Mean})^3}{\text{Variance}^{\frac{3}{2}}}\end{aligned}$$

$$\text{Kurtosis} = \sum_1^n \frac{p_i (\text{Trait}_i - \text{Mean})^4}{\text{Variance}^2}$$

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314

where n is the species richness, p_i is the proportion of leaf area of i^{th} plant species in a specific community, and Trait_i represents stomatal traits (g , f , or e) of the i^{th} plant species.

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The community trait variance, skewness, and kurtosis provide information beyond the community weighted mean, which can over-emphasize the role of dominant species (Enquist et al., 2015). Specifically, the community variance in a given traits represents the functional divergence, skewness the extent of asymmetric distribution of traits, and kurtosis the functional evenness, with a high kurtosis indicating strong trait optimization (Umaña et al., 2021). Skewness and kurtosis are mathematically related, according to skewness-kurtosis relationships (SKR):

$$\text{Kurtosis} \geq \text{Skewness}^2 + 1$$

322

323

Thus, for a given skewness, there is a minimum kurtosis. Here, we calculated the distance between the observed kurtosis and minimum kurtosis (D):

$$D = \text{Kurtosis} - (\text{Skewness}^2 + 1)$$

324

325

D signifies the extent to which functional diversity is maximized, with a $D = 0$ representing the strongest possible maximization of functional diversity (Gross et al., 2017).

326

327 **Climate data and ecosystem productivity**

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Mean annual temperature and precipitation (MAT and MAP, respectively) were derived from the Resource and Environment Data Cloud Platform (<http://www.resdc.cn/>). Then, the de Martonne aridity index (de Martonne, 1926) was calculated the ratio of MAP and $\text{MAT}+10$.

331

To facilitate the interpretation of results, we calculated the climatic aridity index for each site
332
as:

$$CI = 100 - \frac{MAP}{MAT + 10}$$

333

so all the CI values were positive, and higher values of this aridity level indicate drier
334
conditions.

335

In these forests, gross primary productivity and net primary productivity were strongly
336
correlated with each other across sites (Li et al., 2020); here, we focused on gross primary
337
productivity (GPP). The average GPP data from 2000 to 2015 (Li et al., 2020) were obtained
338
from the Numerical Terradynamic Simulation Group
(<http://www.ntsug.umt.edu/project/modis/mod17.php>). This dataset was derived from a widely
340
used Moderate Resolution Imaging Spectroradiometer product, and was calculated using the
341
C5 MOD17 algorithm with data validation from flux towers (Li et al., 2020; Zhao and Running,
342
2010; Zhao et al., 2005).

343

344 **Data analysis**

345

We calculated statistical moments for stomatal traits, including mean, variance, skewness, and
346
kurtosis, for each of the 32 plant community plots. We tested whether to consider plots
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independently, rather than as nested within sites, for calculating community scale moments by
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comparing fixed effects models (*lm* function in R) and mixed effects models (*lmer* function
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from R package *lme4*). The fixed model considered plots as independent, and the mixed
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effects models, considered plots as a random factor nested within each site. Akaike
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information criterion (AIC) represented the support of the model by data, with the model

352

353 having a lower AIC value more likely to underlie the data (Burnham and Anderson, 2004). The
354 AIC values of fixed and mixed effects models were compared, with differences greater than 2
355 considered decisive in selecting one model over another, representing a >100 times higher
356 likelihood that the data were generated by that model. For 12 of the 13 relationships of traits
357 with climate or ecosystem productivity tested in this study, the fixed effects model was
358 selected (Table S1-S5). Thus, in our analyses, we considered each plot as a sample plant
359 community.

360 Spearman rank correlation was used to test relationships between stomatal trait moments
361 and climate variables. Ordinary least square regression was used to quantify relationships
362 between statistical moments of stomatal traits, including the relationship between skewness²
363 and kurtosis, and relationship between variance and kurtosis. To explore whether climatic
364 aridity mediated the relationships between variance and kurtosis, plant communities were
365 classified into wet and dry communities (threshold CI=40), and scatter diagrams of variance
and kurtosis were plotted.

