

1 **Elevational richness patterns of sphingid moths support area effects over climatic drivers in a**
2 **near-global analysis**

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21 **Abstract**

22 **Aim** We test hypotheses on the environmental control of elevational richness patterns of sphingid
23 moths for their global applicability and generality. Specifically, we compare effects of area to climate-
24 related drivers such as primary productivity and temperature, while also considering direct effects of
25 precipitation.

26 **Major taxa** Sphingid moths (Lepidoptera).

27 **Location** Eighty-six mountain ranges of the Old World and the Australia/Pacific region, from
28 Scandinavia and Siberia through the African and Australasian tropics to South Africa and Southern
29 Australia.

30 **Methods** We used a large compilation of point-locality records for 744 species, as well as fine-
31 grained range maps derived from species-distribution modelling of these records, to characterize the
32 elevational pattern of species richness in 86 custom-delineated mountain regions. For both types of
33 data we compared the effects of environmental drivers on richness by comparing standardized
34 coefficients of multivariate models for pooled data after accounting for between-region richness
35 variation.

36 **Results** We observed varying patterns of elevational richness across the research region, with a higher
37 prevalence of midpeaks in arid regions. We found overwhelming support for area as a main
38 determinant of richness, modulated by temperature and productivity, whereas we detected no effect of
39 precipitation.

40 **Main conclusions** Area, productivity and temperature are the main environmental predictors
41 explaining a large proportion of sphingid richness variability. This is consistent not only with other
42 elevational studies, but also with empirical and theoretical biodiversity research in a non-elevational
43 context (with the caveat of some unresolved issues in elevational area effects). However, distinct
44 differences in elevational patterns remain even within the same mountain ranges when comparing

45 with other Lepidoptera, i.e. geometrid moths, which highlights the importance of understanding
46 higher-clade differentiation in ecological responses, within insects as well as in other groups.

47

48

49 **Introduction**

50 Understanding species richness patterns along elevational gradients as an effect of
51 environmental variation has matured into a major field of biodiversity research during the last decades
52 (Rahbek, 2005; McCain & Grytnes, 2010; Kessler *et al.*, 2011; Quintero & Jetz, 2018). Across taxa
53 and biomes, most studies documented either unimodal patterns with highest richness at mid-elevation
54 ('midpeaks'), or declining richness with elevation, or a mix of those pattern types (McCain &
55 Grytnes, 2010). These patterns proved difficult to explain from simple assumptions of environmental
56 causes, such as the almost universal decline in temperature with elevation. Furthermore, the variation
57 of patterns found across studies has only rarely been conceptualized into globally applicable
58 hypotheses of general mechanisms (McCain, 2007a). A multitude of single-gradient studies makes it
59 challenging to evaluate hypotheses for their generality as methodological, taxonomic and regional
60 differences contribute to idiosyncratic findings that are hard to reject in a rigorous testing framework.
61 More informative, spatially replicated studies on the same taxonomic group exist for vertebrates
62 (McCain, 2007a; 2009; 2010; McCain & Sanders, 2010; Quintero & Jetz, 2018), plants (Kessler *et al.*,
63 2011) and a few insect taxa (ants: Sanders, 2002; Szweczyk & McCain, 2016; moths: Beck *et al.*,
64 2017). Such replicated studies are based on compilations of individual datasets, selected for inclusion
65 after quality vetting. Nevertheless, these data were usually sampled and processed by different
66 researchers using different methods and protocols, often to address different research questions and
67 without the intention of inclusion into a replicated meta-study.

68 Findings from these studies indicate that there is no strong support for a single environmental
69 driver for the observed richness patterns. However, corresponding with theory and empirical findings
70 on non-elevational, large-scale richness patterns, climatic factors such as temperature and
71 precipitation were reported to shape elevational richness patterns of many different taxa (Field *et al.*,
72 2009). While there is theoretical underpinning of hypothesized direct temperature effects (Rhode,
73 1992; Brown *et al.*, 2004), precipitation effects presumably act rather indirectly via their effect on
74 plant productivity (Evans *et al.*, 2005). Furthermore, the variation of available area as a function of
75 elevation in mountain ranges was considered to have a major effect on richness patterns (i.e., a

