

Temperature, Body Size, and Altitudinal Gradients of Biodiversity: A Neutral-Metabolic Model

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MRes in Computational Methods in Ecology and Evolution.

1 Declaration

2 The model is based on the Neutral Theory of Biodiversity and the Metabolic Theory of Ecology, but is
3 an original synthesis and application of the two. It moves beyond previous work - the basic algorithm
4 of a neutral model was significantly developed to introduce new mechanisms. My supervisors, Dr James
5 Rosindell and Dr Samraat Pawar, gave excellent support throughout - particularly by allowing ample
6 time to discuss the model's implementation and geometry. I certify that:

- 7 - All theory that is not my own work is properly acknowledged, and extensions to existing work
8 highlighted clearly.
- 9 - All code written in the Python and R languages, to build, simulate, and analyse the model, are my
10 own work.

11 Abstract

12 Nature changes with altitude, and a decline in the number of species with increasing altitude is well-
13 reported. Nevertheless, studies show a variety species-richness curves along mountains - there remains
14 debate on the exact form of the decline. A multitude of mechanisms have been proposed to explain
15 both the gradients general form, and the reasons for the variations on it. However, an over-reliance on
16 studies of correlation has hindered progress. I present a mechanistic model based on the Neutral Theory
17 of Biodiversity and the Metabolic Theory of Ecology. I use this to reconstruct altitudinal biodiversity
18 gradients and test underlying causes. A temperature gradient affects birth, death, and dispersal rates,
19 according to metabolic scaling laws. The simulations were repeated for body-size guilds - the dispersal
20 rate varied according to allometric laws. I also added an area gradient, which decreased the abundance
21 of individuals going up the mountain. Thermal effects on birth and death did not cause an altitudinal
22 biodiversity gradient at dynamic equilibrium. Thermal effects on dispersal caused a hump-shaped curve,
23 with species richness declining towards the base and top. This was due to a combination of narrow thermal
24 niche width, dispersal, and hard boundaries at the top and bottom. Thermal niche width did not vary
25 across body size guilds, so these trends were consistent across sizes. The effect of a decreasing number
26 of individuals due to area produced a decline in alpha and gamma diversity. Beta diversity, however,
27 increased with altitude. Again, the cause was a narrow thermal niche width.

28 Introduction

29 Patterns in Species Richness with Altitude

30 Species richness generally declines with increasing altitude, but it is debated whether the decline is
31 monotonic. A more general trend may be a diversity peak at mid-elevations [McCain and Grytnes,
32 2010, Rahbek, 2005]. The resolution to this is firstly compounded by methodological issues of scale and
33 sampling. Diversity is studied at two scales - local (alpha) diversity and regional (gamma) diversity.
34 Variation in altitudinal diversity trends may be due to the scale of study. Not spreading sampling effort
35 evenly over an elevational gradient impacts estimates of species richness. This can result in a skew - high
36 richness where sampling is high, and low richness where it is low [McCain and Grytnes, 2010, Rahbek,
37 2005].

38 The resolution is also compounded by a reliance on studies of correlation (e.g. [McCain, 2007, O'Brien,
39 1993]). These have been useful for describing the shape and variation of richness trends, but can only elude
40 to potential causal mechanisms. A model based on proposed mechanisms can advance our understanding
41 by directly testing and quantifying the contribution of mechanisms to patterns. The consistency of
42 the decline in species richness with altitude suggests a common underlying cause. One hypothesis to
43 explain the variation in the trends exact form, is that the magnitude of these common factors may vary
44 with environment or taxon. Additional drivers may also exist in some circumstances. What might the
45 underlying factors be?

46 Potential Causes for Patterns

47 The causes for elevation gradients of species richness are broad, ranging from climate to evolutionary
48 history. It has been argued that elevational patterns of species richness may be attributable to the
49 ecology of taxa [McCain and Grytnes, 2010]. Indeed, meta-analyses found that some patterns were found
50 in higher frequency in certain taxa. For example, a mid-elevation peak in small mammals [McCain, 2005].
51 Despite available data, however, for many taxa, such as plants and insects, these analyses have not been
52 performed. There is also a reliance on data on specific taxa, in specific mountain ranges, e.g. Herzog et
53 als (2005) data on Andean bird diversity. Finally, many groups, such as amphibians and bats, show a
54 split among patterns. Differences in patterns among taxa are a useful study tool. It is important to also
55 combine meta-analyses with studies that mechanistically link trends to functional groups.

56 Area decreases going up mountains. The change in number of species with area is one of the few
57 universal laws of ecology. The Species-Area Relationship predicts that the number species should increase
58 towards a mountain base, as surface area is greater. Surprisingly, the effect of area on altitudinal diversity

59 gradients is understudied, and analyses often do not account for it. A prominent part of ecology and
60 mountain geography, it should be expected to have a significant impact on biodiversity gradients [Rahbek,
61 1997, Rosenzweig, 1995, Gaston and Blackburn, 2008].

62 As mentioned, a positive relationship between diversity and temperature is reported. The Metabolic
63 Theory of Ecology puts forward an explanation for this relationship [?]. It predicts that the slope of the
64 thermal response of processes, on a log scale, is -0.65 [Allen et al., 2006]. McCain and Sanders (2010) tested
65 this for the effect of temperature on species richness along mountains, but found no evidence. However,
66 Metabolic Theory is based on equations that describe the thermal response of individual-level traits. The
67 scaling of these relationships up to the ecosystem level is a hot topic. But, it does not necessarily follow
68 that the slope for the response of individuals to temperature will be mirrored in ecosystem-level responses,
69 such as biodiversity patterns. What is more, exact nature of the thermal dependence of processes can
70 deviate from the reported average of -0.65 [Dell et al., 2011]. To investigate the influence of temperature,
71 via Metabolic Theory, it is important to link the temperature-dependence of ecological patterns to specific
72 processes that may be affected by individual-level responses, such as dispersal.

- 73 1 How might spatial variation in temperature affect rates of dispersal, birth, and death on a mountain?
- 74 2 Can variation in these rates, driven by the effect of temperature on metabolism, generate altitudinal
75 gradients of biodiversity?
- 76 3 Does varying the body size of organisms, or the environmental parameters of the mountain, produce
77 a variety of diversity trends?
- 78 4 What are the relative importance of dispersal and birth/death rates, and temperature and area
79 gradients?

80 Method

81 To simplify reality, neutral models assume individuals are ecologically equivalent. This does not necessarily
82 mean individuals have identical traits, it means trait variation is independent of species identity. The
83 models consist of a community and proceed in discrete, uniform time steps. In each step, a randomly-
84 chosen individual dies. With probability v , they are replaced by a new species. With probability $1 - v$,
85 they are replaced, via dispersal, by the offspring of another randomly-chosen individual. For convenience,
86 the models make a zero-sum assumption: Birth and death balance (dead individuals are immediately
87 replaced), so the number of individuals is constant [Hubbell, 2011, Rosindell et al., 2008, Rosindell et al.,
88 2011].

89 I begin with a two-dimensional, spatially explicit version: Individuals occupy cells in a grid, represent-
90 ing positions in space. When individuals reproduce, offspring disperse according to a dispersal kernel - a
91 probability distribution of dispersal distances. In a basic model, death, birth, speciation, and dispersal
92 rates do not vary across individuals.

93 I add an altitudinal temperature gradient that drives variation in death, birth, and dispersal, as
94 predicted by Metabolic Theory. To explore the effect of area, I vary the number of individuals in a cell.
95 Finally, I envision the community consists of guilds; individuals in a guild have the same body size. Each
96 guild is a separate simulation. Among guilds, dispersal ability and the total number of individuals differ,
97 as predicted by allometric scaling. So, temperature drives variation within simulations, whereas body size
98 drives it across simulations. Initially, the model is fully neutral: In a simulation, species are equivalent
99 - individual variation is independent of species identity. However, I add a survival component based on
100 conditions at the dispersal destination - species have a thermal optimum, so the model moves away from
101 neutrality.

102 The Model's Geometry

103 I use a cone's surface as a model of a mountain (Fig. 1). Unfurled, a cone's surface is a circle sector. The
104 polar coordinates, r and θ , describe position on the mountain. The circle centre (mountain tip or cone
105 apex) is the origin, $(0, 0)$. The radial coordinate, r , is the radial distance from the circle centre - how far
106 down the mountain a point is. The angular coordinate, θ , is the angle from the x-axis.

107 In silico, I represent the cone's surface as a square array (grid of cells) (Fig. 1). Rows in the array
108 are altitudinal bands, and columns, positions along a band. Row indices correspond to radial positions,
109 and column indices, to angular positions. The array's top edge is the cone's apex (mountain tip), so has
110 radial coordinate 0. The number of rows and columns does not set the size of the model mountain, it sets
111 the spatial resolution (number of positions). Though the array is depicted as a flat square, it forms a
112 cone: The left and right edges connect, and, going up the mountain, each cell represents an increasingly
113 narrow area.