366 Focusing on the distance to the minimal kurtosis (D) enables resolution of variation
367 across communities in trait evenness (Gross et al., 2021), and a test of the hypothesis that
368 functional niche differentiation of g would be greater in drier communities, by determining
369 the correlation between the distance to the minimal kurtosis (D) and climatic aridity. To
370 clarify whether trait assembly of stomata would maximize stomatal trait diversity, we tested
371 whether observed skewness-kurtosis relationships (SKRs) differed from random expectations,
372 which can reveal the signature of niche differentiation in shaping ecological communities
373 (Gross et al., 2021). We constructed two null models, and predictions from each null model

374 were derived from 2000 randomizations. In the first null model, we randomized the stomatal
375 traits across all species, using the function “richness” in the R package PICANTE (Kembel et
376 al., 2010). In the second null model, we shuffled stomatal traits across species occurring in
377 each community, using the function “independentswap” in the R package PICANTE. These
378 two null models have been the most common for analyzing community assembly, with the
379 second null model more specific in its implication. The first null model allows tests for
380 maximizing trait diversity locally, relative to a scenario of random selection of species from
381 the regional pool. The second null model allows tests for maximizing trait diversity locally
382 relative to a scenario of random selection of species from local pools. Stomatal trait moments
383 were then calculated for each of the 2000 randomizations, for each of the null models used.
384 Then, we assessed whether the observed SKR significantly differed from SKR_{random} . Monte
385 Carlo analysis was used to test whether the observed SKRs differed from random expectations.
386 We compared the observed slope β and intercept α (β_{obs} and α_{obs} , respectively) of the SKR
387 with those generated by null models (β_{random} and α_{random} , respectively). Three Pseudo P values
388 were calculated: $P(\beta|\alpha)$, the frequency of $\beta_{\text{obs}} > \beta_{\text{random}}$ within subset $\alpha_{\text{obs}} < \alpha_{\text{random}}$; $P(\alpha|\beta)$, the
389 frequency of $\alpha_{\text{obs}} > \alpha_{\text{random}}$ within subset $\beta_{\text{obs}} < \beta_{\text{random}}$; and $P(\beta \cap \alpha)$, the frequency of $\alpha_{\text{obs}} <$
390 α_{random} within subset $\beta_{\text{obs}} < \beta_{\text{random}}$. Further, we compared the observed distance to the minimal
391 kurtosis (D_{obs}) with that generated by null models (D_{random}). $P(D)$ is the frequency of $D_{\text{obs}} <$
392 D_{random} .

393 A multiple regression model was used to assess the potential influence of stomatal trait
394 moments on ecosystem productivity, and quadratic terms of stomatal trait moments were also
395 considered as potential drivers of non-linear effects of these variables on ecosystem

396 productivity. All variables, including ecosystem productivity and stomatal trait moments, were
397 standardized (Z-scores) before analysis. We first used the “stepAIC” function (MASS package
398 in R) to exclude less important predictors, then the “dredge” function (MuMIn package in R)
399 was used to select the best models. Finally, the relative effect of each stomatal trait moment
400 on ecosystem productivity was calculated as its absolute parameter compared with the sum of
401 all the absolute parameters in the model.

402 Standardized effect sizes (SES) were used to assess the non-random influence of
403 stomatal traits on ecosystem productivity. SES was calculated as (Bruehlheide et al., 2018)

$$SES = \frac{Adj. r_{obs}^2 - mean(Adj. r_{null}^2)}{s. d. (Adj. r_{null}^2)}$$

404 where $Adj. r_{obs}^2$ is the observed influence of stomatal traits on ecosystem productivity,
405 $Adj. r_{null}^2$ is the influence of stomatal traits on ecosystem productivity of random
406 communities generated from a null model, *mean* represents the average value, and *s. d.* is
407 the standard deviation.