76 species-area relationship, SAR; Rosenzweig, 1995; Rahbek, 2005; McCain, 2007b). However, just
77 like declining temperature, monotonically declining area with elevation alone cannot explain the
78 existence of midpeak richness patterns. Productivity, on the contrary, does exhibit midpeak patterns in
79 some mountain landscapes, due to aridity at the base of mountains. Productivity has often been
80 suggested as a possible cause of observed richness patterns, but the lack of fine-scale and reliable
81 productivity data has prevented direct testing in many empirical studies (McCain 2007a; Phillips *et*
82 *al.*, 2008). Here we utilized high-resolution estimates of primary productivity after assessing their
83 utility at capturing patterns in mountain ecosystems. Furthermore, mechanistic details of the
84 productivity-richness relationship are unclear; e.g., whether it acts via food and population sizes (the
85 ‘more individuals-hypothesis’; Rosenzweig, 1995; Classen *et al.*, 2015; Storch *et al.*, 2018), or
86 whether productivity per area, or summed productivity across the entire area of an ecological zone, is
87 the relevant variable (Storch *et al.*, 2005; Hurlbert & Stegen, 2014). Beck *et al.* (2017) recently
88 presented data indicating strong effects of the latter, area-integrated productivity on geometrid moth
89 richness in elevational richness patterns (see also Jetz & Fine, 2012). The mid-domain effect (MDE),
90 caused by hard geometric borders along a gradient, has also been proposed as an explanation for
91 midpeak patterns of richness (Colwell & Hurtt 1994). However, recent studies viewed MDE as a
92 modulating effect on elevational richness pattern, rather than its primary driver (Dunn *et al.*, 2007;
93 Colwell *et al.*, 2016; Beck *et al.*, 2017).

94 Here we present elevational richness patterns for sphingid moths replicated across a large
95 number of mountain ranges of the Old World and the Australia-Pacific region. This study is unique
96 not only because it provides new and comprehensive elevational richness data for an insect taxon
97 across many tropical regions but also because our data are based on the same methodological
98 approaches for all mountain ranges, rather than being a compilation of local gradient studies, which
99 reduces unwanted variability in analyses.

100 We tested, specifically, the effect of elevational area variation against the two most likely
101 climate-driven environmental effects on richness: net primary productivity (NPP) and annual mean
102 temperature. Assessing the potential of these variables, fine-scaled NPP data in particular, is

103 important for judging whether elevational richness patterns fall within the general mechanisms
104 shaping biodiversity patterns on earth, or whether they must continue to be considered an ecological
105 phenomenon outside the norm. We also investigated direct effects of annual precipitation, and those
106 of area-integrated productivity (sum of NPP within an elevation band). After a first assessment of
107 univariate correlations with richness (searching for a primary driver) we analyzed effects with
108 multivariate models after controlling for richness variation between mountain ranges. Contrasting
109 different types and qualities of richness data, we assure the robustness of our findings. We also
110 compare sphingid elevational patterns with published data for geometrid moths (Beck *et al.*, 2017)
111 from the same mountain regions, which may elucidate the impact of phylogenetic histories and
112 resulting trait variation on such patterns. We provide raw and processed data for future analyses.

113

114 **Methods**

115 Sphingid moths

116 Sphingidae or hawkmoths are a family among the bombycoid Lepidoptera (Kitching &
117 Cadiou, 2000; Regier *et al.*, 2013). Their large body size, intermediate species richness (globally ca.
118 1987 species; Kitching *et al.*, 2018), and their attraction to artificial light sources, which provides a
119 robust means of field collecting, has made them popular among amateur insect collectors and
120 scientific entomologists for centuries. As a consequence, more information has accumulated about
121 their life histories, distribution, and phylogeny than for most other insect taxa. Over the recent decade,
122 they have emerged as a model taxon for investigations into insect macroecology and biogeography for
123 otherwise data-deficient tropical regions in particular (Ballesteros-Mejia *et al.*, 2017). Many
124 hawkmoth species have excellent flight capacity and some cover huge areas within their geographic
125 range, whereas others are geographically restricted endemics (Grünig *et al.*, 2017). Larvae feed on
126 plant leaves with moderate to low host specificity (i.e., specialization below plant family level is
127 uncommon), hence plant species distributions are unlikely to be tightly linked to those of hawkmoths
128 (Beck *et al.*, 2006).

129

130 Elevational range data

131 A total of 108 distinct mountain ranges were defined across our research region. These
132 delineations represent an edited version of data published by Körner *et al.* (2017; see Appendix S1 for
133 detailed methods and map).

134 We used two types of sphingid moth distribution data, point records of species from a multi-
135 source compilation, and comprehensive range maps based on species distribution models (SDMs) at
136 high resolution (Ballesteros-Mejia *et al.*, 2017). Subdividing point-record data further into a ‘lenient’
137 and a ‘strict’ selection of mountain ranges (see below for criteria), we had three datasets to repeat our
138 analyses and compare consistency.

139

140 Point locality data

141 We compiled georeferenced point locality records for all species of the Old World and
142 Australia/Pacific from a multitude of sources, including databasing specimen label information in
143 major natural history museums, private collections, our own field sampling, published literature, and
144 online sources (including the Global Biodiversity Information Facility, GBIF; www.gbif.org). During
145 this ca. 20-year endeavor, taxon and locality information was carefully checked and edited whenever
146 sources seem unreliable. This database is continuously expanded and updated (regarding new records
147 and nomenclature); we used 2014 data here. Raw data for each species can be browsed and
148 downloaded at Map of Life (www.mol.org). More details on data compilation and processing are
149 found in Ballesteros-Mejia *et al.* (2017). As many original records did not contain elevation
150 information, we extracted these from a high-resolution digital elevation model (DEM; 30 arcsec \approx 90
151 m; Robinson *et al.*, 2014; see also Fattorini, 2014) based on latitude and longitude information. After
152 excluding data with imprecise coordinates as well as the GBIF records (which in preliminary analyses
153 were too imprecisely georeferenced), we tested the reliability of extracting elevation data from a DEM
154 using 26,190 points with original elevation data present, yielding $r^2 = 0.753$ in a correlation of original

155 and extracted DEM elevation data. Acknowledging the trade-off between data quality and amount of
156 data available for analysis, as well as replicate analyses based on range maps (see below), we judged
157 this acceptable and utilized ca. 43,000 point records for 744 species located within the above-defined
158 mountain ranges.

