

1 **Elevational Range Sizes of Woody plants Increase with Climate Variability in**
2 **the Tropical Andes**

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25 **Abstract**

26 **Aim**

27 The climate variability hypothesis proposes that species subjected to wide variation in climatic conditions
28 will evolve wider niches, resulting in larger distributions. We test this hypothesis in tropical plants across
29 a broad elevational gradient; specifically, we use a species-level approach to evaluate whether elevational
30 range sizes are explained by the levels of thermal variability experienced by species.

31 **Location**

32 Central Andes

33 **Time period**

34 Present day

35 **Major taxa studied**

36 Woody plants

37 **Methods**

38 Combining data from 479 forest plots, we determined the elevational distributions of nearly 2300 species
39 along an elevational gradient (~209 – 3800 m). For each species, we calculated the maximum annual
40 variation in temperature experienced across its elevational distribution. We used phylogenetic generalized
41 least square models to evaluate the effect of thermal variability on range size. Our models included
42 additional covariates that might affect range size: body size, local abundance, mean temperature and total
43 precipitation. We also considered interactions between thermal variability and mean temperature or
44 precipitation. To account for geometric constraints, we repeated our analyses with a standardized measure
45 of range size, calculated by comparing observed range sizes with values obtained from a null model.

46 **Results**

47 Our results supported the main prediction of the climate variability hypothesis. Thermal variability had a
48 strong positive effect on the range size, with species exposed to higher thermal variability having broader
49 elevational distributions. Body size and local abundance also had positive, yet weak effects, on
50 elevational range size. Furthermore, there was a strong positive interaction between thermal variability
51 and mean annual temperature.

52 **Main conclusions**

53 Thermal variability had an overriding importance in driving elevational range sizes of woody plants in the
54 Central Andes. Moreover, the relationship between thermal variability and range size might be even
55 stronger in warmer regions, underlining the potential vulnerability of tropical montane floras to the effects
56 of global warming.

57 **Keywords**

58 Andes, Bolivia, Climate variability hypothesis, Elevation, Forest plots, Madidi, Range size, Trees

59 **1 INTRODUCTION**

60 Assessing the mechanisms shaping the distribution of species is essential to better understand the
61 assembly of local communities and the potential consequences of environmental drivers on biodiversity
62 patterns (Bellard *et al.*, 2012; Nadeau *et al.*, 2017). This is particularly urgent for mountain regions, areas
63 of great importance for biodiversity conservation (Jung *et al.*, 2021). Mountain ranges are characterized
64 by high environmental heterogeneity across space and time (Rahbek *et al.*, 2019a), and harbor roughly
65 one third of terrestrial living organisms, including many small-ranged species (Rahbek *et al.*, 2019b).
66 Understanding the drivers of montane species ranges, particularly in the tropics, is critical given the
67 threats that climate change and human modifications of the landscape poses to the distribution and
68 persistence of species in these regions.

69 Although species distributions are often modeled as a function of average environmental conditions in a
70 site or a region, temporal variation in these conditions can have profound effects on population and
71 species adaptations, and consequently on their distribution. The climate variability hypothesis proposes
72 that species subjected to wider temporal variation in climatic conditions will evolve tolerances to broader
73 environmental niches, resulting in wider geographic distributions (Stevens, 1989). Correspondingly,
74 species experiencing stable environments would develop narrow tolerances and small geographic
75 distributions. The climate variability hypothesis has been proposed as a potential explanation for some
76 classical patterns in ecology and biogeography. For example, the increases in range size with latitude
77 (Rapoport, 1982) could be a consequence of increases in seasonal or daily climatic variability toward
78 temperate regions (Stevens, 1989; Chan *et al.*, 2016). Similarly, Janzen (1967)' classic proposition that
79 tropical mountains represent physiologically stronger filters for organisms than temperate mountain could
80 also be seen as a special case of the climate variability hypothesis. Janzen's hypothesized that having
81 evolved in less variable environments, montane tropical species will likely have limited acclimation
82 responses and, in consequence, smaller elevational ranges than species in temperate mountains.

83 Within tropical mountains climatic variability can fluctuate significantly across elevation; for example,
84 daily temperature variation can be dramatic at high elevations, but only mild in the lowlands (McCain,
85 2009). If temporal variation in climate influences species distributions within mountains, then species
86 near tropical mountain tops should have more extensive elevational distributions than species in the
87 lowlands. This extension of the climate variability hypothesis to elevation (ECVH; Stevens, 1992) has
88 been tested in many taxa, producing conflicting results (McCain & Knight, 2013; Chan *et al.*, 2016; Shah
89 *et al.*, 2021). Whereas some studies show increases in range size with latitude and elevation (e.g.,
90 Patterson *et al.*, 1996; Pintor *et al.*, 2015), others have refuted these patterns (e.g., (Hawkins & Felizola
91 Diniz-Filho, 2006; Maccagni & Willi, 2022). Contradictory results have fueled a debate regarding
92 whether species responses to climate variation is only a local phenomenon or a consistent pattern (Rohde,
93 1996; McCain & Knight, 2013). Part of the reason for the inconsistent results among studies testing
94 ECVH could be limitations to analyses or data. Geometric constraints in the distribution of species, for
95 instance, have rarely been accounted for when testing ECVH hypothesis, resulting on strong criticisms on
96 the statistical approaches and assumptions behind these studies (Ribas & Schoereder, 2006; McCain,
97 2009; Macek *et al.*, 2021). Additionally, most studies of ECVH carry out assembly-level analyses, where
98 the average range size for groups of species is used, and analyses focus on how these averages change
99 across space (Rohde, 1992; Stevens, 1992). However, the evolution of climatic tolerances and responses
100 to climatic variability are species-specific and, as such, require species-level analysis. Species-level and
101 high-quality datasets are rare, particularly in diverse tropical regions, preventing species-level tests of
102 ECVH in tropical mountains.

103 Studies testing predictions from the ECVH in vascular plants include only a few examples on the sub-
104 tropical floras of the Himalayas (e.g., Liang *et al.*, 2021; Macek *et al.*, 2021) and the temperate Caucasus
105 mountains (Mumladze *et al.*, 2017), as well as studies focusing on smaller sets of temperate plants that
106 extend ECVH predictions to other species characteristics (e.g., trait plasticity; Molina-Montenegro &
107 Naya, 2012; Maccagni & Willi, 2022). To our knowledge the only study that has directly tested the

108 climate variability hypothesis on Neotropical plants has focused only on alpine communities in the Andes
109 (>3000 m; Cuesta *et al.*, 2020). This study found that tropical alpine species had narrower thermal niches
110 than temperate species, supporting predictions derived from the classic CVH, but no significant effects of
111 elevation. In consequence, whether temporal climatic variability shapes the distribution of tropical plant
112 species along elevational gradients is yet poorly understood. A thorough analysis of the predictions of
113 ECVH is necessary, particularly in tropical plants, to understand how species respond to climatic
114 variability, and particularly, whether climatic variability can promote the formation of large geographic
115 ranges.

116 Here, we present the most thorough species-level test of the climate variability hypothesis across
117 elevations (ECVH). Specifically, we evaluate whether species with populations experiencing high levels
118 of temperature variation will have larger elevational distributions. For our study, we use data from the
119 Madidi Project (www.madidiproject.weebly.com), a collaborative effort to document and study the plant
120 biodiversity of the Tropical Andes, and possibly the most extensive dataset on tree occurrences in any
121 tropical mountain. Using this data, we evaluate the effect of climate variability while controlling for the
122 effects of geometric constraints and the potential confounding effects of other factors that have been
123 proposed to affect range size, such as species characteristics (e.g., size), species abundance, and local
124 temperature and precipitation. Our dataset and approach provide a unique opportunity to study the forces
125 that drive the distribution of tree species in one of the most species-rich regions of the planet.

126 **2 METHODS**

127 **2.1 Vegetation Data and Elevational Range Sizes**

128 Species elevational distributions were determined based on a large network of forest plots distributed
129 along the eastern slopes of the Bolivian Andes (Fig. 1). The network consists of 48 1-ha plots (henceforth
130 large plots) and 458 0.1-ha plots (small plots) ranging in elevation from 209 m (Amazon forests) to 4,347
131 m (tree line). Within plots, all individuals of woody plant species with diameters at breast height (dbh)

132 equal or above 10 cm (for large plots) or 2.5 cm (for small plots) were measured and identified. Each
133 individual tree was assigned a species or morphospecies name (henceforth simply species), and extensive
134 taxonomic work was conducted to ensure that names were applied consistently throughout all plots. For
135 this study, we used version 5.0 of the Madidi Project plot database
136 (<https://doi.org/10.5281/zenodo.5160379>). The species-level data and code necessary to replicate our
137 analyses has been deposited and can be freely accessed in Zenodo ([*link will be updated upon*
138 *submission*]).