114 The cone has three parameters: base radius (x), height (h), and slant height (s). Slant height is the
115 distance along the cone's lateral (curved) surface from the apex to the base. Measured in metres, these set
116 the size of the model mountain, and the area grid cells represent. c is the ratio of s and x ; R is the ratio
117 of h and x . A key advantage of the model is it expresses area and distance as proportions. This means I
118 need not pick absolute values for the cone's dimensions and simplifies the model greatly. By varying the
119 parameters' relative values, I can simulate a variety of mountain topologies. I can explore the generality of
120 diversity gradients, and the comparative importance of ecological mechanisms, across mountains. While

121 this is hard with real-world experiments, it is simple and tractable here. The SI demonstrates further
 122 relations among the cone's dimensions and its area, and how, via a conversion between units of metres
 123 and number of cells, distance and area are expressed as proportions.

Symbol	Definition
s	cone's slant height
x	radius of cone's base
c	$\frac{s}{x}$, ratio of s to x
T_r	array's height in number of cells (number of rows) - analogous to the cone's slant height
T_θ	array's width in number of cells (number of columns) - analogous to the circumference of the cone's base
I_r	row index - equal to the distance from the cone's apex in number of cells

Table 1: *Parameters of the Model's Geometry.* The model mountain is the lateral (curved) surface of a cone. In silico, I represent the cone's surface as a square array (grid of cells).

124 0.1 Population Density

125 Each cell in the array has n individuals; n is a function of body mass and area. Population density
 126 (number of individuals per unit area) should decline with body mass as $M^{-0.75}$, if resource supply is
 127 constant. This is because individual resource demand depends on metabolic rate, which increases with
 128 body mass as $M^{0.75}$. Observations in animals and plants support this [Enquist et al., 1998, Damuth,
 129 1987]. A mountain base covers more area than the top. The model mountain is a cone, but, in silico, it is
 130 a square array. So, going up the mountain, each cell in the array represents an increasingly narrow area.
 131 If A_c is cell area, the number of individuals in a cell is:

$$A_c M^{-0.75}$$

132 Then, the area of one cell in an altitudinal band is:

$$\frac{\pi c \left(\left(\frac{(I_r+1)x}{T_r} \right)^2 - \left(\frac{I_r x}{T_r} \right)^2 \right)}{T_\theta}$$

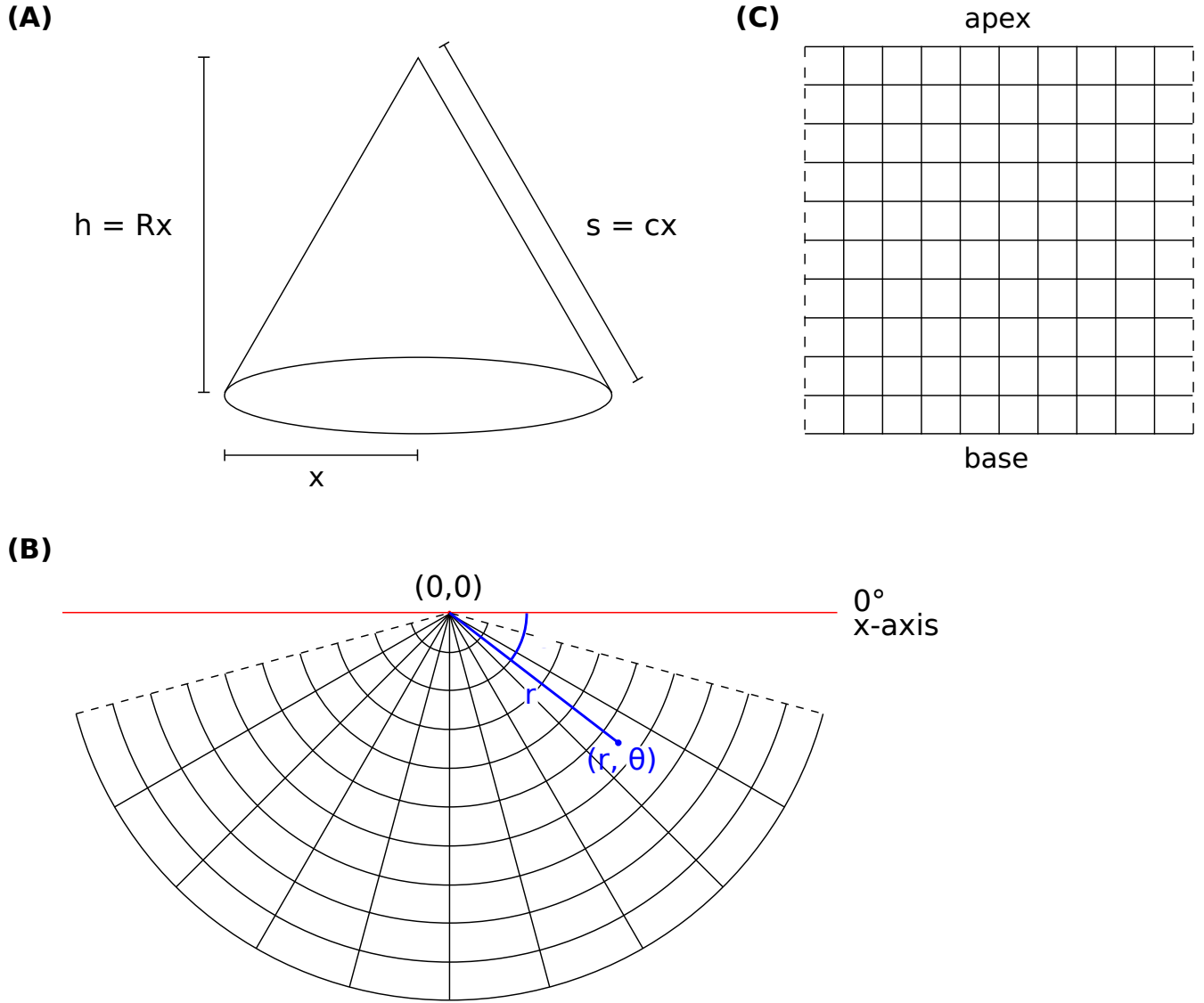


Figure 1: **(A)** The model mountain is a cone, which has three parameters: base radius (x), height (h), and slant height (s). **(B)** Unfurled, a cone's surface is a circle sector. The polar coordinates, r and θ , describe position on the mountain. The circle centre (mountain tip or cone apex) is the origin, $(0, 0)$. **(C)** In silico, I represent the cone's surface as a square array (grid of cells). Rows in the array are altitudinal bands, and columns, positions along a band. Row indices correspond to radial positions, and column indices, to angular positions. The array's top edge is the cone's apex (mountain tip).

133 Cell area is unitless, and instead expressed in terms of x , keeping the model tractable. Please see the
134 SI for the derivation of this equation.

135 Birth and Death Rates

According to the Metabolic Theory of Ecology, metabolic rate (rate at which organisms process matter and energy) affects the rates of growth, reproduction, and dispersal, as well as the longevity of organisms [201, 2012] (Sibly et al 2012). Metabolic rate depends on the body size and temperature of organisms - it increases as a power law with body size, and exponentially with temperature. Gillooly and Brown et al [Gillooly et al., 2001] combined previous work on the body-size and temperature dependence of metabolic rate into a single equation:

$$B = B_0 M^\alpha e^{\frac{-E}{kT}}$$

136 Temperature dependence is described by E , activation energy, k , the Boltzmann constant ($8.617 \times$
137 $10^{-5} eV K^{-1}$), and T , temperature in Kelvin. M^α is the power law describing the relationship between
138 metabolic rate and body size. B_0 is a mass and temperature independent, normalisation constant, which
139 accounts for other variation, and controls the vertical offset of the function. The value of the mass and
140 temperature exponents can vary, but an interspecific average of E is 0.65 [Allen et al., 2006, Dell et al.,
141 2011] (Allen et al 2006, Dell et al 2011).

142 Each row of cells in my model has a temperature. The temperature sets the rate of birth, death, and
143 dispersal. Accordingly, in my model, the probability of selecting an individual to die or reproduce is:

$$e^{\frac{-E}{kT}}$$

144 The per-cell probabilities are then normalised, so they sum to 1. I call the probabilities of birth and
145 death across each position in the landscape the birth and death 'maps'.

146 Dispersal

147 Individuals do not move, but species disperse via birth and death (when an individual reproduces, its
148 offspring fills a gap vacant due to a death). An individual's chance of being chosen to reproduce depends
149 on its birth rate, dispersal ability, and distance from the destination (vacant position). In other words, it
150 is the net probability of birth and dispersal. The challenge is that, across space, birth and dispersal rates
151 vary.

152 Imagine the origin of a dispersal kernel as being centered on the start point; the kernel describes
153 the distribution of destinations. In a sense, in neutral models, the kernel is backwards, as it centered
154 on the destination (position vacant due to death). From the kernel, the models pick a random distance

155 and direction away from the vacant position. This picks the parent whose offspring occupies the vacancy.
156 While convenient computationally, this only works if dispersal (and birth) rates are fixed. To vary dispersal
157 rate, I must amend this usual algorithm. The solution is a set of 'dispersal maps'.