408 Data analyses and visualization were performed using R (<http://www.R-project.org/>).

409 Statistical significance was set at the 0.05 level.

410

411 **Author contribution**

412 N.H. planned and designed the research; C.L. and Y.L. conducted fieldwork and collected
413 data; C.L., L.S. and Y.L. analyzed data and wrote the manuscript; L.S. and C.L. revised the
414 manuscript.

415

416

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420 (2020M680663). There are no conflicts of interest to declare.

421

422 **Data accessibility**

423 The data that support the findings of this study are available from the corresponding author
424 upon reasonable request.

425

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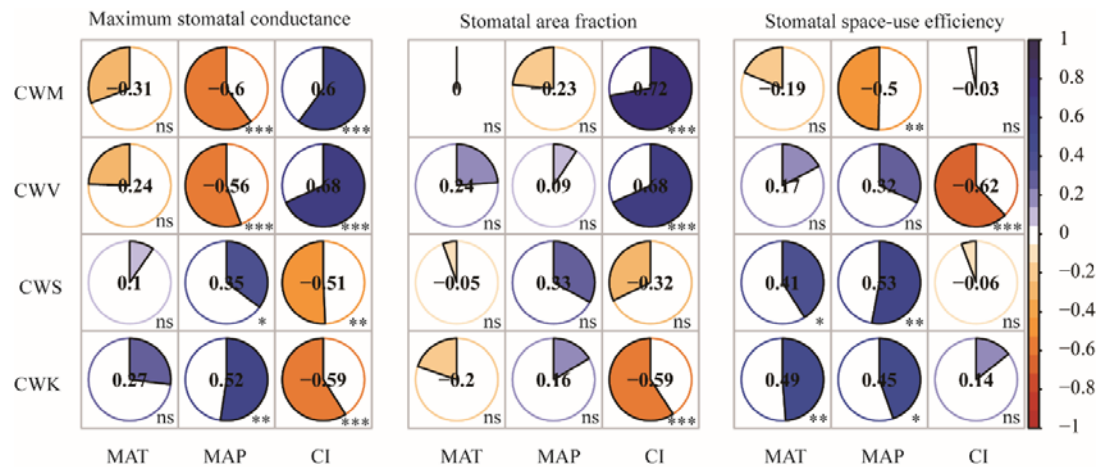
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573

574 **Fig. 1 Stomatal trait moments are broadly related to climatic aridity.**

575 CWM, community-weighted mean; CWV, community-weighted variance; CWS,

576 community-weighted skewness; CWK, community-weighted kurtosis

577 MAT, mean annual temperature; MAP, mean annual precipitation; CI, climatic aridity index;

578 Spearman rank correlation coefficients are shown in the panels.

579 Fan-shaped areas are proportional to the absolute Spearman rank correlation coefficients;

580 negative correlations are drawn with a counterclockwise fan and positive correlations with a

581 clockwise fan. The strength of negative correlation increases from white to red, and the

582 strength of positive correlation increases from white to blue.

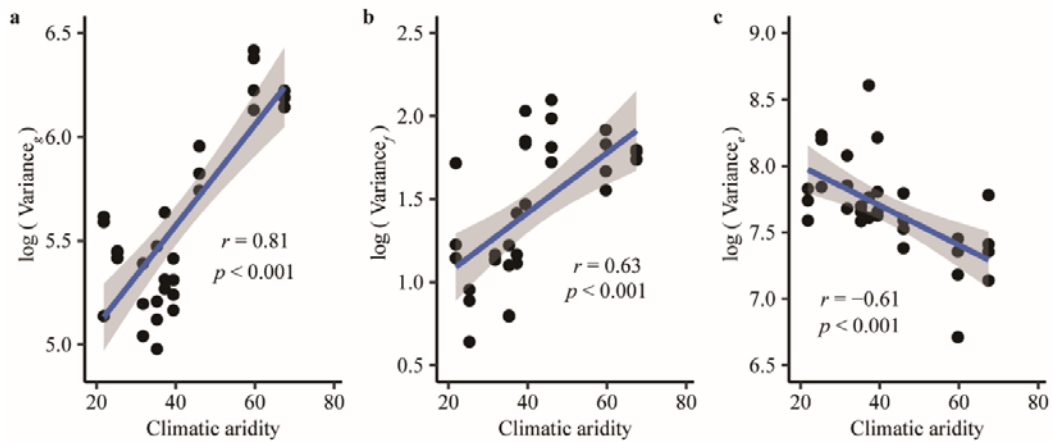
583

584 ns, no significance at the 0.05 level; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$.

