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# 1 **Bridging scales: allometric random walks link movement and biodiversity research**

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3 Running headline: Allometric random walks

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20 dispersal

## 22 **Abstract**

23 Integrating mechanistic models of movement and behavior into large-scale movement  
24 ecology and biodiversity research is one of the major challenges in current ecological science.  
25 This is mainly due to a large gap between the spatial scales at which these research lines act.  
26 Here, we propose to apply trait-based movement models to bridge this gap and generalize  
27 movement trajectories across species and ecosystems. We show how to use species traits (e.g.  
28 body mass) to generate allometric random walks and illustrate in two worked examples how  
29 this facilitates general predictions of species-interaction traits, meta-community structures and  
30 biodiversity patterns. Thereby, allometric random walks foster a closer integration of  
31 movement ecology and biodiversity research by scaling up from small-scale mechanistic  
32 measurements to a predictive understanding of movement and biodiversity patterns in  
33 different landscapes.

34

## 35 **Movement ecology and biodiversity research: from small-scale mechanisms to large-scale** 36 **patterns**

37 At the landscape scale, movement has broad implications for virtually all patterns in  
38 biodiversity and species communities [1–3] (Figure 1). At this spatial scale, new technical  
39 advances in tracking have provided big data of unprecedented quality for analyses in vertebrate  
40 movement ecology [4]. While this facilitates studies how movement trajectories and  
41 biodiversity patterns are related, it requires a complementary understanding of how the  
42 underlying physiological, behavioral and trophic processes drive these patterns and their  
43 correlations (Figure 1b). In addition, the heavy weight of active tracking tags prevents assessing

44 large-scale movement patterns for most of the invertebrates that dominate natural  
45 communities in diversity and abundance [5].

46 A mechanistic understanding of movement and behavioral processes and their correlations  
47 with species traits often takes place at a smaller spatial scale of laboratory or small-scale field  
48 experiments [6]. This leaves a large gap between the measurement of movement parameters  
49 and landscape patterns in movement and their consequences for meta-communities, food  
50 webs, and biodiversity (Figure 1a). Here, we propose to bridge these scales by random-walk  
51 models that implement mechanistic movement processes to enable predictions of movement  
52 and biodiversity patterns at the scale of larger and more heterogeneous landscapes (Figure 1b).  
53 These models can be individual based to account for individual variation in movement and  
54 behavior or employ species averages. So far, their systematic development has been hampered  
55 by the need for parametrization for all species or even all individuals across species. We suggest  
56 to use the traits *body mass* and *locomotion mode* (running, flying, swimming) as predictors of  
57 movement capacities to achieve this parameterization of mechanistic walk models. We present  
58 a possible way of integrating such traits into random walk models to generate allometric  
59 random walks. Furthermore, we demonstrate in two worked examples how to use this approach  
60 to predict species-interaction strengths such as attack rates (worked example I) as well as meta-  
61 community structures and biodiversity patterns (worked example II, Figure 1b).

62

### 63 **Ecological applicability of state-of-the-art movement models**

64 Currently, there is a large gap between movement models and their ecological  
65 applicability to natural movement patterns of many species. Random walk models are

66 conceptually simple and therefore widely used, but in their original form conceptualized animals  
67 as more or less featureless particles, whereas real animals have different traits, make adaptive  
68 decisions, and respond to landscape features. More recent random walk models have included  
69 various features of animal behavior [7], and individual-based movement models gain more  
70 ecological realism by combining these random walks with an animal's decisions in response to  
71 the landscape [1,8]. However, the data needed for developing such models are, despite rapid  
72 development in animal tracking technologies [4], still lacking and those that are available are  
73 species-specific, so that they cannot be generalized for modeling communities comprising  
74 species with substantial variation in traits and consequently movement patterns. Developing  
75 models for a general mechanistic understanding of animal movement across many species and  
76 the resulting biodiversity patterns at larger spatial scales thus requires a novel trait-based  
77 approach.

78

### 79 **The allometric approach**

80 The widespread ecological implications of body mass [9] and the Metabolic Theory of  
81 Ecology [10] have led to the insight that body mass represents a “super trait” determining many  
82 other species traits including physiological rates such as metabolism, growth, reproduction  
83 [11,12], interaction strengths with co-existing species [13,14], and also behavioral  
84 characteristics [15]. Allometric relationships can thus use one single trait to characterize a  
85 species and its other relevant features and can be used to simplify parameterization of  
86 community models that often contain too many parameters and species to allow their direct  
87 measurements for all species [16]. Consequently, recent community models have integrated

88 allometric scaling relationships that predict parameters depending on the population-average  
89 body mass [17,18]. In addition to providing realistic estimates of population parameters across  
90 species, this also avoided, by taking into account trade-offs between traits, the fallacy of  
91 unrealistic parameter combinations within species (e.g. species with low feeding rates but high  
92 biomass production or metabolic rates) that result from random parametrization [19]. These  
93 allometric approaches have helped tailor trait-based models with empirically testable  
94 predictions that hold across ecosystems [13,18,20]. Despite their predictive success in  
95 communities of higher diversity, these population models come at the cost of ignoring (1)  
96 variability among the individuals within populations and (2) effects of movement in habitat  
97 space including consequences of different landscape structures.

98         Here, we present a new trait-based framework for movement modeling based on  
99 allometric scaling relationships, which helps to achieve a general parameterization across  
100 species or even individuals.