159 Point records are necessarily undersampled, as not all possible sites have been visited and
160 thoroughly sampled, so we applied criteria to include only relatively well-sampled mountain ranges in
161 analyses, resulting in the selection of a high-quality dataset ('strict') nested within a lower-quality
162 dataset ('lenient'). For the 'lenient' selection we required a minimum elevation range of 1500 m in a
163 mountain range, 60 percent of the elevational gradient had to be sampled, lowest sampling had to be
164 within 300 m of the mountain base, the mountain range as a whole had to contain a minimum of 10
165 species, and point-record data had to contain at least half of SDM-model predicted richness. This
166 resulted in 40 'lenient'-selected mountain ranges. For the 'strict' selection we required a minimum
167 elevation range of 2000 m, 70 percent of the gradient had to be sampled, lowest sampling had to be
168 within 200 m of the mountain base, the mountain range as a whole had to contain a minimum of 10
169 species, and point-record data had to contain at least 75 percent of SDM-model predicted richness.
170 This resulted in 19 'strict'-selected mountain ranges. See S1 for map, data and method details.

171

172 Range map data

173 Ballesteros-Mejia *et al.* (2017) provided range maps for all hawkmoth species in the region at
174 5 x 5 km resolution. Ranges were estimated using species distribution models (SDMs) informed from
175 the point locality data compilation described above, as well as 13 climate (e.g., annual temperature
176 range, precipitation, etc.) and 3 vegetation variables (percentage of trees, herbs and bare ground).
177 SDM output was then expert-vetted and edited for dispersal limitation. Resulting data was also quality
178 controlled for predictions on emergent phenomena such as species richness (Ballesteros-Mejia *et al.*,
179 2017; data at Map of Life, www.mol.org). Range estimates are considered comprehensive and the
180 entire available elevation gradient was included. However, for inclusion in this study we also

181 demanded a minimum gradient length of 2000 m and a minimum species richness of 10 across a
182 mountain range. This resulted in 86 mountain ranges for analyses.

183 We acknowledge that both types of data, point records and range maps, suffer from potential
184 yet complementary caveats (here and in any comparable studies). Point data are undersampled and
185 require removing a larger number of mountain ranges from analyses, whereas range maps are more
186 complete but are estimates, so not based on observed specimens confirmed to occur at all sites. We
187 compensate for sampling deficiencies by comparing results from analyses of both types of data,
188 focusing on consistency of conclusions. As the results are highly concordant, we present in the main
189 text mainly modelled data, whereas point data are in appendices where appropriate.

190

191 Richness patterns

192 Each mountain range was binned into 100 m elevational bands and we used interpolated
193 species elevational ranges (i.e., assuming presence between the highest and lowest recorded specimen
194 in each range) for both datasets, as is standard in elevational studies. As we used only elevational
195 bands with sphingid presence recorded or modelled, there were no richness data with zero values in
196 analysis.

197 Species richness across the 100 m elevational bands per mountain was visualized and patterns
198 were sorted into four different pattern types (decreasing – D; low plateau – LP; midpeak – MP; low
199 plateau with midpeak – LPMP) according to criteria outlined in McCain (2010) and McCain &
200 Grytnes (2010). We classified mountain ranges as arid (incl. semi-arid) and humid according to the
201 UNEP humidity index map (Deichmann & Eklundh, 1992) to compare for consistent differences in
202 moth richness patterns. We tested, in particular, for associations of midpeak patterns with arid
203 mountain ranges (McCain, 2007a; 2009) using contingency table χ^2 tests.

204

205 Environmental predictors

206 Five predictor variables were tested for effects on elevational species richness, including area
207 of the 100 m elevational bands (A), mean annual temperature (T), annual precipitation (P), net
208 primary productivity (NPP), and the sum of NPP within an elevation band (SNPP; i.e., $A \times NPP$). In
209 preliminary analyses, we also considered the mean temperature of the months ≥ 0 °C (as a proxy of
210 temperature of the growing season) but since the results were nearly identical to T, we do not present
211 these data here.