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590 **Fig. 2 Relationships between the community-weighted variance of stomatal traits and**
591 **climatic aridity**

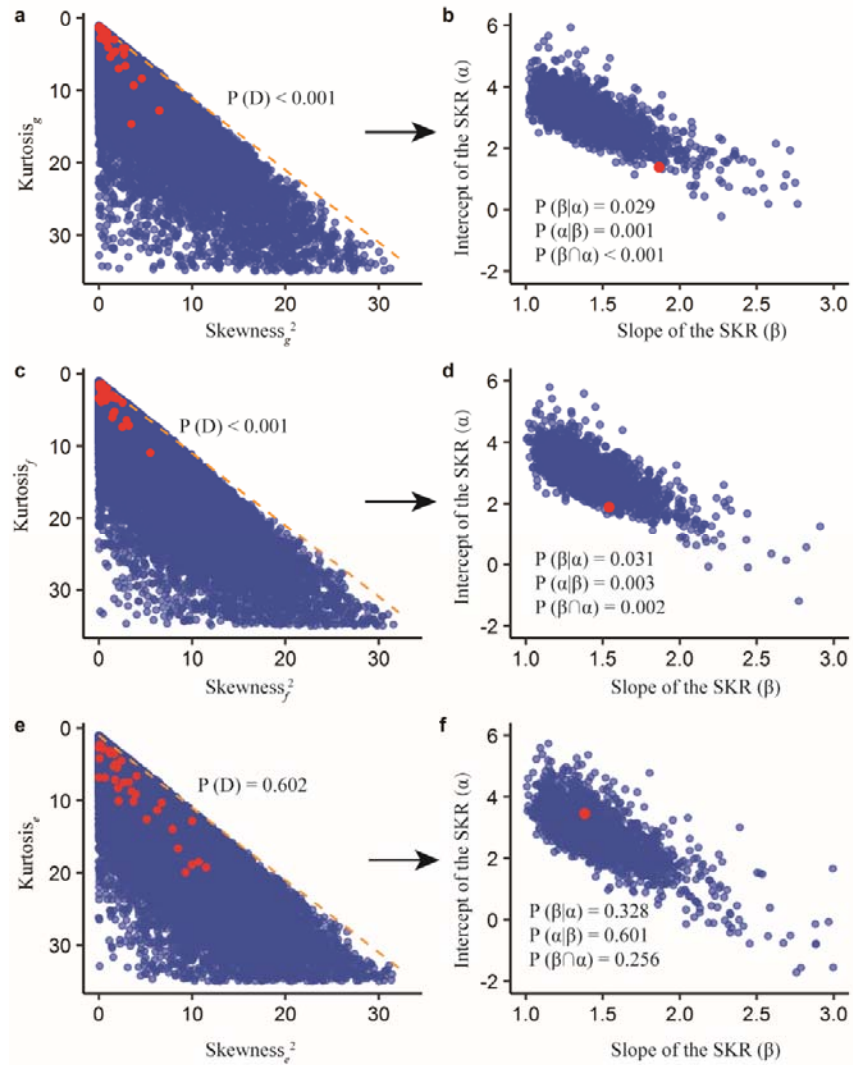
592 Variance, community-weighted variance.

593 g , maximum stomatal conductance; f , stomata area fraction; e , stomatal space-use efficiency.

594 The blue lines are fitted using linear regression, and shaded areas indicate the 95% confidence
595 interval.

596

597



598

599 **Fig. 3 Observed skewness-kurtosis relationships (SKR) and deviation from null**
 600 **expectations.**

601 Skewness, community-weighted skewness; Kurtosis, community-weighted kurtosis.

602 g , maximum stomatal conductance; f , stomatal area fraction; e , stomatal space-use efficiency.