101

## 102 **A new framework: trait-based movement models generalize across species**

103         Just like physiological and morphological locomotor traits of animals [21,22], movement  
104 parameters such as speed [6,23], migration or dispersal distances [24,25], and home range sizes  
105 [26,27] follow allometric scaling relationships. However, environmental conditions such as  
106 resource availability or habitat quality may mask body mass effects, which has for example been  
107 shown for dispersal distances [28]. Thus, what is realized by animals in nature may differ from  
108 the allometric predictions. Nevertheless, the range within which this realized movement occurs  
109 has its upper limit at the maximum physiological capacity, meaning that all movement has to be

110 scaled relative to this maximum to allow ecologically meaningful interpretations. This  
111 physiological capacity is defined by the maximum speed, which is the fundamental constraint  
112 of movement. Recent research has shown that animal maximum speed follows a hump-shaped  
113 relationship with body mass [23]. As this pattern holds across taxa and locomotion modes  
114 (running, flying, swimming), it provides a powerful tool for understanding the physiological  
115 boundaries of animal movement and will therefore form the basis of our framework.

116 In classical random walk models, the speeds of each individual step are drawn from pre-  
117 defined probability distributions and step lengths are obtained by multiplying this speed by  
118 time. These probability distributions have either random parameters [29], or they are based on  
119 species-specific movement tracks [30]. To obtain non-random distributions of step lengths that  
120 are general across species, we suggest including two new trait parameters: *body mass* and  
121 *locomotion mode*. Empirical allometric scaling relationships thereby quantify increases in speed  
122 with individual body masses for each locomotion mode. As maximum speed follows a hump-  
123 shaped relationship with body mass, intermediately sized animals have generally higher speeds  
124 and can therefore cover longer distances than smaller or larger ones. Moreover, *locomotion*  
125 *mode* accounts for differences in these allometric scaling relationships between running,  
126 swimming and flying organisms. This new framework provides real units of movement and  
127 therefore allows species-level predictions of movement trajectories.

128

### 129 [Applying the framework](#)

#### 130 [Creating allometric random walks by integrating trait-based steps](#)

131 The advantage of this framework is the flexibility to integrate the trait-based speeds and  
132 step lengths into any desired movement model. Speeds can thereby either be calculated for

133 each time period of a behavioral state separately by applying behavior-specific allometric  
134 scaling relationships (e.g. foraging, dispersal or migration speeds; *option 1*) or they can be  
135 calculated as proportions of the maximum speed (*option 2*). Here, we chose *option 2* to  
136 transform a simple random walk into an allometric random walk (aRW), because it is currently  
137 difficult to obtain precise allometric scaling relationships for speeds of different behavioral  
138 states, whereas data of high quality are available for maximum speed [23]. As many aspects of  
139 speed including acceleration and locomotion costs are related to body mass [31,32], we  
140 anticipate that the simplifying assumption of all speeds being fixed fractions of maximum speed  
141 (*option 2*) could be replaced by more detailed, empirically-established scaling relationships for  
142 the different speeds (*option 1*) as soon as they are available (see [6] for an example of  
143 invertebrate foraging speed). All speeds are scaled between 0 (resting) and 1 (maximum speed).  
144 Speed values are drawn from a two-parameter beta distribution as it is a continuous probability  
145 distribution that is defined on the interval [0, 1] (see Supplementary Material for details). To  
146 account for the various behaviors, we defined three different beta distributions from which  
147 speeds are drawn: one for low speeds such as foraging or exploratory movement (Figure 2a,  
148 dashed line), one for intermediate speeds of patch-bridging, dispersal, and migration (travelling  
149 speed, Figure 2a, solid line) and one for high speeds as they occur during attack or escape in  
150 predator-prey interactions (Figure 2a, dotted line).

151 Subsequently, the unitless random values drawn from the different beta distributions are  
152 multiplied by  $v_{max}$ , the species-specific maximum speed, which is derived from the species' body  
153 mass and locomotion mode using empirical allometric scaling relationships (Figure 2b). For each  
154 species, the dimension of speed is thus scaled between zero and its body-mass dependent



155 maximum speed. Figures 2c and d illustrate the effect of varying the input parameters body  
156 mass and locomotion mode using an allometric random walk with foraging speeds. Note that  
157 all triplets of trajectories were generated with the same random-number seed and projected  
158 on the same spatial landscape scale. Within the same locomotion mode (here: running),  
159 intermediate body masses lead to higher speeds (here: foraging speeds) and therefore medium-  
160 sized animals have larger step lengths and cover more space in the same amount of time (Figure  
161 2c, middle row) than smaller (Figure 2c, upper row) or larger animals (Figure 2c, lower row). In  
162 addition, the locomotion mode affects the spatial scale of movement tremendously with flying  
163 animals having higher speeds and covering much more space (Figure 2, lower row) than running  
164 (Figure 2d, middle row) or swimming animals (Figure 2, upper row) of the same body mass.

165 Thus, using allometric random walks provide real units of steps and therefore trait-based  
166 movement trajectories. In the following, we will demonstrate possible ways of applying these  
167 allometric random walks to predict (1) species-interaction strengths in a homogeneous  
168 landscape and (2) large-scale biodiversity patterns in a heterogeneous landscape (patch  
169 network). Furthermore, possibilities to include more complex aspects of landscape  
170 heterogeneity are discussed.