212 For A, T and P, data were extracted from Worldclim (Hijmans *et al.*, 2005) at 30 arcsec (~1
213 km) resolution using GIS tools. Global NPP was extracted from MODIS17 (Heinsch *et al.*, 2003,
214 Running *et al.*, 2004) in 30 arcsec resolution. Crucially, for our purposes, we edited NPP data by
215 setting all ‘no data’ values to zero; ‘no data’ on land are caused by lack of vegetation reflectance
216 (indicating vegetation-free regions such as desert, bare rock or ice), hence there is zero NPP. For all
217 variables, sea and larger inland waters were clipped out (based on a polygon map by National Imagery
218 and Mapping Agency, 2009). The mean of each predictor variable was calculated across every 100 m
219 band in all mountain ranges, except for A where the sum was used (reprojected to a 1 km equal area
220 grid), and SNPP. We validated the NPP dataset (Turner *et al.*, 2006) by plotting mean NPP for each
221 elevational gradient and checked patterns for many regions that we knew personally (which convinced
222 us of the appropriateness and overall quality of the dataset).

223

224 Statistical analysis

225 Predictor and response variables were standardized to a mean of zero and unity standard
226 deviation (SD; i.e. $(x-\bar{x})/SD$), which allowed direct comparison of model coefficients. Prior to that,
227 some variables had to be transformed to reach normality. P was square root-transformed whereas A,
228 SNPP and species richness were \log_{10} -transformed. We subsequently fitted models expecting a
229 Gaussian error distribution to the transformed data.

230 For a preliminary assessment of main effects in our data we ran univariate correlations within
231 each mountain range, plotting the frequency distribution of r^2 values across mountain ranges and

232 using median r^2 values to compare which predictor was most strongly supported as a general, single
233 driver of richness patterns. These data can be compared to earlier studies using this approach (e.g.,
234 McCain, 2009; Beck *et al.*, 2017).

235 To identify environmental drivers more rigorously in a multivariate setting, we used
236 generalized linear models (GLM, Gaussian error) with pooled data (i.e., N = number of all 100 m
237 bands across all mountain ranges). However, prior to that we controlled data for mountain range-
238 specific variation in species richness by deducting the average richness of elevation bands within each
239 mountain range (after transformation and standardization, see above). We did this to limit regional
240 effects of richness variation (e.g., latitudinal) lending support to environmental drivers of local
241 richness variation along elevation gradients (this is a variant of using a random intercept mixed
242 model; see Beck *et al.*, 2017 for similar reasoning and application). Trying various predictor
243 comparisons, we evaluated models with the Akaike information criterion (AIC) and computed AIC-
244 weighted averaged coefficients to compare effects. To avoid logical problems we did not include the
245 composite variable SNPP in models containing either NPP or A. We calculated pseudo- R^2 values of
246 best models as linear correlations of predicted vs. observed data. We also replicated multivariate
247 analyses using non-transformed richness data in a GLM with Poisson-distributed error, which had
248 been recommended by O'Hara & Kotze (2010).

249

250 **Results**

251 The majority of mountain regions featured a midpeak (MP) or low plateau-midpeak (LPMP)
252 pattern of sphingid moth species richness (modelled data: 64%; point data, lenient selection: 75%;
253 strict selection: 79%; Fig. 1). With modelled data, 17 of 21 datasets (81%) with MP patterns were
254 located in arid mountains, whereas only 16 of 65 (9%) non-MP patterns were in arid regions. The link
255 of MP patterns and the aridity of landscapes is unlikely to be due to chance (contingency table
256 analysis: $N = 86$, $\chi^2 = 19.0$, $p < 0.001$). For point locality data the associations are somewhat weaker
257 but still significantly supported (lenient: $N = 40$, $\chi^2 = 9.4$, $p = 0.002$; strict: $N = 19$, $\chi^2 = 4.4$, $p =$
258 0.036). The elevation of richness peaks was not affected by mountain-wide species richness (see

259 Appendix S1 for data and implications). Appendix S2 shows plots of elevational richness for each
260 region; the data are published as Appendix S3.

261 Preliminary univariate comparisons (Appendix S4) suggested area (A) as the strongest single
262 predictor of elevational species richness. Temperature (T) and productivity variables (NPP, SNPP)
263 were less strongly supported, whereas we found no support for precipitation (P) as a single, univariate
264 driver of richness (median $r^2 < 0.01$). Notably, despite these clear assessments of variable importance
265 across all mountain ranges, all variables featured the entire range of r^2 -values within single mountain
266 ranges (i.e., from $r^2 < 0.1$ to $r^2 > 0.9$). These first assessments were supported by model-based as well
267 as point locality data (Appendix S4)

268 Multivariate models containing A, T, P and NPP as predictors were always best with a wide
269 margin (according to AIC; modelled data: (pseudo-)R² = 0.689; points-lenient: R² = 0.715; points-
270 strict: R² = 0.795), whereas models containing SNPP are weaker. They are highly concordant in their
271 AIC-based assessment among the three data sources (Appendix S5). Averaged coefficients (Fig. 2)
272 clearly point to the paramount importance of A in predicting richness in all three datasets, followed by
273 T, NPP and SNPP, while P was always a non-significant predictor. Alternative analyses (using
274 untransformed richness and Poisson- error models) confirmed most above effects but were ambiguous
275 on whether there is an effect of P or not (Appendix S6; see there also for discussion on the necessity
276 and reliability of this approach for our data).