139 From these data, we removed all cacti (Cactaceae); bamboos (Poaceae), tree ferns (Dicksoniaceae and
140 Cyatheaceae), gymnosperms (Podocarpaceae), and the non-native genera *Eucalyptus* and *Coffea*. We also
141 removed plots above 3,800 m in elevation, which were dominated by species of *Polylepis* and likely
142 managed by local communities. Finally, because we only sampled individuals with a dbh 2.5 cm or larger,
143 species that rarely reach this size might be present in our data but seriously under-represented relative to
144 their true abundances. Thus, we examined the distribution of species-level maximum size values across
145 our dataset and eliminated all species with maximum size below the lowest 5% of the distribution (this is,
146 all species with maximum size less or equal to 3.24 cm; see Fig. S1). This resulted in the elimination of
147 169 individuals of 126 species. Finally, we eliminated 1,328 individuals that could not be assigned to
148 species or morphospecies (<1% of individuals) and 436 individuals from 16 additional species that could
149 not be placed in the regional phylogeny (see below). After data curation, our dataset contained
150 information on the distribution of 153,084 individuals belonging to 2,292 species across 479 forest plots
151 (48 large plots and 431 small plots).

152 We estimated the elevational distribution of each species in our dataset by recording their highest and
153 lowest elevation of occurrence (Fig. 2A). Elevational range size was calculated as the difference in meters
154 between these two points. Elevational position was characterized by the species' elevational mid-point
155 (the mean between the maximum and minimum elevation of occurrence). For the estimation of
156 elevational distributions, we merged the data from large and small plots with the objective of using all the

157 available information for each species. After this process, we further excluded 461 species that were
158 found in only one plot and thus could not be assigned to a reliable value of elevational range. Elevational
159 range size had a strongly skewed frequency distribution (Fig. 2B). Most species had very small ranges
160 and very few had broad elevational distributions. The mean and median of elevational range size were
161 702 and 607 m respectively; the maximum was 2,812 m.

162 To account for heterogeneity among species in range size estimation and ensure that our conclusions did
163 not depend on the precise collection of species used, we repeated all analyses using two alternative
164 subsets of species (Fig. S2). In the second set of species, we included only species that were present in 3
165 or more sites or that had 5 or more individuals (1,713 species); in the third set, we subsampled forest plots
166 to reduce heterogeneity in sampling effort across elevations. We divided the elevational gradient (209 to
167 3,717 m) into 20 equal-sized bands; in each band, we randomly selected 12 forest plots. This procedure
168 reduced the data to 220 forest plots and 71,165 individuals, resulting in 1,280 species included in the third
169 dataset. Despite considerable differences among these datasets, all analyses support the same conclusions,
170 thus we present results for our complete dataset in the main text and provide results for the two subsets of
171 data in the supplementary materials.

172 **2.2 Temperature and Precipitation Data and Species-Level Predictors**

173 Using the coordinates of each forest plot, we extracted temperature data from WorldClim 2.0 (at ~1km
174 resolution; Fick & Hijmans, 2017). We considered other alternative climate datasets (e.g., Chelsa 1.2;
175 Karger *et al.*, 2017), but we found that WorldClim 2 was the closest match to field measurements of
176 temperature (Fig. S3). We extracted precipitation data from TRMM 2b31-Based Rainfall Climatology
177 Version 1.0 at ~1km resolution; Mulligan, 2006). For each plot, we obtained data on mean annual
178 temperature (MAT), total annual precipitation (TAP), annual temperature range (ATR) and diurnal
179 temperature range (DTR). Across the plot network, mean annual temperature decreases dramatically
180 across elevations from 25.4 to 9 °C (Fig. S4A). Similarly, estimates of total precipitation range from
181 3,819 to 197 mm per year. Although temperature variability generally increased with elevation (Fig.

182 S4B), the pattern was non-linear: annual temperature range showed a small initial dip towards
183 intermediate elevations (with a minimum around 1,250 m), before a steep increase towards the highlands.
184 Finally, diurnal temperature range is closely correlated with annual temperature range (Fig. S4D). For this
185 reason, the effect of annual and diurnal variability could not be disentangled. All analyses use only data
186 on annual temperature range, but similar models were produced when diurnal temperature range was used
187 instead (Table S1). These gradients in climate suggest that populations of species in the highlands
188 experience a higher degree of temperature fluctuations than in the lowlands. The distribution of plots
189 across environmental gradients is depicted in Fig. S5 and S6.

190 For each species, we estimated the degree of temperature variation that individuals experience by using
191 the maximum value of annual temperature range at a site across all occupied plots (Max. ATR).
192 Additionally, we calculated other species-specific predictors that could be important determinants of
193 elevational range size, which were used as co-variables in our analyses. We calculated abundance-
194 weighted mean annual temperature (w-MAT) and total annual precipitation (w-TAP). For these
195 calculations, plot-level values of MAT or TAP contribute to the species mean as a function of the
196 abundance of the species in each plot. These variables represent the most typical environmental
197 conditions occupied by each species. Finally, we calculated species-level maximum size as the 90 %
198 quantile of the distribution of diameters at breast height (DBH) for each species, and species abundance
199 as the maximum value of relative abundances of each species across all occupied plots.

200 **2.3 Statistical test of hypotheses**

201 The climate variability hypothesis across elevations (ECVH) predicts that species with populations
202 experiencing high levels of temperature variation will have larger elevational distributions. To evaluate
203 this prediction, while accounting for shared evolutionary history among species, we used a phylogenetic
204 generalized least squares (PGLS) regression model, where species elevational range size was the
205 dependent variable and maximum annual temperature range (max. ATR) was the main predictor of
206 interest. In this analysis, errors were modeled using a Pagel correlation structure, which is more flexible

207 than a Brownian correlation. Phylogenetic relationships among our species are based on Smith and
208 Brown's (2018) mega-phylogeny, accessed using the R package V.PhyloMaker (Jin & Qian, 2019).
209 Species that were not found in the base phylogeny were added using taxonomic information at base of the
210 branch of the corresponding genus or family using the "S1" option in V.PhyloMaker. While this
211 phylogeny is a coarse description of evolutionary relationships, it allows us to construct phylogenetic
212 regressions that would otherwise be impossible. We used Ives' proposed R2resid metric to characterize
213 the amount of variance in the data explained within a phylogenetic regression model (Ives, 2019); rr2 R
214 package: (Ives & Li, 2018). PGLS models were performed with function gls in R package nlme (Pinheiro
215 *et al.*, 2020).

216 To account for the effects of other potentially important covariates, the PGLS model also included
217 maximum size (i.e., 90th percentile of dbh distribution per species), species abundance, mean annual
218 temperature (w-MAT) and total annual precipitation (w-TAP). To meet model assumptions, elevational
219 range size was square-root transformed, while maximum size and species abundance were log-
220 transformed. Other variables remained untransformed. All predictors were centered to a mean of zero and
221 standardized to a standard deviation to 1 before analyses. In this way, regression coefficients are
222 comparable and measure the relative importance of each predictor in the model. Finally, the model also
223 included the interactions of temperature variability with mean temperature (max. ATR \times w-MAT) and
224 annual precipitation (max. ATR \times w-TAP). We evaluated collinearity among predictors in our PGLS
225 model using variance inflation factors (VIF) using function vif in the R package car (Fox *et al.*, 2022).
226 Most variables had VIFs less than 5 indicating that collinearity is low in our models (Table 1).