171

### 172 [Worked example I: Predicting species-interaction traits](#)

173

174 Allometric random walks help make realistic predictions of species-interaction parameters  
175 such as predator-prey attack rates, competition or pollination, which are mainly based on  
176 encounter rates. In the following, we will use the example of attack rates that depend on  
177 encounters between predator and prey individuals. As encounter rates depend on the length of

178 the path per unit time that is searched and the predator detection range, higher average speeds  
179 of animals generally lead to longer paths and thus higher encounter rates as well as higher  
180 attack rates [33,34]. Attack rates, in turn, affect interaction strengths and ultimately community  
181 attributes such as persistence and stability [35–37] as indicators of local biodiversity. We  
182 demonstrate the ability of allometric random walks to predict species-interaction strengths by  
183 comparing attack rates generated by individual-based models (IBMs) using a standard (non-  
184 allometric) and an allometric random walk. Therefore, we use the model presented by Li et al.  
185 2017 [38] for a standard IBM and modified it following the above described approach to include  
186 allometric step lengths (allometric IBM). Both the standard and the allometric IBM include  
187 allometric scaling of other parameters such as detection range, maximum feeding capacity and  
188 gut clearance rate. The only difference between the two models is that the allometric IBM uses  
189 allometric random walks, whereas the standard IBM uses random step length. To be consistent  
190 with the empirical data for comparisons, we simulated 11 invertebrate predator-prey pairs in  
191 foraging mode with predator body masses ranging from 0.1 - 500 mg, and a predator-prey body-  
192 mass ratio of 100 characterizing typical natural invertebrate communities [39,40]. Prey  
193 abundance was systematically varied, and we fitted functional responses to the data (see [38]  
194 for details). We then analyzed the attack rate in relation to body mass and compared it to  
195 published empirical data on attack rates of terrestrial invertebrates [14,41]. The allometric IBM  
196 generates the realistic pattern of an increase in attack rate with body mass compared to the flat  
197 relationship produced by the standard IBM (Figure S1). The allometric scaling exponent of attack  
198 rates using the allometric IBM (0.29) predicts the empirical scaling exponent of attack rates of  
199 terrestrial invertebrates (0.3 [41], restricted to empirical data for terrestrial 2D interactions)

200 surprisingly well considering the fact that no calibration was involved. The standard IBM only  
201 generates a marginal increase in attack rate with predator body mass (scaling exponent of 0.05),  
202 which is caused by allometric scaling of physiological parameters including that larger predators  
203 have larger gut sizes and therefore are able to feed longer compared to smaller predators (a  
204 property of the model by Li et al. [38]). This effect, however, is partially counteracted by the  
205 higher prey body mass of larger predators.

206 Overall, this worked example illustrates that IBMs with allometric random walks can  
207 accurately predict the strengths of species interactions such as attack rates at the small spatial  
208 scales of laboratory experiments. Very similar allometric approaches could be used to model  
209 other species interactions such as pollination and competition that also depend on encounter  
210 rates. Moreover, this allows scaling up to larger areas or even real landscapes and therefore  
211 enables mechanistic research on how landscape structures affect species interactions by  
212 changing encounter probabilities in different spatial compartments (e.g. patches, refuges or  
213 environmental gradients such as altitude). These simulations require accounting for how  
214 behavior and movement decisions of individuals respond to landscape structures. Eventually,  
215 incorporating these processes in model simulations will yield landscapes of interaction  
216 strengths, attack rates and fear, which would enable a better understanding as well as  
217 prediction of movement trajectories [42,43]. Moreover, as these interaction strengths have  
218 knock-on effects on community persistence, this approach will also allow predicting variation in  
219 species diversity across landscape structures.

## 220 [Worked example II: Predicting meta-community structure and biodiversity patterns](#)

221

222 The connectivity of a spatial meta-community network (i.e. the percentage of realized dispersal  
223 links between pairs of habitat patches) is generally altered via changing the number of habitat  
224 patches (network configuration), which profoundly affects the persistence and dynamics of  
225 species within these meta-communities [44]. However, the same spatial network configuration  
226 can host different species-specific network connectivities that depend on the species'  
227 movement abilities [45,46]. While prior studies have suggested species- and size-specific meta-  
228 community networks [45,46], our approach of allometric random walks offers a novel tool to  
229 predict the links in these spatial networks based on mechanistic, trait-based processes. As  
230 movement speed strongly depends on body mass, the degree of connectivity of a network  
231 should also follow an allometric relationship with medium-sized animals covering longer  
232 distances [25], which leads to connections between more distant patches [45]. Also, the  
233 locomotion mode (flying, running or swimming) should influence the species-specific network  
234 connectivity with flying animals being able to connect more distant patches than running ones.  
235 Consequently, changes in the spatial network configuration will affect species differently. For  
236 instance, increasing the degree of fragmentation (leading to higher distances between patches),  
237 will have a stronger effect on small and running animals than on larger or flying animals.