158 Before running a simulation, I calculate the probability of dispersing from every cell to the destination
159 - a discrete probability distribution, which I call a dispersal map. As each cell is a potential destination
160 and probability depends on distance, there is a map per cell. Upon death, the model uses the maps to
161 immediately pick a random parent. Dispersal maps are an elegant solution because they capture, in a
162 single step of the model, variation in two traits, across three factors (temperature, body size, and area).

163 The model uses a standard normal distribution (mean = 0, standard deviation = 1) as a dispersal
164 kernel. The distribution's scale parameter, σ , determines its spread - the likelihood of long-distance
165 dispersal events. It has thin tails, meaning it predicts lower rates of long-distance dispersal than fat-tailed
166 kernels (which curve away from the x-axis). Being a phenomenological kernel, it does not capture complex
167 dispersal behaviour (Clobert et al 2012). But, it is a simple start point to introduce metabolically-driven
168 (deterministic) variation to dispersal.

169 To apply a metabolic effect to dispersal, I multiply a distance, drawn from the kernel, by a body-size
170 and temperature dependent parameter, y :

$$y = B_0 M^{0.25} e^{\frac{-0.65}{kT}}$$

171 y is proportional to mean dispersal distance, and increases with body mass and temperature.

172 The array has two axes: one runs vertically across rows, the other horizontally across columns. Instead
173 of drawing a random direction, a simple equivalent is to draw a distance along each axis separately. This
174 is a unique, simplifying property of the normal distribution. It also allows me to study the contribution
175 of dispersal vertically (up and down the mountain) and horizontally (round the mountain). Instead of
176 drawing a random distance from the dispersal kernel, I use it to calculate the probability of dispersing a
177 known distance, from a given destination.

178 **Horizontal Dispersal**

179 Going up a mountain, the distance round it decreases (the base covers more area than the top). However,
180 in silico, the system is a square array - horizontal dispersal distance must be adjusted. Towards the top,
181 individuals should be more likely to disperse among cells, within a row (ignoring the effect of temperature).
182 Also, they should be more likely to complete a revolution round the mountain. So, dispersal ability is
183 unaffected by area, but, as area reduces going up, so does the distance among cells.

184 The model expresses distance in relative terms. This maximises the model's relevance (the simulated

185 mountain can be any size) and minimises complexity (I need not pick absolute values for the cone's
186 dimensions). An altitudinal band is a circle round the cone's surface. So, horizontal dispersal (left to
187 right or vice versa) occurs along an arc of a circumference. The probability of dispersing the horizontal
188 distance to the destination is:

$$P\left(V = \frac{n_{\theta} x \pi (S_r + E_r)}{T_{\theta} T_r y}\right)$$

189 Please see SI for derivation. This depends on distance to the destination (an arc, or proportion,
190 of a circumference), body size, and temperature. It decreases as V increases, as V is a variate of the
191 standard normal distribution (mean = 0). Probability increases as body size and temperature increase,
192 and distance reduces. In other words, big individuals, and those in hot places or close to the destination,
193 have a higher chance of reaching the destination.

194 **Revolutions Round the Mountain**

195 So far, I assumed individuals take the shortest route between the start point and destination. This is not
196 necessarily true because the array's left and right edges connect. So, to reach a given location, individuals
197 can go in either direction (left or right). What is more, they can go via any - and a theoretically infinite
198 - number of loops round the mountain. I.e., they have a choice of alternative routes of varying distances.
199 Accordingly, per horizontal position, I sum the probability of each alternative distance to the destination.

200 **Vertical Dispersal**

201 Dispersal up and down the mountain occurs between the apex and base, along the cone's lateral (curved)
202 surface. Unlike the left and right edges, the bottom and top ones are not joined - individuals cannot
203 disperse across them. So individuals can only disperse in one direction. The probability of dispersing up
204 or down the mountain, from one row to another is:

$$P(V = \frac{n_r c x}{T_r y})$$

205 Like d_{θ} , it depends on distance to the destination (a proportion of the slant height), body size, and
206 temperature.

207 I multiply the probabilities of dispersing the horizontal and vertical distances, to get the probability of
208 dispersing from every [row, column] position to the destination. For a given destination, I then multiply
209 the dispersal rate (or probability) at each position with the position's birth rate. This produces a net
210 probability of birth and dispersal, which I normalise so the probabilities sum to one. These map of net
211 birth and dispersal rates are used to, upon a death, immediately pick an individual to reproduce - a

spatial map of the possible parents for immigrants to that cell. Calculating these probabilities before running the simulation is a computationally tractable way to introduce variation in these key ecological rates.

Normalisation of Dispersal Rates

B_0 is usually parameterised using taxon-specific regressions of trait on temperature. Here, however, I set it to be a free parameter. Increasing B_0 uniformly increases dispersal rates everywhere, and decreasing, vice versa. I set it to a moderate values that ensures dispersal is not dominated by: 1. looping round the mountain 2. dispersing within a single cell.

Thermal Optima and the Neutrality Assumption

The rate of vertical dispersal is set by the temperature of the dispersal start point. (In later simulations, I instead change this to the temperature of the altitude halfway between the start and destination). However, as an individual disperses up or down the mountain, their temperature environment changes. Modelling a dynamically-changing effect of temperature on dispersal would involve combining successive transformations of the dispersal kernel. This is complex.

The physiology of species limits the range of temperatures in which they survive. It is not necessarily realistic that, once a species disperses to a new temperature environment, their fitness is unchanged [Angilletta, 2009]. To compensate for the mechanism of vertical dispersal, the model has a survival component. All individuals in the model have a temperature optimum (T_{opt}). An individual's T_{opt} is: - the temperature at which it is most likely to survive - at the start of the simulation or for a new species, the temperature of its position - otherwise, the same as its parent's. The probability of surviving at different temperatures is a normal distribution; the mean of which is the T_{opt} (highest probability of survival). Upon dispersal, the temperature of the destination is used to extract the probability of survival from the normal distribution. If an individual does not survive, the algorithm picks another individual to disperse, until the dispersing individual survives.

The scale parameter of the normal distribution is akin to thermal niche width, and defines a new parameter of the model. Increasing thermal niche width, would increase dispersal among altitudinal bands, and decreasing it, vice versa.

Individuals are no longer equivalent - the model is no longer neutral. As the thermal optimum is passed from parent to offspring, this property is not independent of species identity. It is important to note that species T_{opt} do not change in the model, there is no adaptation or acclimation to new environments.

242 Parameter Space Analysis

243 The model's parameters, in addition to the geometric ones in Table 1, are listed in Table 2. I begin
244 with a basic neutral model with no temperature or area gradient. I then apply the following three effects
245 independently and in concert with each other: - metabolic effect on i) dispersal, and ii) birth/death,
246 via a thermal gradient - area gradient, which affects the distance round the mountain and the number
247 of individuals per altitudinal band. In this way, I could test the relative importance of dispersal and
248 birth/death, and area and temperature.

249 I simulated the full model (with all effects) for body size values that span two orders of magnitude.
250 Note that the absolute body-size values of these guilds is not important - it is the relative difference
251 that is important. The reason is a computational limitation. There must be at least one individual per
252 cell in the landscape - I normalise the scaling of abundance accordingly. Therefore, the model likely has
253 unrealistic levels of abundances. So, the model is not designed to precisely predict the number of species,
254 but can predict general trends and patterns.

255 Finally, I vary the following parameters: - thermal niche width (standard deviation of a normal
256 distribution) - the ratio between the mountain's height and base radius, R , which controls the mountain's
257 steepness - the normalisation constant for dispersal, B_0 - speciation rate, v

258 Increasing the height or base radius of the mountain, leads to an increase in area and thus abundances
259 of individuals. To keep the size of communities tractable, I fixed the area, but varied the mountain's
260 steepness by varying the ratio of height to base radius. The default temperature gradient was 10-25 °C,
261 which approximates that on a tropical mountain. I also uniformly decreased the mountain's temperature
262 by 10 °C, to simulate a hypothetical temperate mountain. These parameters represent abiotic factors,
263 and factors related to the species traits. Thus, I could also test whether any apparent general trends in
264 diversity, changed under different scenarios.

265 I wrote code for the model and simulations in Python 3, and ran the simulations for 48 hours on the
266 High Performance Computing Cluster at Imperial College London. I ran at least 10 replicates of each
267 parameter combination. More replicates would be preferred - the number reflects what was possible in
268 the project's time frame, given the number of parameter combinations.