227 **2.4 Accounting for Geometric Constraints and Sampling Effects on Elevational Range Sizes**

228 Geographic ranges are subject to geometric constraints given by the limits of the domain over which
229 species are distributed. In our study, the domain is the elevational gradient ranging from Amazon forests
230 at 209 m in elevation and the timberline at 3,717 m. Species in our study are constrained to be distributed
231 between these elevations (Fig. 2C). The effect of this constrained domain is expressed in the relationship

232 between elevational position and elevational range size. Species with distributions centered in the
233 lowlands (low elevational mid-points) or in the highlands (high elevational mid-points) cannot have large
234 elevational ranges. Species with distributions centered at intermediate elevations, on the other hand, are
235 free to have small or large elevational distributions. This constraint is potentially problematic for our
236 analysis and could mask the effects of environmental or biological variables on the extent of the
237 geographic distribution of species.

238 To account for this potential effect, we calculated an alternative metric of range size that is less affected
239 by these geometric constraints. First, for a focal species, we calculated the distance d between its
240 elevational mid-point to the closest edge of the elevational domain (i.e., to 209 m or 3,717 m whichever is
241 closest; Fig. 3A). This distance determines the strength of the geometric constraint on a species'
242 distribution; as this distance decreases, the range of possible elevational range sizes decreases (Fig. 3A).
243 Then, we found a pool of other species under similar geometric constraints. This pool was defined as all
244 species with d values equal to that of the focal species ± 50 m (Fig. 3A and B). Species close to both ends
245 of the domain of distribution can contribute to this pool of species with similar constraints (Fig. 3A). We
246 calculated a standardized effect size (SES) that compares the elevational range size of the focal species to
247 those of the other species in its pool (Fig. 3B). SES is simply the difference between the elevational range
248 size of the focal species and the mean range size of all other species in its pool divided by the standard
249 deviation of the range sizes in the pool. A positive SES value indicates that the focal species has a
250 distribution that is larger than other species under similar constraints, while a negative value means the
251 species has a smaller distribution. SES values were calculated in this way for all species. The statistical
252 analyses described above for elevational range size were repeated using SES of range size.

253 Finally, it is possible that relationship between range size and climate variability could be spuriously
254 produced by a sampling effect; species with large elevational ranges might also occupy many sites (high
255 occupancy). In turn, species present in many sites are able to sample the environmental space better and -
256 by chance - find higher values of climatic variability (e.g., max. ATR). To account for this potential

257 effect, we (1) examined the relationships between species occupancy (number of plots with presence of
258 the species) and elevational range size and max. ATR, and (2) repeated our PGLS regressions including
259 occupancy as a covariate. We found no evidence of this potential sampling bias in our analyses; while
260 high occupancy does lead to larger ranges (Fig. S7A), high occupancy does not necessarily imply larger
261 values of temperature variability (Fig. S7B). Moreover, the main conclusions of our analyses did not vary
262 when including occupancy as a covariate in our PGLS models (Table S2).

263 **3 RESULTS**

264 Our results provide strong evidence that elevational range sizes are shaped by temporal variation in
265 climate, particularly temperature. We found that maximum annual temperature range was the strongest
266 predictor included in our models (Table 1) and had a clear positive effect on elevational range size (Fig.
267 4). Species exposed to higher temperature variability have broader geographic distributions. This effect
268 was highly consistent across our different analyses; maximum annual temperature range had a strong
269 positive effect whether elevational range size or standardized effect sizes were used as response variables
270 (Fig. 4; Fig. S8). Similarly, maximum annual temperature range had a consistent positive effect when
271 elevational distributions were characterized using species with at least 2 occurrences (Fig. 4, Table S1), or
272 when using species with at least 3 occurrences or 5 individuals (Fig. S9, Table S3), or with a dataset that
273 has been reduced to homogenize effort across elevations (Fig. S10, Table S4).

274 We found evidence that temperature variability interacts with mean annual temperature, but not with total
275 annual precipitation (Fig. 4 A and B). While the effect of temperature variability is always positive, the
276 strength of this effect is greater for species with distributions in warmer climates (Fig. 5A and B). On the
277 other hand, the effect of annual temperature range is consistent regardless of levels of precipitation (Fig.
278 5C and D). Finally, several other species characteristics had a significant effect on elevational range size,
279 but the effect sizes were small (Fig. 4; Fig. S8). Range size increased for larger species (maximum size),
280 and species that were more locally common (maximum abundance). Furthermore, species had larger

281 elevational ranges in warmer and more humid places. These results were also robust when using
282 alternative datasets.

283 **4 DISCUSSION**

284 **4.1 Thermal variability and mean temperature interact to determine elevational range size**

285 Using species-specific responses for ~2300 plant species to climate variability across an extensive
286 elevational gradient in the Central Tropical Andes, we found strong support for the climate variability
287 hypothesis across elevations (ECVH; (Janzen, 1967; Stevens, 1992). Our findings show a strong positive
288 relationship between local climate variability, particularly in temperature, and the elevational range size
289 of woody plants (Table 1). In fact, the effect of variability in temperature is stronger than that of any other
290 factor considered in our models. Importantly, our results were robust to all variations in analyses to
291 account for potential biases related with species rarity and range size variability, uneven sampling across
292 elevations and geometric constraints. The overall trend for elevational restricted species to occupy less
293 climatically variable environments, regardless of their elevation of occurrence (i.e., not limited to lower
294 elevations), suggests that elevational range restriction in Andean trees is likely related to narrow thermal
295 tolerances rather than to biotic interactions or habitat specificity, two processes hypothesized to be more
296 prevalent at lower elevations (MacArthur, 1984; Brown *et al.*, 1996; Paquette & Hargreaves, 2021).

297 Previous studies have tested for the relationship between thermal variability and elevational range size,
298 independent of the elevation of occurrence. Like ours, these studies found this relationship to be posited,
299 despite using different methods of assessing climatic variability and focusing on different taxa (Pintor *et*
300 *al.*, 2015; Beck *et al.*, 2016; Maccagni & Willi, 2022). Only a few studies have, however, tested
301 predictions from the ECVH in vascular plants and their conclusions have been limited by their data or
302 analyses. For instance, using a large empirical dataset on plant elevational distributions in the Western
303 Himalaya, (Macek *et al.*, 2021) found no support for the ECVH. As recognized by the authors, the lack of
304 relationship between climate variability and elevational ranges in their study might result from the fact

305 that the lowest elevation in their study is ~2650 m a.s.l, and thus their dataset lacks information of
306 lowland species and lower elevation climatic variability. A similar reason might have caused the lack of
307 relationship between thermal niche breadth (maximum – minimum temperature a species experienced)
308 and elevation in alpine plants (> 3000 m a.s.l.) of the Andes in the study by Cuesta et al. (2019). Here, we
309 take advantage of a naturally extreme elevational gradient (~ 200 - ~3750 m a.s.l.) in the Central Tropical
310 Andes and can extend our hypothesis testing to the whole set of woody plants. To our knowledge, no
311 other comparable dataset exists for tropical plants where sampling of species has been as intensive and
312 systematic over a large elevational gradient, and empirical data was obtained with standardized and
313 homogeneous taxonomic information across species and sites. When including a full gradient of climatic
314 variability, we found a strong positive relationship between thermal variability and the elevational range
315 sizes.

316 While we found that climate variability has a strong positive effect on elevational range size, we also
317 found that the magnitude of this effect depends on whether species are distributed in warmer or colder
318 regions (i.e., a significant interaction between maximum annual temperature range and abundance-
319 weighted mean annual temperature). Specifically, the positive effect of climate variability was stronger
320 for species in warmer regions (e.g., lower elevations) than for species in colder regions (e.g., higher
321 elevations). This finding is consistent with previous studies that found that both mean climatic conditions
322 and climate variability are important drivers of species' range sizes in different taxa (e.g., (Luo *et al.*,
323 2011; Chan *et al.*, 2016; Liang *et al.*, 2021). Although studies in terrestrial vertebrates have considered
324 the interaction between average environmental conditions and climate variability (Chan *et al.*, 2016), to
325 our knowledge our study is the first one on woody plants to include these effects when testing the ECVH.
326 For example, Liang et al. (2021) considered mean environmental variables besides thermal variability in
327 their study of plant elevational ranges. They found that both mean annual temperature and mean annual
328 precipitation had a significant relationship with plant elevational ranges; they did not, however, consider
329 interactions among these and climate variability in their analyses. Similarly, Mumladze et al. (2017),

330 examined the correlations between the thermal range size of plant species (and not directly its elevational
331 range) and the maximum temperature seasonality in two elevational gradients of the Caucasus. In their
332 paper, Mumladze et al. (2017) separately tested the correlation with precipitation ranges and precipitation
333 seasonality but did not test for interactions nor examined the relative importance of different
334 environmental variables on species ranges. Our study, therefore, is the first one to show how
335 environmental conditions modulate the effect of climate variability on the climatic tolerances and range
336 size of plant species.