238 We illustrate this concept of species-specific network connectivities in Figure 3 using a  
239 simplified example of our approach, which applies species-averages of all parameters and thus  
240 ignores variation across individuals for the sake of simplicity. Future studies, however, can easily  
241 realize this approach with individual-based models in which the parameters such as speed and  
242 feeding rates vary according to traits of individuals. In our simplified conceptual example, the

243 dispersal links between the patches can be created by running allometric random walks (here  
244 simplified to the mean allometric travelling speeds of the species, Fig. 2a) over the maximum  
245 travel time through unfavorable habitat. We assume that this maximum travel time should also  
246 be body-mass dependent with larger species having lower energetic costs while travelling  
247 (lower per unit biomass metabolic rates) and higher energy storage capacities in their body  
248 tissue [9]. Thus, larger animals should have more time available for patch-bridging events than  
249 smaller ones before they are exhausted or return to the original patch [47]. However, to get  
250 accurate quantitative predictions of this scaling relationship, detailed empirical analyses of  
251 animal movement between patches and the maximum travel time are needed. In our simplified  
252 allometric concept, travelling speeds times maximum travel time yield maximum patch-bridging  
253 distances that depend on the body mass of the species. In Figure 3, all patches with distances  
254 lower than these allometric patch-bridging distances are linked, which creates species-specific  
255 network connectivities (Figure 3a) as well as the corresponding link networks (Figure 3b) and  
256 hypothetical link networks in case of a higher degree of fragmentation with several patches  
257 removed from the network (Figure 3c). The number of links in the network increases with body  
258 mass up to intermediate sizes (Figure 3a, b, c from left to right), but it decreases with increasing  
259 fragmentation (Figure 3b vs. c).

260 Over a larger body mass scale, the network connectivity increases with body mass following  
261 a hump-shaped relationship (Figure 3d). The exact shape of this scaling relationship, however,  
262 depends on the interplay of the allometric scaling of maximum travel time and the hump-  
263 shaped scaling relationship of speed. A sensitivity analysis varying the exponents showed that  
264 the increase in connectivity with body mass from low to intermediate sizes is generally

265 supported, but the effect at higher body masses strongly depends on the assumed scaling of  
266 maximum travel time. Hence, research on the allometric scaling of maximum travel time is  
267 urgently needed. With higher fragmentation (i.e. larger distances between patches), the  
268 increase of the curve is shifted towards higher body masses, implying that species of the same  
269 body mass have a lower connectivity in more fragmented landscapes (Figure 3d). This  
270 conceptual example is based on two simplifying assumptions. First, we assume that all species  
271 regardless of their individual body mass use the same type of patches in the spatial network.  
272 However, small species might integrate different patches (e.g. also use smaller patches as  
273 habitats) in their spatial networks than large species. Hence, an integration of the allometric  
274 scaling of required patch size into allometric spatial networks represents an important future  
275 step towards realistic trait-based patch networks. Second, we assume that travel speed is a fixed  
276 proportion of maximum speed implying that it also follows a hump-shaped relationship with  
277 body mass. However, different realized scaling relationships of travel speed could alter the  
278 allometry of network connectivity shown in Figure 3. Overall, allometric random walks can be  
279 an important tool to quantitatively predict how species or individuals connect patch networks  
280 depending on their traits and how these networks change with ongoing fragmentation. This  
281 allows integrating trait-based movement, behavioral decisions, and responses to different  
282 landscape structures into predictions of species-specific patch networks.

283 In the following, we describe a concept how the combination of species-specific patch  
284 networks with ecological networks analyses (here: secondary extinction analysis in food webs  
285 as an example) could be used for predictions of how strongly biodiversity declines in altered  
286 landscapes. We start with an unfragmented landscape (Figure 4, landscape A) and its

287 corresponding features such as biodiversity, body mass-distribution of coexisting species, and  
288 food web structure, which can be calculated from the body-mass distribution using feeding  
289 kernels for species [18] or individuals as in worked example 1 [38]. In a hypothetical  
290 fragmentation scenario, patches are randomly knocked out from the landscape matrix. In this  
291 new, fragmented landscape (Figure 4, landscape B), the animals of body mass and locomotion  
292 mode as given by the body-mass distribution move according to allometric random walks. Based  
293 on the allometries of step lengths and travel times included in the random walk and the  
294 allometry of population abundances [48], trait-based extinction probabilities can be calculated.  
295 Prior secondary extinction studies have employed a variety of different trait-based extinction  
296 probabilities [49,50]. Here, we chose a simple scenario to illustrate the interplay of one of these  
297 traditional scenarios, low abundance, with a spatial extinction scenario, in which animals face  
298 extinction depending on the number of habitat patches that are still connected in the network  
299 (based on species-averaged random walks as in Figure 3). In the simplified spatial extinction  
300 scenario, small and large animals will have lower connectivities and a higher probability of  
301 extinction in the new landscape than species of intermediate size (Figure 4, extinction scenario  
302 B<sub>1</sub>). However, the higher population density would in turn decrease extinction probabilities of  
303 smaller species (Figure 4, extinction scenario B<sub>2</sub>). This implies that the largest species have the  
304 highest extinction risk, because of their low abundance and the low connectivity of their spatial  
305 networks. The relative extinction risks of small species with high abundances and  
306 intermediately-sized species with highly connected spatial networks can vary substantially  
307 depending on the allometric scaling exponents of abundance [48] and travel speeds. Moreover,  
308 extinction risks can also be affected by patch size and resource abundance. For instance, small

309 animals might survive in only one patch of the network if it is large enough and the resource  
310 availability high enough. Scenarios that are more realistic could also include disturbances, and  
311 stochastic extinctions or long-distance dispersals. Ultimately, these features can help dovetail  
312 the model to the conditions of specific landscapes and communities.