269 Results

270 Dispersal Maps: Hoes does the Pattern of Dispersal Change Going up the Mountain?

271 In the absence of a temperature gradient, dispersal rate is the same everywhere. However, the area
272 gradient (the mountain's conical geometry) affects distance round the mountain, and thus the probability

273 of dispersing to a given cell. For a destination at the top, individuals from any side round the mountain
274 are almost equally likely to disperse in (Figure 2). The probability of dispersing to the destination is
275 mostly unaffected by horizontal distance to the destination. This is because distance round the mountain
276 is short. In contrast, the mountain base is wide - distances among cells are further. Immigration to a
277 destination there, is only likely to occur from the same side of the mountain. While vertical distance to
278 the destination is more important, the effect is mostly the same regardless of the destination altitude. A
279 destination at the base receives slightly more immigrants that are vertically further away. This is because
280 I normalise probabilities so they sum to one, and there is less horizontal dispersal.

281 Adding a temperature gradient increases the chance of receiving immigrants from altitudes lower than
282 the destination (Figure 3). This is true regardless of destination altitude. Crucially, this contrasts with
283 the effect of area alone. The cause is that temperature, and thus dispersal rates, reduce going up the
284 mountain. Similarly to the area effect, a destination at the top is equally likely to receive immigrants from
285 any side round the mountain (horizontal distance is unimportant). This is despite the colder temperature.
286 However, for a destination at the base, horizontal dispersal increases. This suggests temperature drives
287 the dispersal pattern at the base, but area drives it at the top.

288 Bigger individuals disperse further. At all altitudes, in all directions, bigger organisms have a wider
289 pool of immigrants (Figure 4). Uniformly increasing the temperature of the whole mountain (studying the
290 hypothetical tropical mountain, instead of the temperate one), has a similar effect (Figure 3). Visualising
291 the dispersal maps helped to parameterise the model by identifying extreme scenarios. Increasing or
292 decreasing by an order of magnitude the normalisation constant for dispersal (higher or lower dispersal
293 rates overall), overrode the variation induced by area and temperature but to different ends: By increasing
294 it, the probability of dispersing to a destination is almost the same everywhere. Decreasing it largely
295 restricted individuals to one cell (Figure 5).

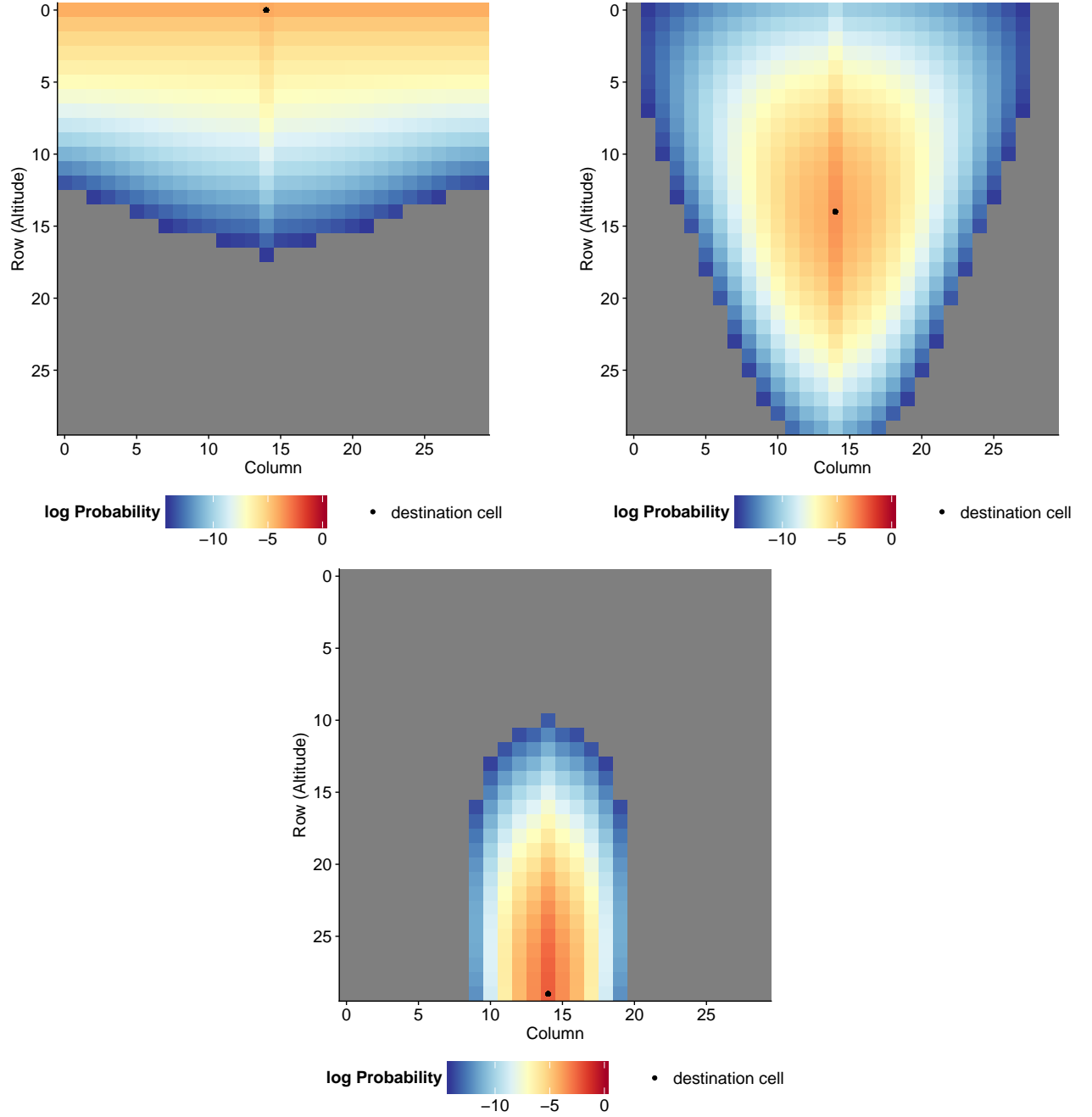


Figure 2: **Dispersal Patterns on a Model Mountain - the Effect of Area.** Temperature is the same everywhere ($15\text{ }^{\circ}\text{C}$). The heat map shows the probability of dispersing to a destination at the top, middle, and bottom of the mountain. Grey cells represent probabilities $\leq 1 \times 10^{-6}$. A mountain base covers more area than the top. But, in silico, the model mountain is a square array; going up it, each cell represents an increasingly narrow area. Row 0 is the top. Other parameter values: body size, $M = 100\text{ g}$; ratio of the mountain's height and base radius, $R = 1.5$.