337 Although we argue that the most direct way to test predictions of the ECVH is to study the response of
338 individual species to different levels of climate variability, most studies use the average range size of co-
339 occurring species as response variable (e.g., Mumladze et al. 2017; Liang et al. 2021; Macek et al. 2021).
340 These studies average the range sizes of all species occurring at a given site or elevational band (i.e., the
341 “Steven’s method”) or average the range size of species whose distributional middle point falls within a
342 given elevational band (i.e., the “midpoint method”). Because species relationships with climate variables
343 is idiosyncratic (McCain & Knight, 2013), this aggregation of species responses could be a confounding
344 factor, resulting in inconsistent results. Assemblage-level averages hide important variation among
345 species. In a study with mayflies, for example Gill *et al.*, (2016) found great variability in elevation range
346 sizes even among closely related species that was likely related with variation in species physiological
347 and dispersal traits. Species-specific differences in traits may result in large variation in elevational ranges
348 across plant clades that co-occur at any given elevation, variability that could be dismissed when using
349 assemblage-level metrics. Thus, conclusions reached with assemblage-level analyses should be taken
350 cautiously.

351 **4.2 Limitations of our study and recommendations for future analyses**

352 A potential caveat of our study is the use of climate information from global databases. The coarse
353 resolution of global databases might result in inaccurate information in mountain regions (e.g., (Browoski
354 & Schickhoff, 2017). The complex landscape of the Andes likely adds to thermal variability; adjacent

355 areas with different topographic exposures may differ notoriously in temperature and thermal variability,
356 creating contrasting micro-habitat variation (Jackson & Forster, 2010). This small-scale spatial variability
357 might be better captured with local climatic information obtained, for example, from data-logger
358 installed across elevations. We partially address this concern by comparing the climatic patterns in global
359 datasets with a few data-logger located in the study region (Fig. S3). We found WorldClim v.2
360 matched most closely the climate patterns we detected *in situ* with data-logger. Furthermore, the use of
361 highly localized climate data collected by data-logger has its own limitations. With a forest canopy that
362 might surpass 30 m of height, environmental information obtained from sensors located below 3 m
363 (where most data loggers are set due to logistical constraints; (Bach *et al.*, 2003) might represent poorly
364 the thermal environment that most trees experience. Indeed, it has been shown that climatic conditions
365 experienced by understory vs. canopy species can vary substantially (Frey *et al.*, 2016), with canopies
366 potentially experiencing greater temperature variability (De Frenne *et al.*, 2019). Future studies might
367 explore the differences in climate variability experienced by understory and canopy species and how these
368 further affects species' distribution across environmental gradients.

369 Finally, it is important to consider that although we found range sizes to be strongly associated with
370 climate variability, other mechanisms might also act as determinants of Andean plant species' ranges. We
371 found a significant effect of tree size and local abundance, both of which had a positive effect on range
372 size. These results are consistent with other studies on the ecological factors shaping the size of species
373 distributions (Stahl *et al.*, 2014). Moreover, other processes that we did not consider in our analyses could
374 also be important. Biotic interactions such as specialized mutualisms or competitive interactions have
375 been found to shape species ranges across latitudes and elevation (Brooker *et al.*, 2007; Jankowski *et al.*,
376 2010; Wisz *et al.*, 2013). Dispersal abilities might also play a role in the realized range size of plants; with
377 climate stability potentially having a stronger effect on groups with lower dispersal capacities (Xu *et al.*,
378 2018). Finally, phenotypic plasticity or local adaptation can both contribute to shaping elevational range
379 sizes (Bradshaw, 1965) (Van Nuland *et al.*, 2017; Buckley *et al.*, 2019). Future studies should focus on

380 disentangling which and how these mechanisms might further restrict or extend species' elevation
381 distributions in tropical mountains.

382 **4.3 Implications for environmental change**

383 Understanding how climate shapes species distributions along environmental gradients is becoming
384 increasingly urgent in a rapidly changing world, particularly because many tropical species are
385 responding to global warming through range shifts (Nadeau *et al.*, 2017; Fadrique *et al.*, 2018; Freeman *et*
386 *al.*, 2018). Our study points to the overriding importance of thermal variability in driving elevational
387 range sizes in woody plants in the Central Tropical Andes. Moreover, we found evidence suggesting that
388 in warmer mountains the relationship between thermal variability and range size might be even stronger.
389 Our results have implications not only to understand drivers of range size, but to predict how
390 environmental change might impact biodiversity (Nadeau *et al.*, 2017).

391 Combined, our findings highlight the great vulnerability of tropical floras to the enhanced effects of
392 climate change in mountain ranges (Sentinella *et al.*, 2020). Under a climate warming scenario, species
393 with smaller thermal tolerances (often in warm, tropical regions) might be more vulnerable as their
394 distributions seem to be strongly related with their climatic stability. Furthermore, species at low
395 elevations not only have narrower climatic tolerances and small ranges, but they often also experience
396 temperatures closer to their upper tolerance limits (Colwell *et al.*, 2008). This could mean that species
397 inhabiting tropical lowlands will likely face greater impacts of warming temperatures. Species might
398 respond to such changes in local conditions either by tracking suitable climates and moving upslope to
399 match their historical niches (e.g., Feeley *et al.*, 2011), by persisting in situ in thermally buffered micro-
400 habitats created by topography and other physiographic features (e.g., Suggitt *et al.*, 2018), potentially
401 resulting in fragmented populations, or by decreasing in abundance and potentially going extinct. By the
402 same logic, species that are adapted to more variable environments and have broader distributions might
403 be best able to cope with significant environmental change. On the other hand, as thermal variability
404 along elevation is mostly determined by variation in minimum rather than maximum temperatures (lower

405 temperatures decrease at a faster rate), species adapted to highly variable climates may struggle surviving
406 in habitats with temperatures closer to their maximum tolerances. Having no place to “escape” from
407 higher temperatures, high elevation floras in the tropics might be particularly vulnerable to rising
408 temperatures. Climate variability, its effect on species climate tolerance and spatial distribution, can
409 provide important clues into how species, communities and ecosystems will change in response to
410 environmental shifts.

411 **REFERENCES**

412 Bach, K., Schawe, M., Beck, S., Gerold, G. & Gradstein, S.R. (2003) Vegetation, soil and climate in
413 different altitudinal belts in montane cloud forests of the Yungas, Bolivia: first results. *Ecología en*
414 *Bolivia*, **38**, 3–14.

415 Beck, J., Liedtke, H.C., Widler, S., Altermatt, F., Loader, S.P., Hagmann, R., Lang, S. & Fiedler, K.
416 (2016) Patterns or mechanisms? Bergmann’s and Rapoport’s rule in moths along an elevational gradient.
417 *Community Ecology*, **17**, 137–148.

418 Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. & Courchamp, F. (2012) Impacts of climate
419 change on the future of biodiversity. *Ecology Letters*, **15**, 365–377.

420 Bradshaw, A.D. (1965) *Evolutionary Significance of Phenotypic Plasticity in Plants. Advances in*
421 *Genetics* (ed. by E.W. Caspary) and J.M. Thoday), pp. 115–155. Academic Press.

422 Brooker, R.W., Travis, J.M.J., Clark, E.J. & Dytham, C. (2007) Modelling species’ range shifts in a
423 changing climate: The impacts of biotic interactions, dispersal distance and the rate of climate change.
424 *Journal of Theoretical Biology*, **245**, 59–65.

425 Brown, J.H., Stevens, G.C. & Kaufman, D.M. (1996) The Geographic Range: Size, Shape, Boundaries,
426 and Internal Structure. *Annual Review of Ecology and Systematics*, **27**, 597–623.

427 Browoski, B. & Schickhoff, U. (2017) Why input matters: Selection of climate data sets for modelling the
428 potential distribution of a treeline species in the Himalayan region. *Ecological Modelling*, **359**, 92–102.

429 Buckley, J., Widmer, A., Mescher, M.C. & De Moraes, C.M. (2019) Variation in growth and defence
430 traits among plant populations at different elevations: Implications for adaptation to climate change.
431 *Journal of Ecology*, **107**, 2478–2492.