313       Following the trait-based probabilities for primary extinctions, a new community with new  
314 body-mass distribution, food-web structure and lower biodiversity emerges (Figure 4,  
315 biodiversity and food web B). Simulations of secondary extinctions will generate a new food  
316 web and a community with even lower biodiversity (Figure 4, biodiversity and food web C).  
317 Together, this multi-step modeling approach (Figure 4) helps gain mechanistic insights in  
318 landscape-scale biodiversity patterns as well as predicted extinction scenarios following habitat  
319 fragmentation. Moreover, this concept can easily be transferred to other ecological networks  
320 such as plant-pollinator networks [51].

## 321 322 **Outlook & Conclusion** 323

324       In this conceptual framework, we highlighted the importance of including trait-based step  
325 lengths in movement models to make more realistic predictions of movement and biodiversity  
326 patterns at the landscape scale. We focused on the basic principle of including body-mass and  
327 locomotion-mode dependent speeds in these models, a basis to which important extensions  
328 can be added (see Outstanding Questions). These include (1) other important functional and  
329 behavioral traits and (2) other aspects of landscape heterogeneity. First, functional traits  
330 affecting animal space use such as hunting modes (sit-and-wait vs. cursorial) [52] or feeding  
331 types (e.g. predator vs. herbivore) [6,26] as well as other behavioral facets such as animal



332 personality (e.g. boldness) [53] could be added to this concept. Second, also abiotic conditions  
333 and landscape structures play an important role in shaping the space use of animals [54]. By  
334 supplying different distributions and qualities of resources or by providing refuge places, the  
335 landscape structure actively changes movement speeds, detection efficiencies, and ultimately  
336 the type and strengths of predator-prey interactions. Moreover, the spatial arrangement of the  
337 individual habitat domains (habitat space that predator and prey use while foraging) can alter  
338 predator-prey interactions and even shift the direction of predatory effects [55–57]. Schmitz et  
339 al. 2017 [57] developed an elegant approach on how to calculate the overlap between these  
340 habitat domains by assessing individual predator and prey movement trajectories. Using  
341 allometric random walks could represent an easy way of producing multiple realistic species-  
342 specific predator-prey movement scenarios, in which the individuals exhibit behavioral  
343 responses to the abiotic (e.g. habitat structure) and biotic (presence of prey or predators)  
344 characteristics of the landscape. This will help make general predictions on predator-prey  
345 interactions across landscapes of varying structure and heterogeneity. Moreover, large-scale  
346 effects on predator-prey interactions could be assessed on a landscape-complexity gradient. For  
347 instance, impacts of movement corridors, barriers, or hiding places on functional responses in  
348 simple agricultural vs. more structured landscapes could be identified and finally provide  
349 important information on the persistence of species communities. How these additional aspects  
350 of landscape heterogeneity (e.g. barriers, environmental gradients) affect the step length  
351 distributions of the allometric random walk needs to be explored in future studies, but it is likely  
352 that generic trait-based relationships can be devised (see Outstanding Questions). Eventually,

353 all these processes do not only constrain the behavior and interactions between species but  
354 indirectly also link to biodiversity patterns of landscapes.

355 Bridging between the spatial scales of (1) movement and behavioral processes and (2)  
356 movement and biodiversity patterns requires the implementation of trait-based movement  
357 models, as we cannot determine all relevant movement parameters for all species. We present  
358 the new framework of allometric random walks and its potential to fill this gap by being  
359 empirically realistic yet general across species. On the one hand, they represent the movement  
360 of real species better than random walks with stochastic parameters. On the other hand, they  
361 can be generalized more easily across species and communities than walk models based on  
362 tedious measurements of species-specific movement parameters. Therefore, this novel  
363 approach will provide realistic yet also generalized predictions and critically important  
364 mechanistic understanding of large-scale movement and biodiversity patterns.

365

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367

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372

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- 479

480 **Figure 1: The different scales of processes and patterns in movement ecology and biodiversity**  
481 **research. (a)** The spatial scale: a mechanistic understanding of movement and behavioral  
482 processes takes place at a laboratory or small-scale experimental scale while movement and  
483 biodiversity patterns are mainly described at larger scales of heterogeneous landscapes. This  
484 gap can be bridged by parameterizing movement models to obtain trait-based models such as  
485 allometric random walks, which are introduced in the course of this study. **(b)** The scale of  
486 biological organization: by integrating parameters of individual behavior (e.g. speed) into  
487 movement models, species-interaction traits such as attack rates and interaction strengths can  
488 be predicted (see worked example I) and possibly scaled up to larger areas or heterogeneous  
489 landscapes to gain a mechanistic understanding of how landscape structures affect predator-  
490 prey interactions and consequently community persistence and diversity. Furthermore,  
491 parameterized movement models can be used to directly predict meta-community structures  
492 and assess the effects of habitat fragmentation and landscape heterogeneity on food webs and  
493 biodiversity patterns (see worked example II).

494

495 **Figure 2: Effects of body mass and locomotion mode on movement trajectories in an**  
496 **allometric random walk. (a)** The three beta distributions from which speeds are drawn for  
497 different behaviors (see Supplementary Material for details). (b) Allometric scaling relationships  
498 of maximum speed (Hirt et al. 2017) for the different locomotion modes. (c) Effect of body mass  
499 on the movement trajectory of an allometric random walk with foraging speeds. (d) Effect of  
500 the locomotion mode on the movement trajectory of an allometric random walk with foraging  
501 speeds. Note that all triplets of trajectories were generated by using the same seed for random  
502 numbers and are projected on the same spatial landscape scale.