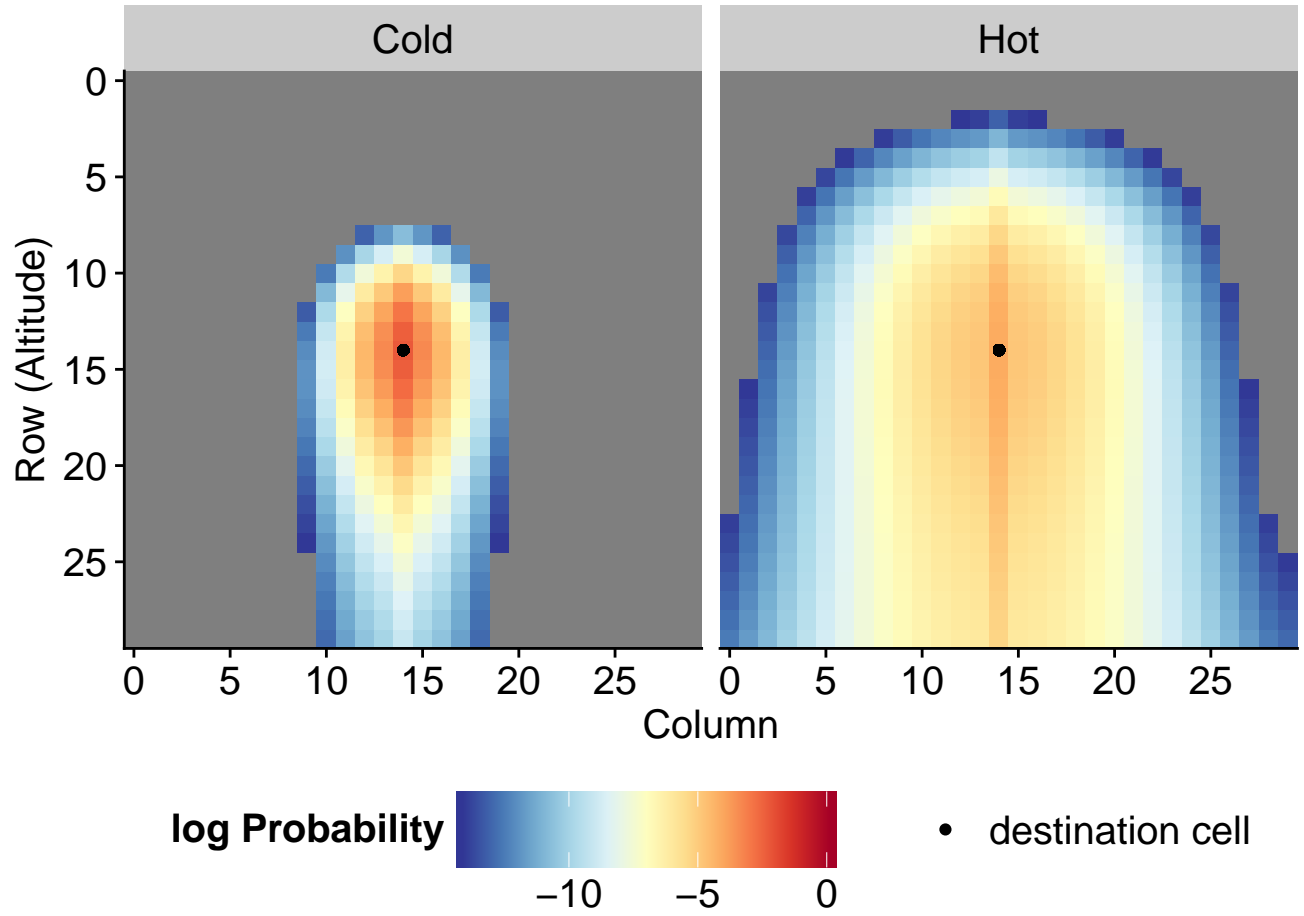


Figure 3: **Dispersal Patterns on Model Mountains - the Effect of Temperature.** In the left plot, the temperature gradient approximates that on a temperate mountain (0-15 °C from top to base); on the right, a tropical mountain (10-25 °C). Temperature affects dispersal rate as per the Metabolic Theory of Ecology. The heat maps show the probability of dispersing to a mid-altitude destination. Grey cells represent probabilities $\leq 1 \times 10^{-6}$. A mountain base covers more area than the top. But, in silico, the model mountain is a square array; going up it, each cell represents an increasingly narrow area. Row 0 is the top. Other parameter values: body size, $M = 100$ g; ratio of the mountain's height and base radius, $R = 1.5$.

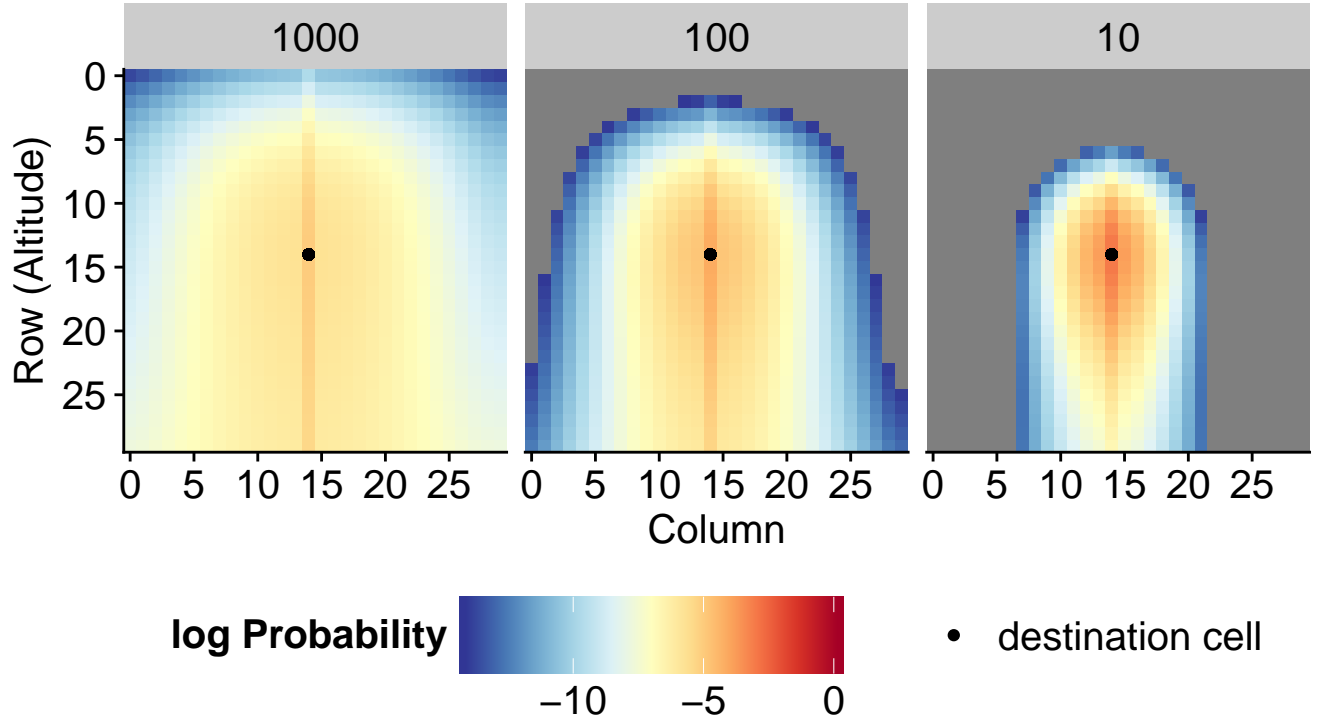


Figure 4: **Dispersal Patterns on a Model Mountain - the Effect of Body Size.** Body size and temperature affect dispersal rate as per the Metabolic Theory of Ecology. The heat maps show the probability of dispersing to a mid-altitude destination. Grey cells represent probabilities $\leq 1 \times 10^{-6}$. The body sizes are 1000, 100, and 10 g, from left to right. The temperature gradient approximates that on a tropical mountain (10-25 °C). A mountain base covers more area than the top. But, in silico, the model mountain is a square array; going up it, each cell represents an increasingly narrow area. Row 0 is the top. Other parameter values: body size, $M = 100$ g; ratio of the mountain's height and base radius, $R = 1.5$.

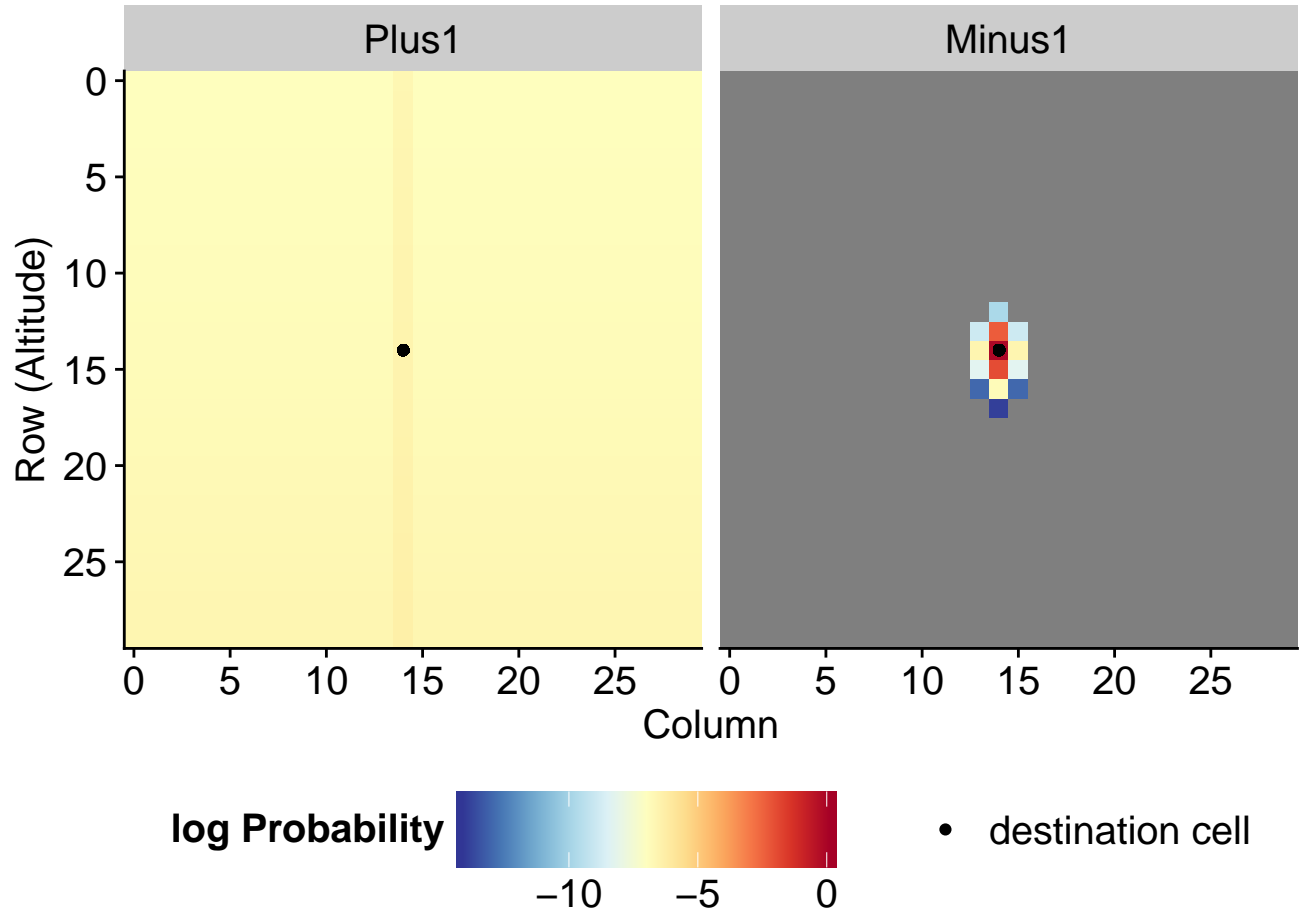


Figure 5: **'Making Mountains Out of Molehills': Dispersal Patterns on a Model Mountain, under Extreme Parameters.** Temperature affects dispersal rate as per the Metabolic Theory of Ecology. For the left plot, I increased the normalisation constant for dispersal by an order of magnitude. For the right, I reduced it by an order. The heat maps show the probability of dispersing to a mid-altitude destination. Grey cells represent probabilities $\leq 1 \times 10^{-6}$. The temperature gradient approximates that on a tropical mountain (10-25 °C). A mountain base covers more area than the top. But, *in silico*, the model mountain is a square array; going up it, each cell represents an increasingly narrow area. Row 0 is the top. Other parameter values: body size, $M = 100$ g; ratio of the mountain's height and base radius, $R = 1.5$.