432 Chan, W.-P., Chen, I.-C., Colwell, R.K., Liu, W.-C., Huang, C. & Shen, S.-F. (2016) Seasonal and daily
433 climate variation have opposite effects on species elevational range size. *Science*, **351**, 1437–1439.

434 Colwell, R.K., Brehm, G., Cardelús, C.L., Gilman, A.C. & Longino, J.T. (2008) Global Warming,
435 Elevational Range Shifts, and Lowland Biotic Attrition in the Wet Tropics. *Science*, **322**, 258–261.

436 Cuesta, F., Tovar, C., Llambí, L.D., Gosling, W.D., Halloy, S., Carilla, J., Muriel, P., Meneses, R.I.,
437 Beck, S., Ulloa Ulloa, C., Yager, K., Aguirre, N., Viñas, P., Jácome, J., Suárez-Duque, D., Buytaert, W.
438 & Pauli, H. (2020) Thermal niche traits of high alpine plant species and communities across the tropical
439 Andes and their vulnerability to global warming. *Journal of Biogeography*, **47**, 408–420.

440 De Frenne, P., Zellweger, F., Rodríguez-Sánchez, F., Scheffers, B.R., Hylander, K., Luoto, M., Vellend,
441 M., Verheyen, K. & Lenoir, J. (2019) Global buffering of temperatures under forest canopies. *Nature
442 Ecology & Evolution*, **3**, 744–749.

443 Fadrique, B., Báez, S., Duque, Á., Malizia, A., Blundo, C., Carilla, J., Osinaga-Acosta, O., Malizia, L.,
444 Silman, M., Farfán-Ríos, W., Malhi, Y., Young, K.R., Cuesta C., F., Homeier, J., Peralvo, M., Pinto, E.,
445 Jadan, O., Aguirre, N., Aguirre, Z. & Feeley, K.J. (2018) Widespread but heterogeneous responses of
446 Andean forests to climate change. *Nature*, **564**, 207–212.

447 Feeley, K.J., Silman, M.R., Bush, M.B., Farfan, W., Cabrera, K.G., Malhi, Y., Meir, P., Revilla, N.S.,
448 Quisiyupanqui, M.N.R. & Saatchi, S. (2011) Upslope migration of Andean trees. *Journal of
449 Biogeography*, **38**, 783–791.

450 Fick, S.E. & Hijmans, R.J. (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global
451 land areas. *International Journal of Climatology*, **37**, 4302–4315.

452 Fox, J., Weisberg, S., Price, B., Adler, D., Bates, D., Baud-Bovy, G., Bolker, B., Ellison, S., Firth, D.,
453 Friendly, M., Gorjanc, G., Graves, S., Heiberger, R., Krivitsky, P., Laboissiere, R., Maechler, M.,

454 Monette, G., Murdoch, D., Nilsson, H., Ogle, D., Ripley, B., Short, T., Venables, W., Walker, S.,

455 Winsemius, D., Zeileis, A. & R-Core (2022) car: Companion to Applied Regression.

456 Freeman, B.G., Scholer, M.N., Ruiz-Gutierrez, V. & Fitzpatrick, J.W. (2018) Climate change causes

457 upslope shifts and mountaintop extirpations in a tropical bird community. *Proceedings of the National*

458 *Academy of Sciences*, **115**, 11982–11987.

459 Frey, S.J.K., Hadley, A.S., Johnson, S.L., Schulze, M., Jones, J.A. & Betts, M.G. (2016) Spatial models

460 reveal the microclimatic buffering capacity of old-growth forests. *Science Advances*, **2**, e1501392.

461 Hawkins, B.A. & Felizola Diniz-Filho, J.A. (2006) Beyond Rapoport's rule: evaluating range size

462 patterns of New World birds in a two-dimensional framework. *Global Ecology and Biogeography*, **15**,

463 461–469.

464 Ives, A.R. (2019) R\$^2\$ for Correlated Data: Phylogenetic Models, LMMs, and GLMMs. *Systematic*

465 *Biology*, **68**, 234–251.

466 Ives, A.R. & Li, D. (2018) `rr2': An R package to calculate R^2 s for regression models. *Journal of*

467 *Open Source Software*, **3**, 1028.

468 Jackson, L.S. & Forster, P.M. (2010) An Empirical Study of Geographic and Seasonal Variations in

469 Diurnal Temperature Range. *Journal of Climate*, **23**, 3205–3221.

470 Jankowski, J.E., Robinson, S.K. & Levey, D.J. (2010) Squeezed at the top: Interspecific aggression may

471 constrain elevational ranges in tropical birds. *Ecology*, **91**, 1877–1884.

472 Janzen, D.H. (1967) Why Mountain Passes are Higher in the Tropics. *The American Naturalist*, **101**, 233–

473 249.

474 Jin, Y. & Qian, H. (2019) V.PhyloMaker: an R package that can generate very large phylogenies for

475 vascular plants. *Ecography*, **42**, 1353–1359.

476 Jung, M., Arnell, A., de Lamo, X., García-Rangel, S., Lewis, M., Mark, J., Merow, C., Miles, L., Ondo,

477 I., Pironon, S., Ravilius, C., Rivers, M., Schepaschenko, D., Tallowin, O., van Soesbergen, A., Govaerts,

478 R., Boyle, B.L., Enquist, B.J., Feng, X., Gallagher, R., Maitner, B., Meiri, S., Mulligan, M., Ofer, G.,

479 Roll, U., Hanson, J.O., Jetz, W., Di Marco, M., McGowan, J., Rinnan, D.S., Sachs, J.D., Lesiv, M.,

480 Adams, V.M., Andrew, S.C., Burger, J.R., Hannah, L., Marquet, P.A., McCarthy, J.K., Morueta-Holme,
481 N., Newman, E.A., Park, D.S., Roehrdanz, P.R., Svenning, J.-C., Viole, C., Wieringa, J.J., Wynne, G.,
482 Fritz, S., Strassburg, B.B.N., Obersteiner, M., Kapos, V., Burgess, N., Schmidt-Traub, G. & Visconti, P.
483 (2021) Areas of global importance for conserving terrestrial biodiversity, carbon and water. *Nature
484 Ecology & Evolution*, **5**, 1499–1509.

485 Karger, D.N., Conrad, O., Böhner, J., Kawohl, T., Kreft, H., Soria-Auza, R.W., Zimmermann, N.E.,
486 Linder, H.P. & Kessler, M. (2017) Climatologies at high resolution for the earth's land surface areas.
487 *Scientific Data*, **4**, 170122.

488 Liang, J., Hu, H., Ding, Z., Lie, G., Zhou, Z., Singh, P.B., Zhang, Z. & Ji, S. (2021) Climate-driven
489 elevational variation in range sizes of vascular plants in the central Himalayas: A supporting case for
490 Rapoport's rule. *Ecology and Evolution*, **11**, 9385–9395.

491 Luo, Z., Tang, S., Li, C., Chen, J., Fang, H. & Jiang, Z. (2011) Do Rapoport's Rule, Mid-Domain Effect
492 or Environmental Factors Predict Latitudinal Range Size Patterns of Terrestrial Mammals in China?
493 *PLOS ONE*, **6**, e27975.

494 MacArthur, R.H. (1984) *Geographical Ecology: Patterns in the Distribution of Species*, Princeton
495 University Press.

496 Maccagni, A. & Willi, Y. (2022) Niche breadth and elevational range size: a comparative study on
497 Middle-European Brassicaceae species. *Philosophical Transactions of the Royal Society B: Biological
498 Sciences*, **377**, 20210005.

499 Macek, M., Dvorský, M., Kopecký, M., Wild, J. & Doležal, J. (2021) Elevational range size patterns of
500 vascular plants in the Himalaya contradict Rapoport's rule. *Journal of Ecology*, **109**, 4025–4037.

501 McCain, C.M. (2009) Vertebrate range sizes indicate that mountains may be 'higher' in the tropics.
502 *Ecology Letters*, **12**, 550–560.

503 McCain, C.M. & Knight, K.B. (2013) Elevational Rapoport's rule is not pervasive on mountains:
504 Elevational Rapoport's rule. *Global Ecology and Biogeography*, **22**, 750–759.