503

504 **Figure 3: Species-specific landscape connectivity over a fragmentation gradient. (a)** An  
505 exemplary naturally fragmented landscape with different species-specific connectivities for four  
506 example animals of different body masses (low to intermediate). **(b)** Corresponding link network  
507 to the landscape connectivity in **a**. **(c)** Link network with a higher degree of fragmentation:  
508 patches B, D, F, I, K, and L have been removed from the network. **(d)** Landscape connectivity

509 over a continuous body mass range (given as the percentage of realized links in the network).  
510 The degree of fragmentation increases from link network A to B to C. Link network A and B  
511 correspond to the networks in **b** and **c**. In the additional link network C, patches A, D, G, I, M, O  
512 and Q have been removed.

513

514 **Figure 4: Predicting biodiversity loss due to fragmentation in natural landscapes by applying**  
515 **allometric random walks.** An existing community in landscape A with biodiversity A holds a  
516 certain body-mass distribution A of species. Using feeding kernels [18], the corresponding food  
517 web (food web A) can be generated from this distribution. In a hypothetical fragmented  
518 landscape B, species-averaged allometric random walks (body masses are derived from the  
519 frequency distribution) allow calculating trait-dependent extinction probabilities in the new  
520 landscape. These primary extinctions yield a new community with a different body-mass  
521 distribution.  $B_1$  illustrates the spatial extinction scenario where intermediately sized animals  
522 have the highest connectivity potential and therefore lowest extinction risk; scenario  $B_2$   
523 additionally includes abundances, with higher abundances reducing the extinction probability  
524 of small species. These new body-mass distributions then yield a new food web structure (food  
525 web B) and biodiversity (biodiversity B). Subsequent biodiversity loss can be predicted by  
526 simulating secondary extinctions in the food web (food web C and biodiversity C). Note that  
527 food webs B and C represent meta food webs, whereas detailed predictions of local food webs  
528 require model simulations.

**Small-scale**  
mechanistic understanding of  
movement and behavior

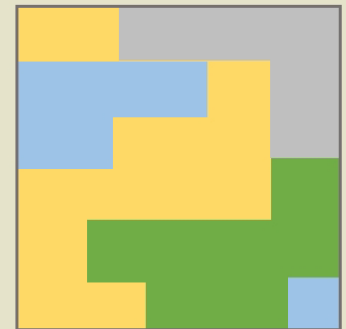
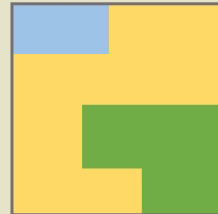
**Large-scale**  
patterns in movement  
and biodiversity

(A)

**Laboratory and small-scale field  
experiments**

**Landscape patterns**

**Trait-based movement modelling**  
(e.g. allometric random walks) in  
**heterogeneous landscapes**



**Area and heterogeneity**

(B)

**Worked example I:**  
Prediction of species-  
interaction traits

**Predictions via  
community models**  
(not shown here)

**Individual behavior**

Quantification of functional  
traits, e.g.

- Body mass
- Speed & locomotion
- Animal personality
- Hunting or feeding type

**Species interactions**

Functional relationships,  
e.g.

- Encounter rates
- Attack rates
- Interaction strengths

**Species communities**

Large-scale patterns, e.g.

- Movement tracking
- Meta-community structure
- Biodiversity & food webs

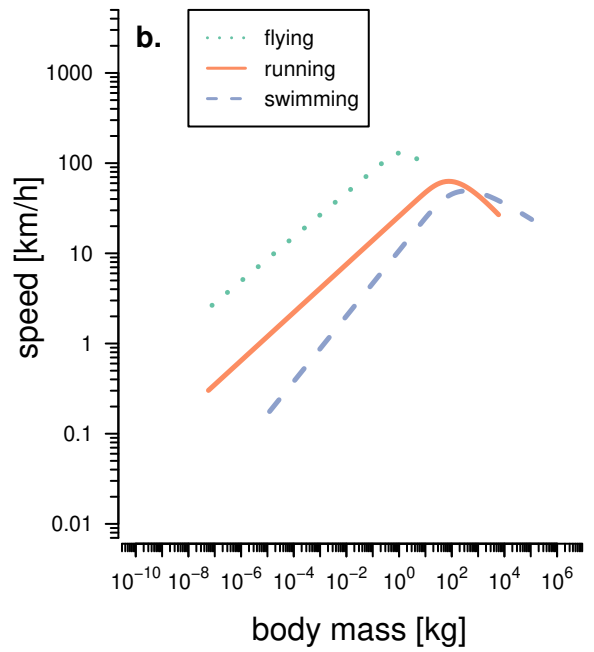
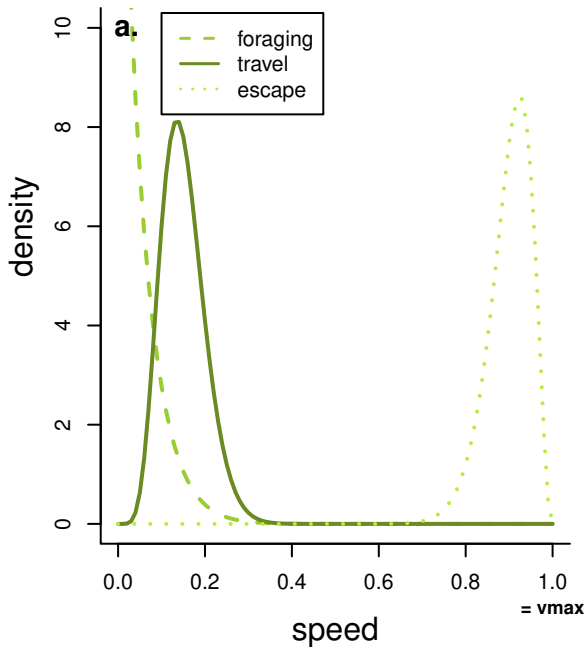
**Worked Example II:**  
Prediction of meta-community  
structure and biodiversity  
patterns