296 Altitudinal Biodiversity Gradients

297 A basic neutral model, which had no temperature and area mechanisms, did not produce a biodiversity
298 gradient at dynamic, extinction-speciation equilibrium. Rows in the array had a similar species richness,
299 but with some stochasticity. Running the model, but with a metabolic effect on birth and death rate, via
300 a thermal gradient, produced similar results.

301 By adding a metabolic effect on dispersal rate, an equilibrium gradient emerged - the species richness
302 curve was hump-shaped (Fig. 6). Diversity was highest and plateaued along a wide, mid-elevational
303 portion (the curve did not have a pointed peak), and declined towards the base and top. The gradient
304 was consistent for diversity metrics, but, for gamma diversity, the gradient was stronger than for alpha.
305 Mean gamma values at mid-elevation were twice those at the base; for alpha, the difference was 1.5 times.
306 The trend in beta diversity was extremely weak, though consistent - a difference in the probabilities of
307 only 0.06. Diversity at the base and top were similar, but, except for beta, the top was slightly and
308 consistently more specious.

309 When I applied an area gradient (with no temperature variation), the diversity metrics showed different
310 trends (Fig. 7). For alpha diversity, the species richness curve was almost horizontal, before reducing
311 about a fifth of the way up the mountain. Mean values at the base were twice those at the top. Gamma
312 diversity, however, declined consistently, in a non-linear, monotonic way. Mean values at the base were
313 18.2 times those at the top - again, a stronger gradient than alpha. In stark contrast, beta diversity, and
314 gamma per unit area, increased with altitude. (Beta diversity is the probability that individuals, within
315 a band, on opposite sides of the mountain, are the same species. A low probability means high diversity.)
316 Unlike the temperature model, the beta-diversity gradient was strong. At the mountain top, cells within
317 an altitudinal band had almost completely different species to each other (probability close to 0). Per
318 unit area, gamma diversity at the top was 3.2 times that of the base. So, in terms of number of species,
319 local and regional diversity declined. But, the opposite was true, per unit area, and when looking at how
320 well-mixed species within a band were.

321 When modeling the temperature and area gradients together, their effects seemed to combine (Fig. 8).
322 On alpha and gamma diversity, the effect seemed additive: diversity reduced with altitude, but peaked
323 at a low-to-mid elevation, not the base. Whereas gamma declined linearly from the peak richness, alpha
324 declined non-linearly, decreasing faster towards the top. Per unit area, gamma diversity resembles the
325 hump-shaped gradient of the temperature model. The addition of an increase at the top reflects that seen
326 in the area model. Beta diversity (especially at the base and through mid-elevations) is similar to the
327 temperature model. The dissimilarity to the gradient in the area model, suggests an interaction between
328 area and temperature for beta diversity. What is more, in the area model, beta diversity at the mountain

top was very high. While in the temperature model it was low, here it is even lower. The potential interaction effect is in contrast to the other metrics, but must be verified by further investigation.

The patterns of alpha, beta, and gamma diversity were very consistent across body size guilds (I only varied body size in the combined model), though the exact number of species increased with decreasing body size - i.e., curves were shifted vertically. The hypothetical temperate mountain (uniformly decreasing the temperature by 10 °C) also showed no deviation, neither did increasing nor decreasing the mountains steepness. Increasing the normalisation constant for dispersal (higher dispersal rates overall - probability of dispersing to a destination is almost the same everywhere), only produced a slight increase, at the top, in beta diversity and gamma per unit area.

Some parameter combinations did alter the patterns. Most notably, increasing thermal niche width by an order of magnitude to 10, produced the same patterns as those in the area model. However, decreasing thermal niche width by an order of magnitude to 0.1, accentuated the patterns of the combined model. For alpha and gamma diversity, the low-to-mid elevation peak disappeared, and the trends were more linear. While the total number of species decreased, the proportional difference between the top and base increased. Mean gamma values at the base were 41 times those at the top; for alpha, it was 11 times. But for a sharp increase at the top, beta diversity, and gamma per unit area mostly did not differ across altitudinal bands. So the mid-elevation plateau for gamma per unit area disappeared.

In contrast to increasing it, decreasing the normalisation constant for dispersal () pronounced the strength of the gradients in alpha and beta diversity (but had no effect on gamma) - the decline towards the top was more marked. Beta diversity at the base strongly increased (the probability changed from 0.21 to 0.02 - higher values mean lower diversity). It remained low at the top and reduced slightly (0.36 instead of 0.33). The result of decreasing diversity towards the top on gamma per unit area was a slight peak at mid-to-low elevations, instead of a horizontal plateau. The increase at the very top (after the plateaus decline) was still present, though the increase was no longer to a maximum.

In summary, when applied independently, area and temperature have different effects. The temperature model produced a plateau in richness at mid-elevations, across metrics. In contrast, the area model showed a decrease with altitude in alpha and gamma - but an increase in beta diversity. Applied in concert, the effects were additive, but beta diversity resembled that in the temperature model. For beta, this suggests an interaction between area and temperature. The trends of the combined model were consistent across many parameter combinations. Notable exceptions were increasing the thermal tolerance of species, and decreasing the normalisation constant for dispersal. This implies, under these conditions, the balance between the area and temperature effects changed.

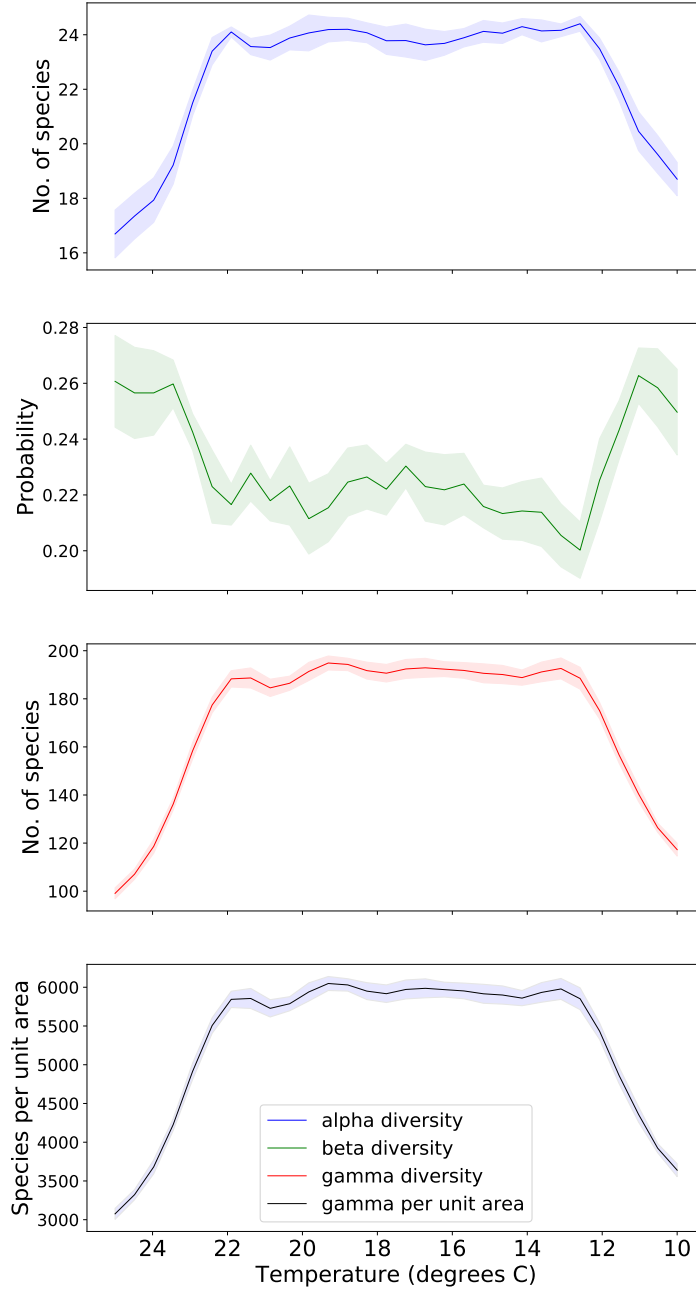


Figure 6: **The Effect of a Temperature Gradient on Biodiversity.** The gradient approximates that on a tropical mountain (10-25 °C from base to top). Area, however, is fixed along the gradient (the model system is actually a cylinder, not a cone). Temperature affects birth, death, and dispersal rates as per the Metabolic Theory of Ecology.