277 Repeating univariate correlation analyses separately for humid and arid mountains, we found
278 slightly higher fits of richness with temperature in humid mountains but lower, rather than higher, fits
279 in NPP in arid mountains contrary to predictions (Appendix S7). Both arid and humid mountain data
280 individually supported the same conclusions drawn for the combined dataset.

281 Spingid and geometrid moth elevational richness along 15 elevational gradients did not
282 strongly correspond, with geometrids featuring mid-peak (or LPMP) patterns more often than
283 sphingids. This may indicate that taxon-specific effects contribute to shape these patterns (see
284 Appendix S8 methods and details).

285

286 **Discussion**

287 Our study provides the most comprehensive analysis of elevational gradients for any insect
288 taxon, covering 86 mountain ranges from the northern-temperate, tropical to the southern-temperate
289 regions (Figs. 1, Appendix S1). This allowed us to compare the variation in species richness patterns
290 across ecologically diverse zones with different biogeographic histories, and test hypotheses on
291 environmental drives of richness for their global generality. Consistent for different data types
292 (modelled range maps, point locality records) and analytical approaches (multivariate and univariate),
293 we found that the area of elevational bands (i.e., the topography of mountains) had the strongest
294 impact on measured richness. Multivariate modelling (Fig. 2) indicated that this area-shaped pattern is
295 further modulated by temperature and primary productivity (NPP), but not by precipitation per se. We
296 did not find strong support for the area-integrated metric of productivity (SNPP).

297

298 Mountain topography and its effect on species richness

299 Our finding of strong elevational area effects is consistent with earlier regional studies on
300 other taxa such as vertebrates (Rahbek, 1995; McCain 2007b) and plants (Karger *et al.*, 2011). It is
301 also consistent with non-elevational species-area relationships (SAR; Preston, 1962; Rosenzweig,
302 1995), ‘ecology’s most general pattern’ (Lomolino, 2000). The same mechanisms that shape non-
303 elevational SARs, among them more comprehensive sampling and higher habitat heterogeneity in
304 larger areas, could affect regional-scale richness in mountains (i.e., richness of elevational bands),
305 which could then ‘echo’ down to a (weakened) area effect on the species richness in local samples
306 (Rosenzweig & Ziv, 1999; Romdal & Grytnes, 2007). Consistent with this idea, many elevational
307 studies based on local samples of richness also reported correlations with area (e.g., Kessler *et al.*,
308 2009; Beck *et al.*, 2017). Furthermore, Karger *et al.* (2011) showed that an area-correction of regional
309 richness yields higher correspondence of regional and local richness patterns than uncorrected data,
310 supporting the causal link of area to regional to local richness. However, we see at least three issues

311 that cast some doubt on this apparent consensus of (largely non-elevational) SAR theory and
312 empirical studies on mountain biodiversity.

313 First, although area effects seem best-supported even in our univariate analyses (with very
314 high median r^2 values; Appendix S4), area alone cannot account for the highly prevalent richness
315 midpeaks (or similar curvilinear patterns; Fig. 1). Area usually declines, often monotonically, with
316 elevation except in landlocked landscapes (where lowest elevations can occur in valleys or ravines;
317 McCain, 2007b), as long as the surrounding lowlands are included (our selection included lowlands
318 contained approximately within 50 km pixels, see Methods). Thus, there must be additional,
319 modulating effects on richness patterns (McCain, 2007b). Among the candidates for such modulation,
320 climate and productivity patterns (see below) could lead to a variation in richness patterns in different
321 parts of the world (as observed; Fig. 1; McCain, 2007a, b), whereas the mid-domain effect (not
322 addressed here; Colwell & Hurtt, 1994; Colwell *et al.*, 2016) would lead to symmetrical midpeaks
323 uniformly among all mountain ranges (not observed).

324 Second, given the ubiquitous pattern of declining temperature on almost all mountain ranges
325 of the world (Barry, 1992), combined with theoretically sound and empirically well-documented
326 temperature effects on richness, it is unwise *a priori* to ‘correct’ richness for area via residuals from
327 the Arrhenius-function (as is commonly done; e.g., Rahbek, 1995; Sanders, 2002; Karger *et al.*,
328 2011). Such an *a priori* area correction is likely to capture variation of other potential, collinear
329 predictors, such as temperature, which leads to biased estimates of effects (i.e., overestimating area
330 effects, underestimating collinear effects; Freckleton, 2002). Furthermore, parameter estimates of area
331 effects are often uncertain due to small sample sizes (i.e., number of elevation bands on a mountain).
332 Empirically measured SAR slopes (‘z-values’) are highly variable in non-elevational empirical studies
333 (Dengler, 2009) despite the elegant theoretical deduction of $z = 0.27$ in idealized landscapes (Preston,
334 1962). In an elevational context there is not even any certainty of what to expect theoretically. Instead,
335 area effects should be accounted for as partial coefficients in a multivariate setting (Freckleton, 2002).
336 However for illustration, we carried out an *a priori* correction for area effects (Appendix S9), results
337 of which highlighted the problems listed above.