505 Molina-Montenegro, M.A. & Naya, D.E. (2012) Latitudinal Patterns in Phenotypic Plasticity and Fitness-
506 Related Traits: Assessing the Climatic Variability Hypothesis (CVH) with an Invasive Plant Species.
507 *PLOS ONE*, **7**, e47620.

508 Mulligan, M. (2006) Global Gridded 1km TRMM Rainfall Climatology and Derivates. V 1.0.

509 Mumladze, L., Asanidze, Z., Walther, F. & Hausdorf, B. (2017) Beyond elevation: testing the climatic
510 variability hypothesis vs. Rapoport's rule in vascular plant and snail species in the Caucasus. *Biological
511 Journal of the Linnean Society*, **121**, 753–763.

512 Nadeau, C.P., Urban, M.C. & Bridle, J.R. (2017) Climates Past, Present, and Yet-to-Come Shape Climate
513 Change Vulnerabilities. *Trends in Ecology & Evolution*, **32**, 786–800.

514 Paquette, A. & Hargreaves, A.L. (2021) Biotic interactions are more often important at species' warm
515 versus cool range edges. *Ecology Letters*, **24**, 2427–2438.

516 Patterson, B.D., Pacheco, V. & Solari, S. (1996) Distribution of bats along an elevational gradient in the
517 Andes of south-eastern Peru. *Journal of Zoology*, **240**, 637–658.

518 Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. & Development Core Team, R. (2020) nlme: Linear and
519 Nonlinear Mixed Effects Models.

520 Pintor, A.F.V., Schwarzkopf, L. & Krockenberger, A.K. (2015) Rapoport's Rule: Do climatic variability
521 gradients shape range extent? *Ecological Monographs*, **85**, 643–659.

522 Rahbek, C., Borregaard, M.K., Antonelli, A., Colwell, R.K., Holt, B.G., Nogues-Bravo, D., Rasmussen,
523 C.M.Ø., Richardson, K., Rosing, M.T., Whittaker, R.J. & Fjeldså, J. (2019a) Building mountain
524 biodiversity: Geological and evolutionary processes. *Science*, **365**, 1114–1119.

525 Rahbek, C., Borregaard, M.K., Colwell, R.K., Dalsgaard, B., Holt, B.G., Morueta-Holme, N., Nogues-
526 Bravo, D., Whittaker, R.J. & Fjeldså, J. (2019b) Humboldt's enigma: What causes global patterns of
527 mountain biodiversity? *Science*, **365**, 1108–1113.

528 Rapoport, E.H. (1982) *Areography: Geographical Strategies of Species*, Elsevier.

529 Ribas, C.R. & Schoereder, J.H. (2006) Is the Rapoport effect widespread? Null models revisited. *Global
530 Ecology and Biogeography*, **15**, 614–624.

531 Rohde, K. (1992) Latitudinal Gradients in Species Diversity: The Search for the Primary Cause. *Oikos*,
532 **65**, 514.

533 Rohde, K. (1996) Rapoport's Rule is a Local Phenomenon and Cannot Explain Latitudinal Gradients in
534 Species Diversity. *Biodiversity Letters*, **3**, 10–13.

535 Sentinella, A.T., Warton, D.I., Sherwin, W.B., Offord, C.A. & Moles, A.T. (2020) Tropical plants do not
536 have narrower temperature tolerances, but are more at risk from warming because they are close to their
537 upper thermal limits. *Global Ecology and Biogeography*, **29**, 1387–1398.

538 Shah, A.A., Woods, H.A., Havird, J.C., Encalada, A.C., Flecker, A.S., Funk, W.C., Guayasamin, J.M.,
539 Kondratieff, B.C., Poff, N.L., Thomas, S.A., Zamudio, K.R. & Ghalambor, C.K. (2021) Temperature
540 dependence of metabolic rate in tropical and temperate aquatic insects: Support for the Climate
541 Variability Hypothesis in mayflies but not stoneflies. *Global Change Biology*, **27**, 297–311.

542 Stahl, U., Reu, B. & Wirth, C. (2014) Predicting species' range limits from functional traits for the tree
543 flora of North America. *Proceedings of the National Academy of Sciences*, **111**, 13739–13744.

544 Stevens, G.C. (1992) The Elevational Gradient in Altitudinal Range: An Extension of Rapoport's
545 Latitudinal Rule to Altitude. *The American Naturalist*, **140**, 893–911.

546 Stevens, G.C. (1989) The Latitudinal Gradient in Geographical Range: How so Many Species Coexist in
547 the Tropics. *The American Naturalist*, **133**, 240–256.

548 Suggitt, A.J., Wilson, R.J., Isaac, N.J.B., Beale, C.M., Auffret, A.G., August, T., Bennie, J.J., Crick,
549 H.Q.P., Duffield, S., Fox, R., Hopkins, J.J., Macgregor, N.A., Morecroft, M.D., Walker, K.J. & Maclean,
550 I.M.D. (2018) Extinction risk from climate change is reduced by microclimatic buffering. *Nature Climate
551 Change*, **8**, 713–717.

552 Van Nuland, M.E., Bailey, J.K. & Schweitzer, J.A. (2017) Divergent plant–soil feedbacks could alter
553 future elevation ranges and ecosystem dynamics. *Nature Ecology & Evolution*, **1**, 1–10.

554 Wisz, M.S., Pottier, J., Kissling, W.D., Pellissier, L., Lenoir, J., Damgaard, C.F., Dormann, C.F.,
555 Forchhammer, M.C., Grytnes, J.-A., Guisan, A., Heikkinen, R.K., Høye, T.T., Kühn, I., Luoto, M.,
556 Maiorano, L., Nilsson, M.-C., Normand, S., Öckinger, E., Schmidt, N.M., Termansen, M., Timmermann,

557 A., Wardle, D.A., Aastrup, P. & Svenning, J.-C. (2013) The role of biotic interactions in shaping
558 distributions and realised assemblages of species: implications for species distribution modelling.
559 *Biological Reviews*, **88**, 15–30.

560 Xu, W., Svenning, J.-C., Chen, G., Chen, B., Huang, J. & Ma, K. (2018) Plant geographical range size
561 and climate stability in China: Growth form matters. *Global Ecology and Biogeography*, **27**, 506–517.

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563

564 **Table 1. Testing for the effect of temperature variability and other predictors on size of elevational**
565 **distributions.** Phylogenetic generalized least-square regressions (PGLS) were used. Elevational range
566 size (ERS) or a standardized effect size for range size (SES) were modeled as the response variable in
567 separate models. Regardless of the response used, we found that maximum annual temperature range
568 (max. ATR) was a strong predictor and had a significant interaction with abundance-weighted mean
569 annual temperature (w-MAT). Additional predictors included species maximum size, maximum
570 abundance among occupied plots, and abundance-weighted total annual precipitation (w-TAP). For each
571 predictor, we report standardized coefficients, p-values and variation inflation factors (VIF). Model fit is
572 characterized by Ives' residual R^2 value for phylogenetic modes, as well as Pearson's correlation between
573 observed and model-predicted values of the response variable. Finally, we used a likelihood ratio test
574 (LRT) to obtain a model-wide p-value by contrasting each PGLS against a null model. The null model
575 had only an intercept and the same phylogenetic structure estimated for the main PGLS model. Details on
576 univariate models and other competing models are detailed in Table S1.

Response	Predictor	Coeff.	P-value	VIF	Obs.-Pred. Corr.	R^2_{resid}	LR	LRT: P-value
ERS	Intercept	27.011	< 0.001					
	log(Max. Size)	1.688	< 0.001	1.054				
	log(Max. Abund.)	3.033	< 0.001	1.156				
	w-MAT	1.730	< 0.001	2.069	0.618	0.389	890.6	< 0.001
	w-TAP	2.602	< 0.001	1.952				
	Max. ATR	9.592	< 0.001	4.071				
	w-MAT \times Max. ATR	3.735	< 0.001	5.877				
	w-TAP \times Max. ATR	0.309	0.310	3.591				
SES	Intercept	0.237	< 0.001					
	log(Max. Size)	0.136	< 0.001	1.055				
	log(Max. Abund.)	0.252	< 0.001	1.157				
	w-MAT	0.474	< 0.001	2.035	0.647	0.419	994.5	< 0.001
	w-TAP	0.257	< 0.001	1.946				
	Max. ATR	0.968	< 0.001	4.014				
	w-MAT \times Max. ATR	0.280	< 0.001	5.806				
	w-TAP \times Max. ATR	0.018	0.494	3.550				

Figure 1. Map of the study region and network of forest plots. (A & B) Location of the study region within and around Madidi National Park in Bolivia. **(C)** The forests' plots dataset used in our analyses include 48 large plots (1-ha in area) and 458 small plots (0.1-ha).