**Number of species**

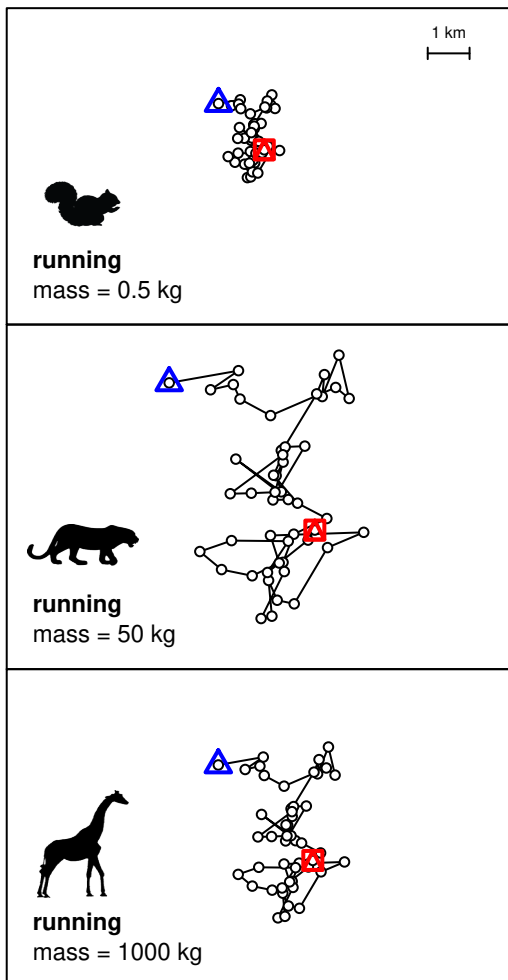
**Spatial scale**

**Biological scale**

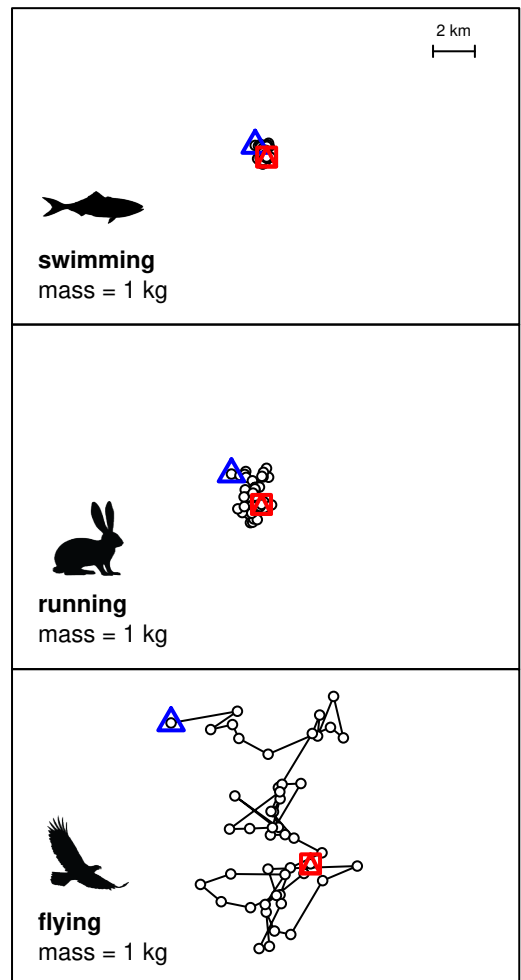




**c. body mass effect**



**d. locomotion effect**



Increase in body mass  $M$  →

Allometry of landscape connectivity

Natural Landscape

Habitat patches

$M = 0.01$  kg



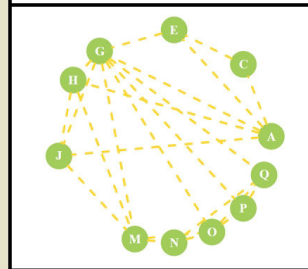
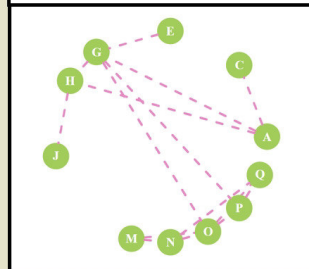
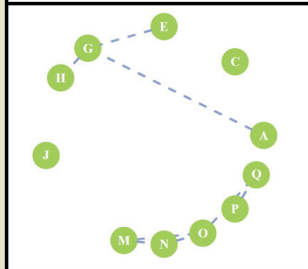
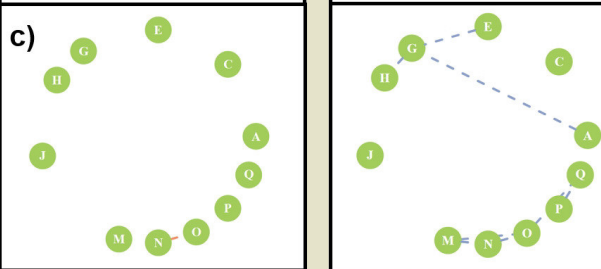
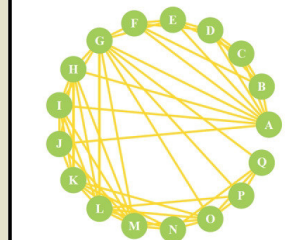
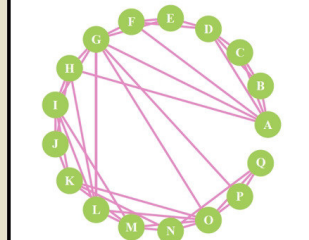