Each row of cells in the system has a temperature. The plot shows alpha, beta, and gamma diversity per row, and gamma diversity divided by row area - a proportion of the cylinders surface area. Solid lines indicate means, and shading, 95% confidence intervals. Alpha (local) diversity is the mean number of species per cell. Beta diversity, the probability that individuals on opposite sides of the cylinder are the same species (high probability means low diversity). Gamma diversity, the total number of species.

Other parameter values are the defaults: body size, $M = 1000$ g; community size, 27 000 individuals; speciation rate, $v = 0.01$; ratio of the mountain's height and base radius, $R = 1.5$.

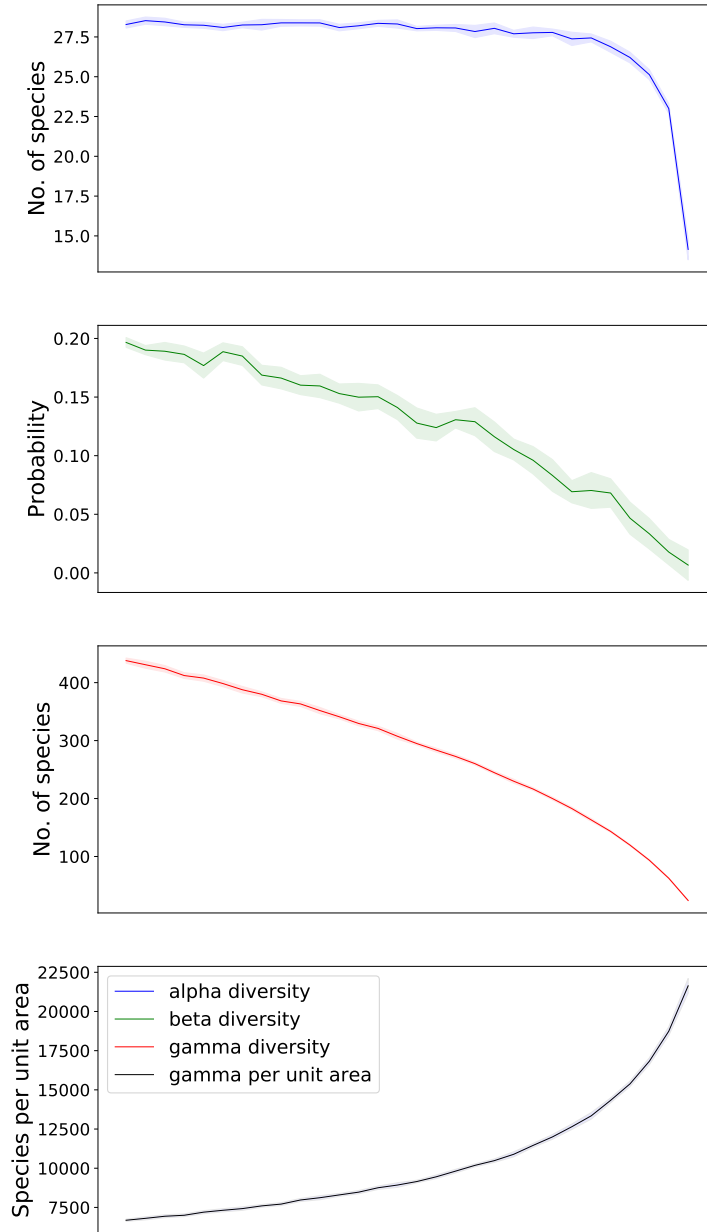


Figure 7: **The Effect of Area on Altitudinal Biodiversity Gradients.** Temperature is the same everywhere (15 °C). The model mountain is a cone - the base covers more area than the top. But, in silico, it is a square array; going up the mountain, each cell in the array represents an increasingly narrow area. Area has two effects, going up the mountain: 1) There are fewer individuals per altitudinal zone (population density is fixed, but area reduces). 2) The dispersal distance among cells reduces.

The plot shows alpha, beta, and gamma diversity per altitudinal band, and gamma diversity divided by band area - a proportion of the cone's surface area. Solid lines indicate means, and shading, 95% confidence intervals. Alpha (local) diversity is the mean number of species per cell. Beta diversity, the probability that individuals on opposite sides of the mountain are the same species (high probability means low diversity). Gamma diversity, the total number of species.

Other parameter values: body size, $M = 1000$ g; community size, + 27 000 individuals; speciation rate $v = 0.01$; ratio of the mountain's height and base radius, $R \approx 1.5$.

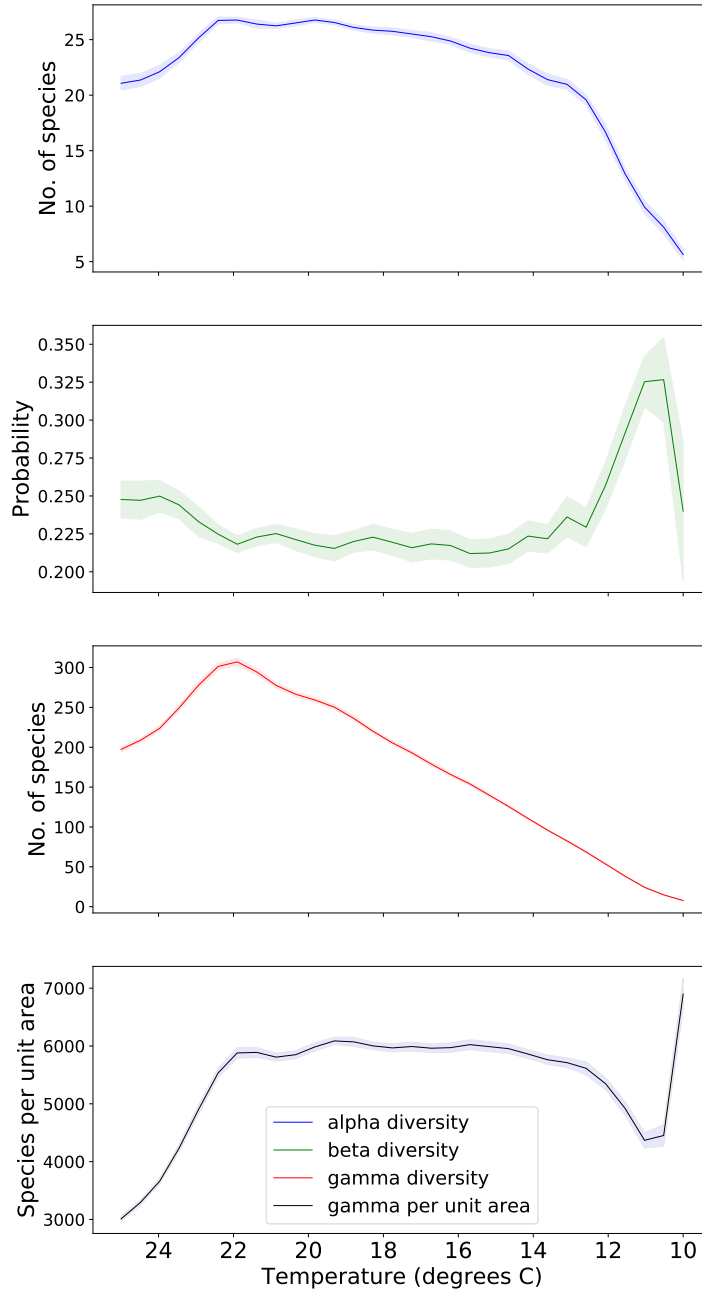


Figure 8: **Altitudinal Biodiversity Gradients.** Area reduces going up the mountain. Thus, the number of individuals, and dispersal distance among cells, reduce. The temperature gradient approximates that on a tropical mountain: 10-25 °C from base to top. Temperature affects birth, death, and dispersal rates as per the Metabolic Theory of Ecology.

The plot shows alpha, beta, and gamma diversity per altitudinal band, and gamma diversity divided by band area - a proportion of the cone's surface area. Solid lines indicate means, and shading, 95% confidence intervals. Alpha (local) diversity is the mean number of species per cell. Beta diversity, the probability that individuals on opposite sides of the mountain are the same species (high probability means low diversity). Gamma diversity, the total number of species.

Other parameter values: body size, $M = 1000$ g; community size, 27 000 individuals; speciation rate, $v = 0.01$; ratio of the mountain's height and base radius, $R \approx 1.5$.