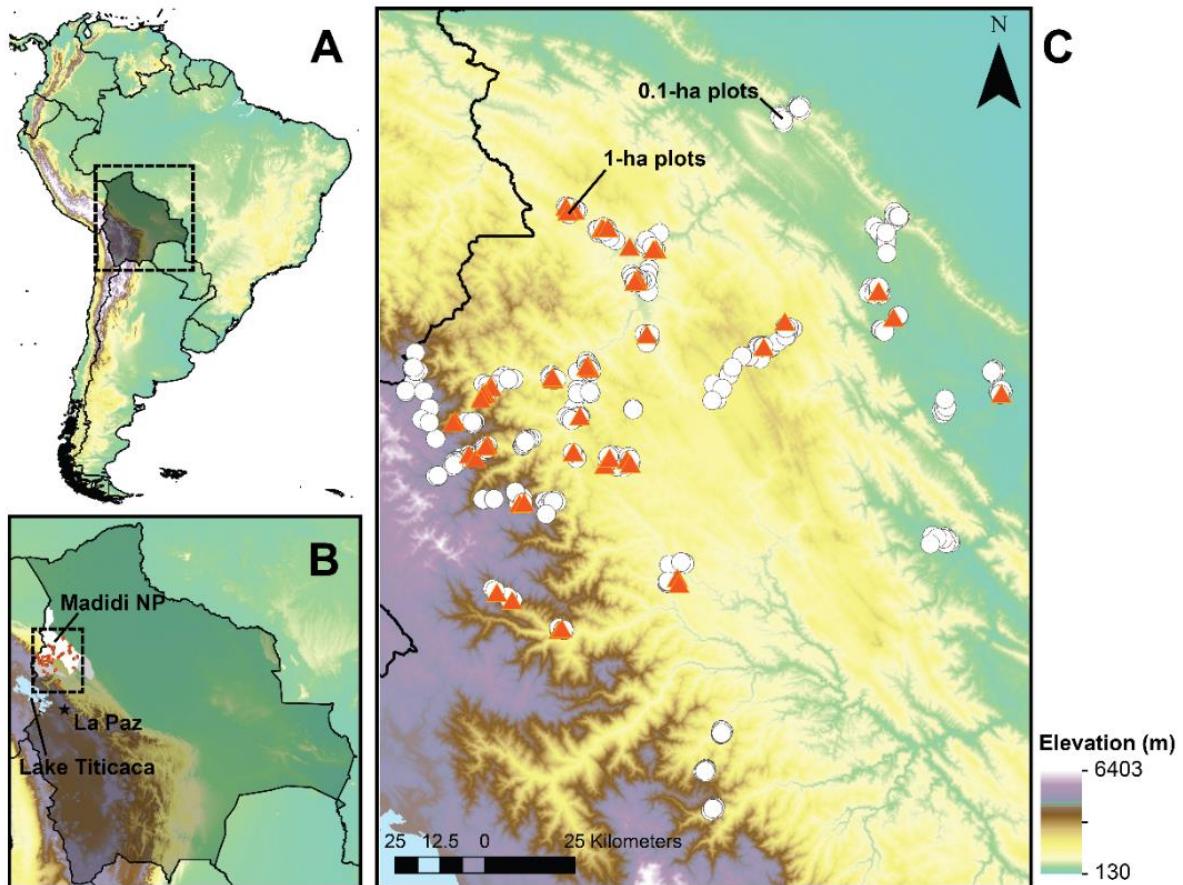


Figure 2. Elevational ranges for woody plant species in the Andes of northwestern Bolivia. (A) Vertical lines connect the lowest and highest elevations recorded for each species used in our analyses. In this way, the lines describe the elevational extent of species' distributions (i.e., their elevational ranges). Species are ranked in the x-axis by their elevational mid-point of distribution. (B) Frequency distribution of elevational range sizes showing that most species have small ranges. (C) Relationship between elevational range size and elevational mid-point. The range size of each species is constrained geometrically by its position with respect to the upper and lower limits of the gradient. Species that have an elevational mid-point in the lowlands or highlands are constrained to having small ranges, while species that have a mid-point at intermediate elevations are free to have either small or large range sizes. The grey area shows the possible distribution of points; the black edges mark the geometric limits to this relationship. (D) Relationship between the standardized effect size of range size and elevational mid-point. Standardized effect size for a species was calculated by comparing its empirical range size to a subset of ranges of similar geometric constraints (see Methods for details & Figure 3). SES values greater than zero indicate ranges that are larger than expected by their constraints.