338 Third, area effects on richness, even when strongly supported as a single driver in elevational
339 studies (Appendix S4), imply effects of environmental variation along mountain slopes on the level of
340 individual species. Without elevational habitat or climatic specificity for individual species that lead
341 to range limits there could be no elevational SAR; such elevational zones (or bands) would be
342 identical, continuous habitat. Elevational range limits can only be caused by environmental variables
343 (abiotic or biotic) because the proximity of elevational bands in a mountain range makes dispersal
344 limitation an implausible mechanism. Most organisms covered in elevational biodiversity studies can
345 be assumed to be sufficiently mobile to be able to disperse to suitable available habitat within the
346 studied mountain slope, which often covers only few kilometers in travel distance. This is in contrast
347 to non-elevational SARs where dispersal limitation could theoretically cause distinct geographical
348 ranges even in a 'neutral' world (Preston, 1962). Thus, elevational area effects require the assumption
349 of environmentally determined elevational range limits of species to explain a non-environmental,
350 area-driven effect on the emergent level of species richness. This is not a contradiction to elevational
351 SARs, but spelling out its inherent assumptions draws strong parallels to the mid-domain effect,
352 where the same assumption of *a priori*-set, species-specific elevational ranges had sparked a very
353 controversial discourse (e.g., Hawkins *et al.*, 2005).

354

355 Temperature and productivity, but not precipitation

356 Our multivariate analyses indicated independent, partial effects of temperature as well as
357 productivity (Fig. 2); temperature is also supported as a single 'main driver' of richness (Appendix
358 S4) whereas NPP is not. Both effects are consistent with a very large number of studies on the
359 environmental control of biodiversity yet both assume mechanistic underpinnings that are
360 controversial and not yet well-substantiated. Temperature or kinetic energy, as a direct driver of
361 richness variation, has been hypothesized to affect generation times, speciation rates, and the speed of
362 evolution (Rhode, 1992), for example through its effect on chemical reaction speeds and metabolism
363 (e.g., the 'metabolic theory of ecology'; Brown *et al.*, 2004; Allen *et al.*, 2007). Empirical evidence

364 for the precise predictions on temperature effects on richness is mixed (Brown *et al.*, 2004; Hawkins
365 *et al.*, 2007).

366 Primary productivity is clearly affected by climatic factors such as temperature and
367 precipitation as well as evaporation rates, but its effect on richness, empirically shown here and in
368 many other studies (Mittelbach *et al.*, 2001; Ballesteros-Mejia *et al.*, 2017) must not be confused with
369 direct effects of these variables. Potential energy supplied into a system by photosynthesis could
370 affect richness through various hypothetical mechanisms (Mittelbach *et al.*, 2001; Evans *et al.* 2005;
371 Storch *et al.*, 2005; Allen *et al.*, 2007), but the most commonly assumed causal pathway is via
372 increased food resources and thus population sizes, which would reduce extinction rates in a system
373 (the ‘more individuals-hypothesis’; Evans *et al.*, 2005). Surprisingly, given its relevance for the
374 understanding of biodiversity patterns, there are very few rigorous, comprehensive tests of all four
375 aspects of this idea (productivity-food resources-population sizes-diversity), yielding mixed results
376 (Classen *et al.*, 2016; McCain *et al.*, 2018) and tests for two or three variables are also equivocal.
377 Because overall productivity may not necessarily be tightly linked to the fraction of productivity
378 available to a given taxon (e.g., due to feeding specialization or competition from other taxa), analyses
379 of NPP may underestimate the relevance of available food resources on richness (but see McCain *et*
380 *al.*, 2018).

381 One potential mechanism for how area as well as productivity could affect richness may be
382 their combined influence of both, for example the area-integration of productivity. The reasoning
383 behind this is that the total, regional amount of potential energy, not its local average, affects
384 population sizes hence extinction rates (Evans *et al.*, 2005; Storch *et al.*, 2005; Jetz & Fine, 2012;
385 Hurlbert & Stegen, 2014). Although Beck *et al.* (2017) presented supporting data for such a
386 mechanism in an elevational context for geometrid moths, these data did not indicate superior effects
387 of SNPP over area alone (but rather weaker ones) for sphingid moths. Nevertheless SNPP was a
388 stronger single ‘main’ driver of richness than NPP alone (Appendix S4). Further evaluations of SNPP
389 by exploring landscapes with uncorrelated or even opposite area and NPP gradients, may thus be
390 informative.