361 Discussion

362 The Importance of Thermal Niche Width

363 Independently applying a metabolic effect to dispersal, via a thermal gradient, produced a hump-shaped
364 species-richness curve. You may think this is an edge effect: Hard boundaries at the mountain base
365 and top mean increased dispersal of species towards mid-elevations. You would then expect a similar
366 effect in the basic model (with no temperature or area gradient), but this did not occur. This does not
367 dismiss the edge effect, but suggests it is more nuanced, and implicates the temperature gradient. Due
368 to temperature, dispersal rates are higher at the base than the top. Yet, the declines in diversity towards
369 the base and top mirror each other. Thus, variation in dispersal rate, driven by temperature, does not
370 seem a satisfactory explanation either. Thermal niche width is another temperature effect, included as
371 part of the dispersal mechanism. As it was the same across altitudes, it may explain the symmetry of
372 the diversity trend. The default thermal niche was narrow, which restricts vertical dispersal (species are
373 unlikely to survive far from their thermal optimum). Owing to the edges, dispersal drives species towards
374 the middle, but a narrow thermal niche stops them spreading further. So the hump-shaped trend is a
375 distinct temperature effect. The mechanism seems to be narrow thermal niches, in tandem with hard
376 boundaries at the base and top, and dispersal. It does not seem to be influenced by variation in dispersal
377 rate.

378 You would expect the thermally-mediated edge effect to disappear with wide thermal niches. Widening
379 the thermal niche by an order of magnitude meant, upon dispersal, individuals could survive anywhere.
380 Although this was performed in the combined area and temperature model, the results matched those
381 of the area model - the temperature effect indeed disappeared. Gradients for species with wide thermal
382 tolerances, such as endotherms, may then contrast to those with narrow tolerances. Uniformly decreasing
383 the mountains temperature (the hypothetical temperate location) did not change the pattern - this is
384 expected. Diversity patterns, driven by thermal niche, would be changed, not by shifting temperatures
385 overall, but by changing the gradients steepness. The effect of a shallow temperature increment may
386 mirror wide thermal niches. I can modify the models parameters to test this.

387 Hard boundaries at the base of the model mountain may be unrealistic. It may be true if an ocean or
388 valley bounds the mountain, or human settlements at the base cause habitat destruction. But in other
389 cases, instead of being a source habitat, the base may receive immigrants widely from areas round the
390 mountain. A barrier at the top may be more realistic, but species may disperse over the top, depending
391 on dispersal mode and mountain geology. It would be simple to modify the model, to quantify, instead
392 of speculate, how these situations may alter the trend. The results for the temperature effect elude to

393 mechanisms that may explain variation in diversity trends across environments and species.

394 **Gradients of Beta Diversity a New Trend?**

395 The first trend in beta diversity was an increase towards the mountain top in the area model. This
396 was surprising. Given the narrow area, you expect more dispersal among cells in an altitudinal band,
397 thus more similarity in their species composition. The key factor was that the abundance of individuals
398 declined at the top. Low abundances lead to a high turnover of species, via two possible mechanisms:
399 Firstly, at low abundances, species are more likely to go extinct locally. Secondly, temperature everywhere
400 is the same - thermal niche width is irrelevant. So, dispersal up and down the mountain is unrestricted
401 and may lead to more immigration and emmigration. In contrast to the dispersal maps, the result shows
402 that, when temperature is fixed, dispersal vertically may be more important than horizontally.

403 The combined model was a stark contrast - beta diversity decreased sharply at the top. This is
404 counterintuitive and suggests an interaction between area and temperature, and a shift to dispersal being
405 dominated horizontally. At high altitudes, given the cold temperature, you may expect high beta diversity
406 - less dispersal and thus similarity in the species composition among cells. On the other hand, given the
407 narrow area, you may expect more mixing of species. Again, the key effect is the narrow thermal niche
408 width. Dispersal up and down the mountain is restricted by species thermal niche width, so species tend
409 to spread within a band than across them, becoming well mixed.

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449 **Supplementary Information**

450 **The Model's Geometry**

451 If c is the ratio of s and x :

$$\frac{s}{x} = c$$

$$s = cx$$

$$x = \frac{s}{c}$$

452 R is the ratio of h and x :

$$\frac{h}{x} = R$$

453 The area, A , of a cone's lateral surface is:

$$\pi xs = \pi cx^2$$

454 Using Pythagoras' theorem:

$$h^2 + x^2 = s^2$$

455 To convert between metres and number of cells:

$$cx \text{ metres} = T_r \text{ cells} \tag{1}$$

$$1 \text{ m} = \frac{T_r}{cx} \text{ cells} \tag{2}$$

$$\frac{cx}{T_r} \text{ m} = 1 \text{ cell} \tag{3}$$

456 **Area of a Grid Cell**

457 A key advantage of the model is it expresses area in relative terms. This means I need not worry about
458 x 's absolute value and greatly simplifies the model. The edge of an altitudinal band is a circle round the
459 cone's surface. Knowing this circle's radius, you can get the area of a grid cell. Imagine the band's edge
460 is the cone's base. The slant height is the band's radial position (distance from apex). Thus, to get the
461 radius:

$$x' = \frac{s'}{c}$$

462 As row index corresponds to radial position:

$$x' = \frac{I_r}{c}$$

463 Convert I_r to metres, as x' is in m:

$$\begin{aligned} x' &= \frac{I_r c x}{c T_r} \\ &= \frac{I_r x}{T_r} \end{aligned}$$

464 A cone's surface area (excluding the base) is:

$$\pi x s = \pi c x^2$$

465 When a cone is cut by two planes parallel to the base, the shape between the planes is called a frustum.

466 An altitudinal band is the surface of a frustum; the band's edges are the planes. The area of an altitudinal

467 band, A_f , is:

$$\pi c b^2 - \pi c t^2 = \pi c (b^2 - t^2)$$

468 b and t are the base and top radii of the frustum. Using row index (I_r) and equation 3 to express b

469 and t :

$$A_f = \pi c \left(\left(\frac{(I_r + 1)x}{T_r} \right)^2 - \left(\frac{I_r x}{T_r} \right)^2 \right)$$

470 Then, the area of one cell in an altitudinal band is: divide by the array's width (in # cells) to get

$$\frac{\pi c \left(\left(\frac{(I_r + 1)x}{T_r} \right)^2 - \left(\frac{I_r x}{T_r} \right)^2 \right)}{T_\theta}$$

471 Thus, cell area is unitless, and instead expressed in terms of x , keeping the model tractable.

472 Horizontal Dispersal

473 The horizontal distance to the destination, expressed in number of cells and as a proportion, is:

$$\frac{n_\theta}{T_\theta}$$

The distance in metres (d_θ) is:

$$d_\theta = \frac{n_\theta}{T_\theta} 2\pi x'$$

You can obtain, in metres, the radius, x' , of an altitudinal band, from the band's row index (see equation X):

$$x' = \frac{S_r x}{T_r}$$

However, area reduces with increasing altitude: So, I use the radius of the altitudinal position halfway between the dispersal event's start and end:

$$x' = \frac{(S_r + E_r)x}{2T_r}$$

$$d_\theta = \frac{n_\theta}{T_\theta} \frac{2\pi(S_r + E_r)x}{2T_r}$$

$$= \frac{n_\theta x \pi (S_r + E_r)}{T_\theta T_r}$$

I multiply variates of the normal distribution by y , a body-size and temperature dependent parameter. Instead of randomly picking distances from the kernel, I want the probability of dispersing a known distance, d_θ . So, d_θ (horizontal distance in metres to the destination) is the product of y and a variate, V , of the normal distribution:

$$d_\theta = yV$$

$$\frac{d_\theta}{y} = V$$

By evaluating at V the normal distribution's probability density function, you get the probability of dispersing d_θ metres.

So, in summary, the probability of dispersing horizontally, round the mountain, from one column to another is:

$$P\left(V = \frac{n_\theta x \pi (S_r + E_r)}{T_\theta T_r y}\right)$$

This depends on distance to the destination (an arc, or proportion, of a circumference), body size, and temperature. It decreases as V increases, as V is a variate of the standard normal distribution (mean

489 = 0). Probability increases as body size and temperature increase, and distance reduces. In other words,
 490 big individuals, and those in hot places or close to the destination, have a higher chance of reaching the
 491 destination.

$$492 \quad (S_r == I_r)$$

493 Vertical Dispersal

The vertical distance to the destination, expressed in number of cells and as a proportion, is:

$$\frac{n_r}{T_r}$$

494 The distance in metres (d_r) is:

$$d_r = \frac{n_r}{T_r} cx$$

495 cx ($= s$) is the cone's slant height (distance between apex and base). Like d_θ , vertical distance (d_r) is
 496 the product of y and a variate of the normal distribution:

$$d_r = yV$$

$$V = \frac{d_r}{y}$$

$$= \frac{n_r cx}{T_r y}$$

497 The probability of dispersing up or down the mountain, from one row to another is:

$$P(V = \frac{n_r cx}{T_r y})$$

498 Like d_θ , it depends on distance to the destination (a proportion of the slant height), body size, and
 499 temperature.