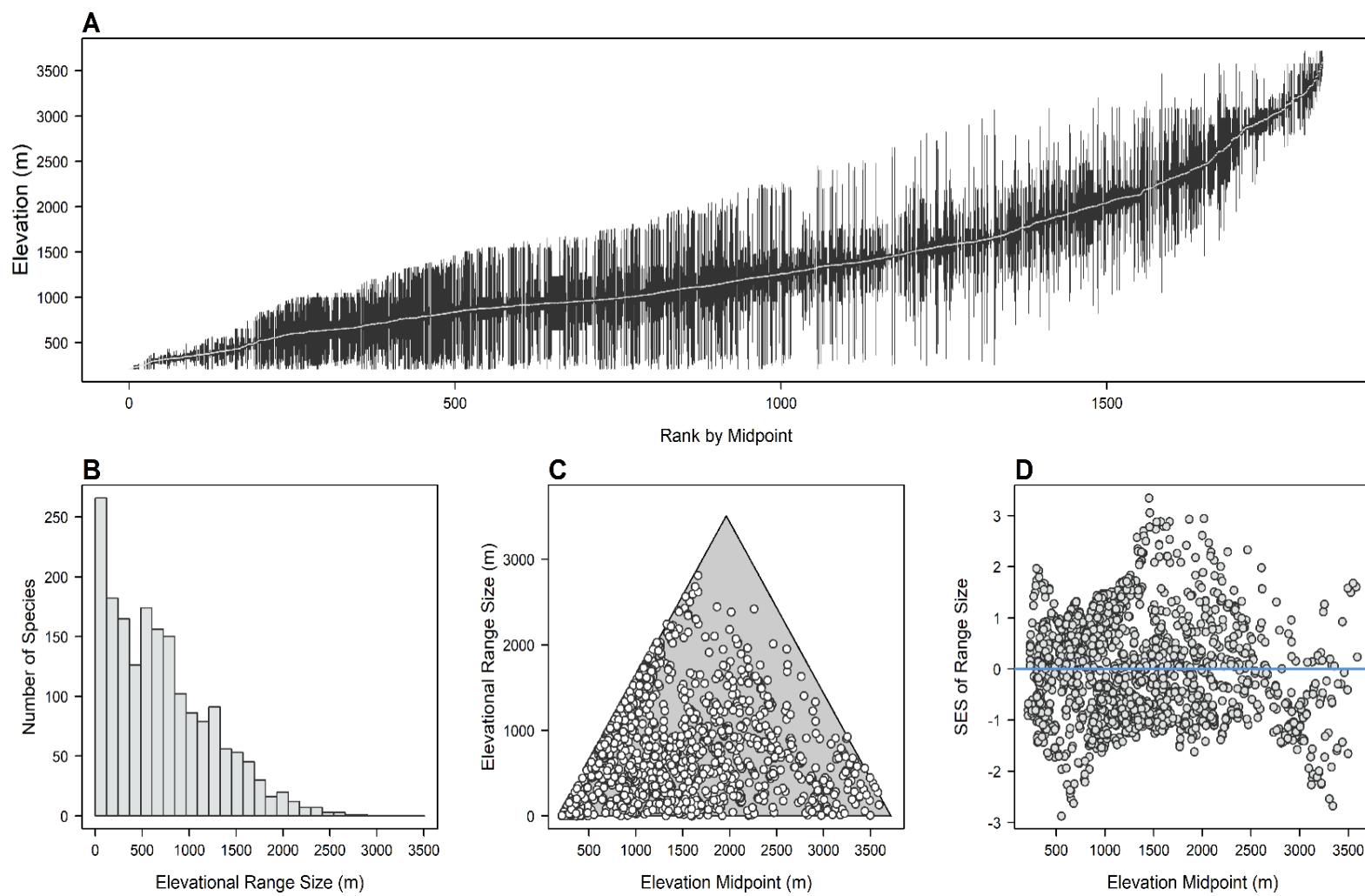


Figure 3. Calculation of standardized effect sizes of range size. To account for geometric constraints on elevational distributions, we compared the range size of each species to the range sizes of all other species that suffer from a similar constraint. In the example shown here, the range size and midpoint of a focal species is indicated by the orange circle in (A) and the vertical orange line in (B). All species that suffer a similar constraint to the focal species are indicated by dark gray circles in (A) and gray bars in (B). All other species are shown in white. Species with a similar constraint to the focal species are those that (1) have a midpoint in a region 50 m above or below the midpoint of the focal species, or (2) have a midpoint 50 m above or below an elevation that is equidistant from the opposite edge of the gradient (distance d). The range sizes of all species in these elevational bands represent a pool of potential values that the focal species could take given its midpoint. Thus, to calculate a standardized effect size, we (1) sampled 1,000 values of range size from the pool of similar species, and then (2) subtracted the mean of the random values from the empirical range size and divided this by the standard deviation of the random distribution. In this way, a standardized effect size measures the breadth of elevational distribution while accounting for geometric constraints. A positive value indicates a range size that is larger than other ranges with similar constraints; a negative value indicates a range size that is smaller than other similar ranges.

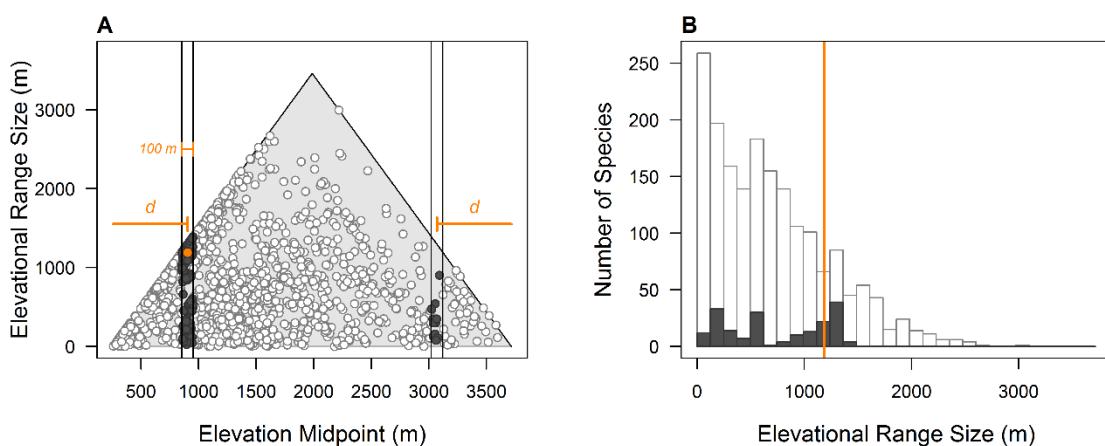


Figure 4. Effects of climate variability and other predictors on the breadth of elevational distributions. (A) Standardized coefficients showing the effect of each predictor on elevational range size. The height of each bar indicates the coefficient estimate, while the lines show the 95% confidence interval. Ives' R^2_{resid} is also shown. (B) Same as (A), but where the response variable was the standardized effect sizes of range size (i.e., range size after accounting for geometric constraints). (C) Empirical values of range size plotted against predictions made by the regression model in (A). The 1:1 correspondence is indicated by the solid blue line. (D) Same as (C), but where the response variable was the standardized effect sizes of range size (regression model in B). Size: maximum size (90th percentile of diameter at breast height); Abund.: maximum local relative abundance; w-MAT: abundance-weighted mean annual temperature; w-TAP: abundance-weighted total annual precipitation; ATR: maximum annual temperature range.

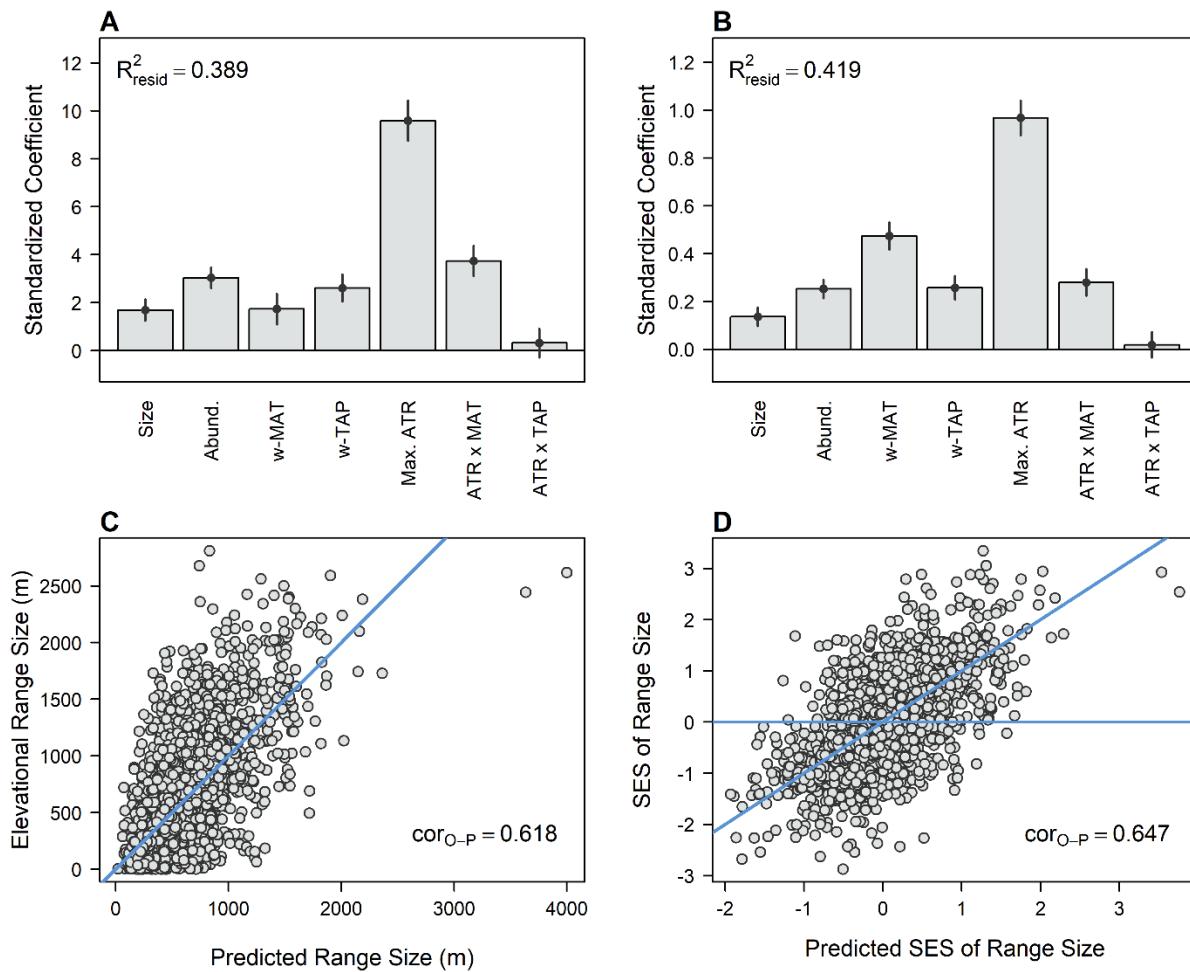


Figure 5. Interactions between temperature variability and mean temperature or total precipitation. Each panel shows the effect of temperature variability (maximum annual temperature range; max. ATR) on elevational range size (left column) and standardized effect sizes (right column) for different values of mean annual temperature (top row) and total annual precipitation (bottom row). In each case, the gray line depicts the effect of max. ATR for the mean value of the interacting variable. The colored lines depict the effects of max. ATR for values one standard deviation above and below the mean of the interacting variable. These results demonstrate that increases in mean temperature significantly amplify the effect of temperature variability (**A & B**). On the other hand, increases in total precipitation do not modify the effects of temporal variability (**C & D**).