391 Our analyses reject any direct effect of precipitation on richness (but see Appendix S6, and
392 discussion therein). However, we found a higher prevalence of midpeak patterns in arid regions,
393 which points towards a precipitation-influenced midpeak of productivity. In arid regions, water
394 availability is usually the limiting factor for plant growth (hence productivity), and arid mountains
395 typically feature higher precipitation at mid-elevation compared to the base of the mountains (as
396 precipitation increases with elevation across the mountains; Barry, 1992; McCain & Colwell, 2011).
397 Thus, we suggest that earlier reports of precipitation effects on richness may in parts have been
398 indirect due to its effect on primary productivity, data for which were not readily available in many
399 past studies. In arid mountains, for example, (actual) evaporation and productivity typically peak at
400 mid-elevations where both precipitation (increasing with elevation) and temperature (declining with
401 elevation) are not too low. However, neither temperature nor precipitation necessarily has a direct
402 effect on richness in such situations despite detected empirical correlations. Exceptions may be
403 taxonomic groups whose life history is tightly bound to water (e.g., ferns, amphibians). A caveat to
404 this assessment, however, is the unreliability of Worldclim interpolated precipitation data from
405 tropical regions with few weather stations (Soria-Auza *et al.*, 2010). This may have hidden
406 precipitation effects. Nonetheless, when restricting analysis to 15 European mountain ranges (where
407 raw climate data used for interpolation were presumably more comprehensively sampled), we also
408 found no evidence for positive precipitation effects on richness (i.e., for model data, univariate
409 analysis: median $r^2 = 0$; all but one mountain range featured negative coefficients). Our published data
410 (Appendix S3) will allow future retesting with alternative or future improved climate data.

411 Our study does not exclude the possibility of further modulation of richness patterns by
412 variables not included in our analysis, among them the mid-domain effect (Colwell *et al.*, 2016), past
413 climatic change (Colwell *et al.*, 2008), biotic interactions, geology, and locally idiosyncratic
414 evolutionary histories. Furthermore, human landscape modification has the potential to affect richness
415 patterns. Diversity-eroding habitat modifications, agriculture in particular, is most prevalent in
416 lowlands, and it has been suggested that human impacts could therefore shift naturally declining
417 richness patterns towards midpeaks (McCain & Grytnes, 2010). If this were true, we would find

418 midpeaks predominantly in region of high, long-lasting human disturbance. We could not rigorously
419 address this hypothesis here due to uncertainties of the timing of human disturbance in relation to
420 point record data sampling in our sphingid data. However, preliminarily, Fig. 1 does not lend support
421 to low-elevation disturbance and midpeaks. For example, whereas the Alps, as a region of heavy
422 human impact for many centuries, exhibit a midpeak (consistent with the hypothesis), the neighboring
423 and equally disturbed Dinarids and Pyrenees show a decreasing pattern, as do heavily disturbed
424 regions in eastern Asia. Furthermore, some regions with the world's least and most recent human
425 disturbance, such as Borneo, New Guinea, Central Asia and Siberia, also feature (low-plateau)
426 midpeaks. Beck *et al.* (2017) concluded the same for geometrid moth data across the globe.

427 Concurrent with elevational studies on various taxa (McCain, 2007a,b; Kessler *et al.*, 2011;
428 McCain & Beck, 2016; Beck *et al.*, 2017) we observed high idiosyncrasies of results from individual
429 mountain ranges despite finding clear, interpretable results from pooled data. This implies that single-
430 gradient studies can lead to spuriously different results on the drivers of diversity. Our study also
431 highlights how range maps based on fine-grained SDMs can be used in combination with point
432 locality records to balance each other's weaknesses and uncertainties.

433 Raw richness differed clearly between point records and model data in many mountain ranges
434 (Appendix S2). Most point data indicate overall lower richness than model data (probably due to
435 undersampling in point records), but a similar richness trend with elevation. Furthermore, some
436 mountains richness patterns differ because point records often show a faster decline of richness
437 towards high elevations compared to model data. Possibly high elevations are particularly
438 undersampled, likely due to difficulties of access. Alternatively, model data may overestimate ranges
439 at high elevations in particular. SDMs were fitted to point records including data from lowland
440 regions (not analyzed in this study). If a species occurred widely across lowlands of a given climate, it
441 may also be predicted on a mountain of similar climate even if mountain-specific environmental
442 circumstances may cause its absence. Because mountains overall have a small area compared to
443 lowlands, their impact on SDM fitting and evaluation may be too small to avoid such effects.
444 Furthermore, the grain size of SDMs (5 km) may cause error at high elevations where environmental

445 gradients are often very steep (i.e., 5 km may encompass a large elevational variation in mountain top
446 regions). However, we do not have the relevant data to address these speculations empirically. Other
447 pattern variability occurred in particular where undersampling seemed an issue (i.e., large difference
448 in absolute numbers between point records and model data) or on small mountains with few
449 elevational bands (Appendix S2), both pointing towards random effects. To reiterate, both point
450 records and modelled data led to very similar conclusions with regard to the environmental drivers of
451 richness.