603 The red dots in the left panels represent the observed skewness and kurtosis values; blue dots

604 in the left panels represent the skewness and kurtosis values of simulated random

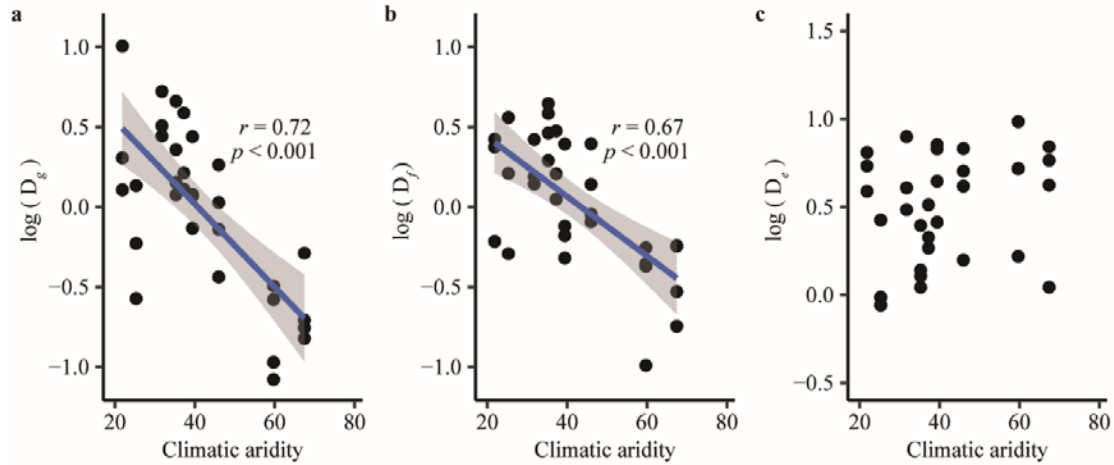
605 communities. The orange line represents $y = x + 1$.

606 Red/blue dots in the right panels represent the observed/random slope (α) and intercept

607 (β) of the SKRs. We indicate the conditional pseudo P values from null model ‘richness’ for

608 the slope β , $P(\beta | \alpha)$, the y-intercept α , $P(\alpha | \beta)$, the whole model, $P(\beta \cap \alpha)$ and the distance to

609 the lower boundary, $P(D)$ (see Table S6 for details).



610

611 **Fig. 4 Relationships between the distance to the lower boundary (D) and climatic aridity.**

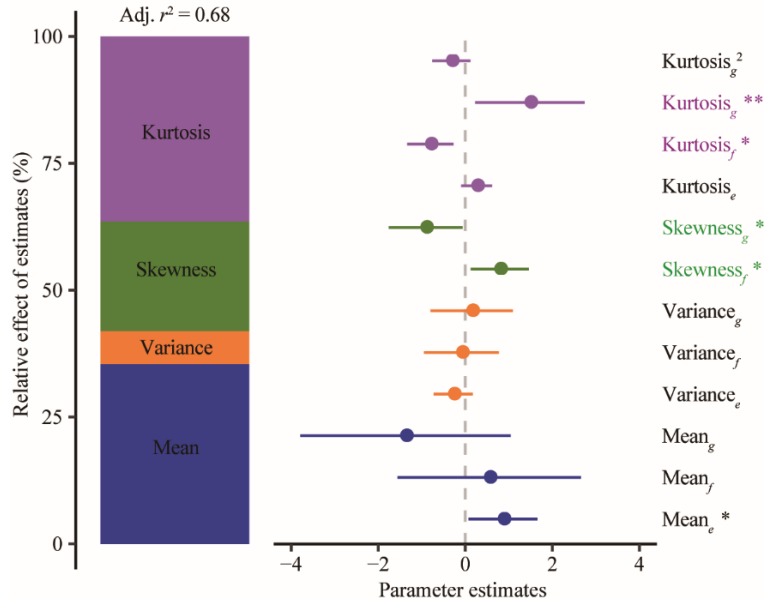
612 g , maximum stomatal conductance; f , stomatal area fraction; e , stomatal space-use efficiency.

613 The blue lines were fitted using linear regression and the shaded areas indicate the 95%

614 confidence interval.

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619 **Fig. 5 Community-weighted skewness and kurtosis of g and f showed opposite effects on**
620 **ecosystem productivity.**

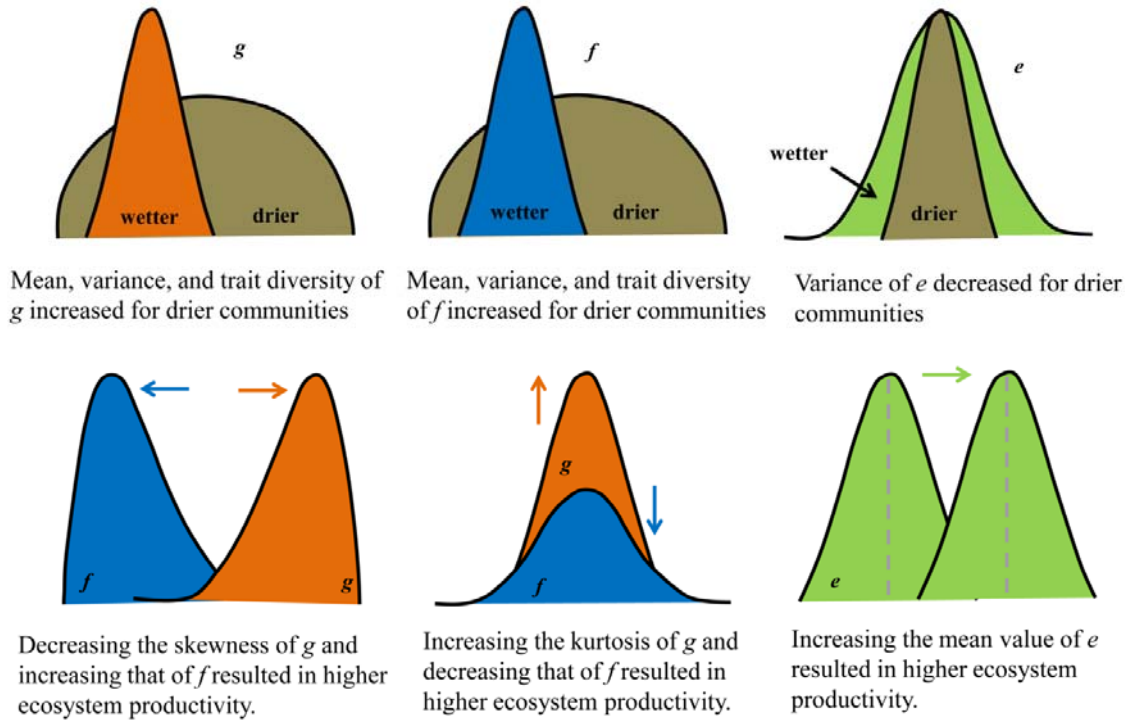
621 Mean, community-weighted mean; Variance, community-weighted variance; Skewness,
622 community-weighted skewness; Kurtosis, community-weighted kurtosis.

623 g , maximum stomatal conductance; f , stomatal area fraction; e , stomatal space-use efficiency.

624 Average parameter estimates (standardized regression coefficients) of model predictors,
625 associated 95% confidence intervals, and relative importance of each factor, expressed as the
626 percentage of explained variance.

627 The adjusted r^2 of the averaged model and the p value of each predictor are given as: *, $p <$
628 0.05; **, $p < 0.01$. Colored labels in the right highlighted the different effects of g and f on
629 ecosystem productivity.

630



631

632 **Fig. 6 Conceptual diagrams of how stomatal trait distributions adapt drought stress and**
633 **regulate ecosystem productivity.**

634 g , maximum stomatal conductance, shown by orange; f , stomatal area fraction, shown by blue;

635 e , stomatal space-use efficiency, shown by green.

636