452 This study is another step towards summarizing and conceptualizing the wealth of
453 Lepidoptera data on elevation gradients. Comparing pattern variation and underlying differences in
454 adaptations among this hugely diverse order may help to formulate and test novel hypotheses on
455 evolutionary impacts on the environment-richness relationship. Data on geometrid moths (i.e.,
456 inchworms) from Beck *et al.* (2017; see Appendix S8) show predominantly midpeak richness patterns
457 irrespective of the geographic position of gradients, whereas we have shown here strong variation in
458 patterns for sphingids particularly between arid and humid mountains (Fig. 1). The likely causes for
459 the incongruent patterns between geometrid and sphingid moths is currently far too complex for
460 speculation, as geometrids and sphingids differ in many aspects of their ecology – among which are
461 body size, mobility and larval host plant specificity (see Appendix S8 for further discussion). Future,
462 comprehensive multi-gradient assessments for other major moth taxa (such as arctiine erebids; Brehm,
463 2009; pyraloids; Fiedler *et al.*, 2008) may help to pinpoint more clearly how ecological differences
464 co-vary with richness patterns. Due to their high diversity, potential for experimental studies, and
465 more detailed descriptive analyses that include more difficult-to-measure variables (such as local
466 productivity, taxon-specific food resources, and species' abundances), we see potential in insects and
467 other understudied taxonomic groups for testing macro-scale predictions on biodiversity effects in
468 relation to major life history traits, as has been attempted already in vertebrates (Buckley *et al.*, 2012).
469 For birds, the arguably best-studied taxon in macroecology, Quintero & Jetz (2018) have recently
470 gone one step further by studying phylogenetic patterns along elevational gradients (i.e.,
471 diversification rates). With the proliferation of phylogenetic information in other clades, increasingly

472 so within insects, future research will also involve cross-taxon comparisons of such patterns. By
473 publishing our data, raw as well as condensed for elevational analysis, we help make sphingid moths a
474 part of such comparative endeavors, possibly as the presently only insect representative.

475

476 Outlook

477 Our results on global-scale elevational richness pattern variability as well as on the main
478 drivers of richness patterns are consistent with patterns found in other taxonomic groups, and with
479 main environmental correlates of richness found in non-elevational settings, in sphingid moths
480 (Ballesteros-Mejia *et al.*, 2017) and other taxa (e.g. Davies *et al.*, 2007; Kreft & Jetz, 2007; Fritz *et*
481 *al.*, 2017). Rather than viewing this as a lack of novelty, we find it highly reassuring. Elevational
482 gradients have been proposed as model systems to study larger-scale richness pattern, but the repeated
483 observation of midpeak patterns of richness variation in many mountains had cast doubt on this. It
484 seemed as if something fundamentally different goes on in shaping mountain biodiversity. Our study
485 tentatively suggests that this is not the case for sphingids – it just requires the inclusion of fine-grained
486 primary productivity data as a driver of richness to explain not only such seemingly strange patterns,
487 but also where they occur and where not (McCain, 2007a). Pseudo- R^2 values between 0.7 and 0.8
488 from our relatively simplistic, one-fits-all global multivariate models indicate a very good fit given the
489 inevitable error and uncertainty in predictor and response data, which are estimates themselves. This
490 suggests that while clade-specific adaptations and their effects urgently require better understanding,
491 the principal mechanisms shaping biodiversity patterns can be reconciled among elevational and non-
492 elevational studies. Elevational richness gradients, however, will continue to play a central role in
493 biodiversity research due to their natural replication, exclusion of unwanted dispersal limitation
494 effects, and breadth of environmental gradients within small study regions, among other advantages.

495

496

497 **Supporting Information**

498 **Appendix S1** Mountain ranges used for analyses

499 **Appendix S2** Plots of elevational species richness for all mountain ranges

500 **Appendix S3** Richness data per 100m elevation band for all mountain ranges (csv file)

501 **Appendix S4** Univariate correlations

502 **Appendix S5** AIC-based model comparisons

503 **Appendix S6** Alternative modelling

504 **Appendix S7** Humid vs. arid mountains

505 **Appendix S8** Comparison of geometrid and sphingid elevational patterns

506 **Appendix S9** *A priori* correction for area

507

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514

515 **Biosketch**

516 Florian Bärtschi completed his MSc in the research team of JB, which focussed on insect
517 macroecology and the environmental impacts on biodiversity. *Author contributions:* FB and JB
518 designed the study and analysed data, supported by NB and CMM; JB, LB-M and IJK provided
519 sphingid moth data; JB, FB and CMM wrote the manuscript, with input from all authors.

520

521 **Data availability statement**

522 Raw distribution records can be viewed, model-based range maps for all non-American sphingid
523 species can be viewed and downloaded* at www.mol.org.

524 Richness data per 100 m elevation band are available in spreadsheet format (Appendix S3).

525

526 *) will be made accessible upon publication

527

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696 FIGURE CAPTIONS

697

698 **Fig. 1** Mountain ranges and their prevailing richness pattern for sphingid moths (LPMP = low
699 plateau-midpeak; pattern definitions and inset sketches based on McCain & Grytnes 2010). “No
700 pattern” identifies regions that did not fit any of these categories (see Appendices S2 & S3 for plots
701 and data of all richness patterns).

702

703 **Fig. 2** Averaged standardized coefficients (bars; AIC weighted) and 95% confidence intervals
704 (whiskers) from multivariate linear models (see Appendix S5 for model details; S = strict selection, L
705 = lenient selection). Positive associations were expected for all predictors (Appendix S4).