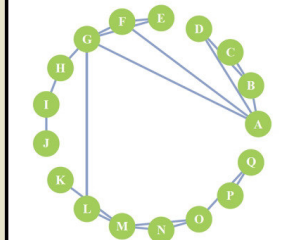
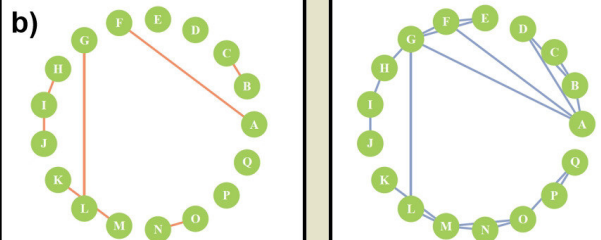
$M = 1$  kg



$M = 5$  kg



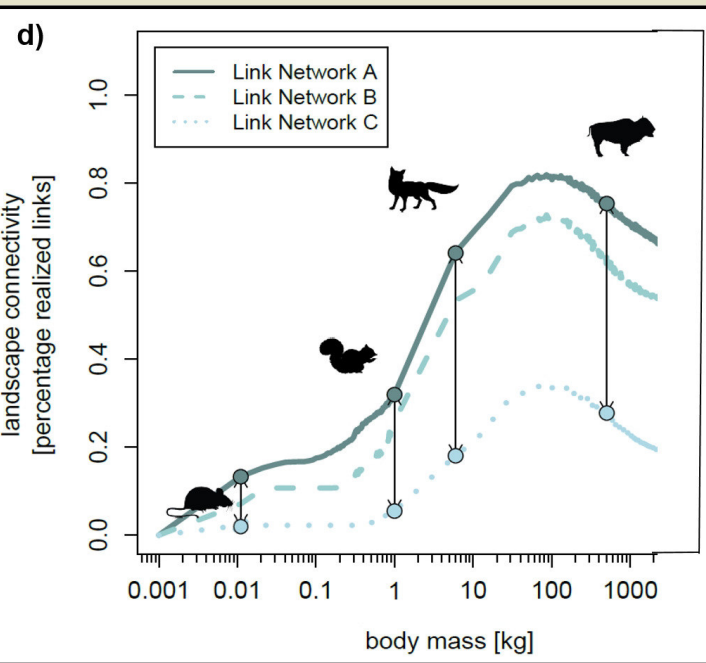
$M = 20$  kg



Increase in fragmentation ↓

Link Network A

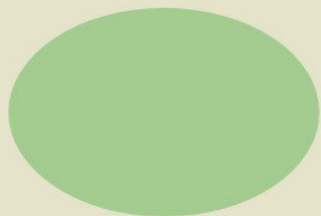
Link Network B



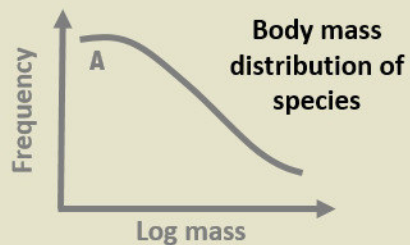
## Existing community

Landscape A

Biodiversity A



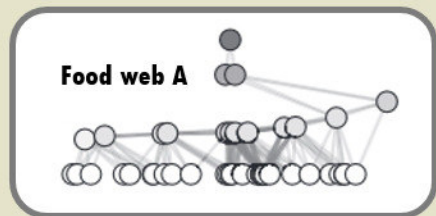
yields



Body mass distribution of species

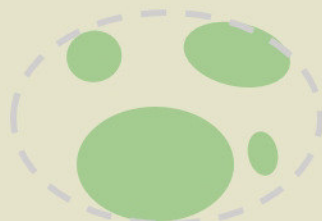
input masses

generates



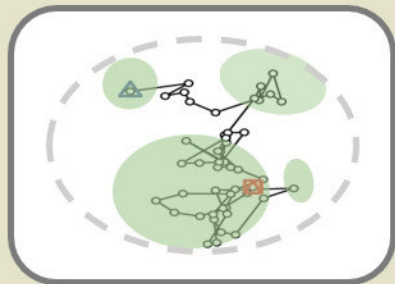
## Simulated fragmentation

Landscape B



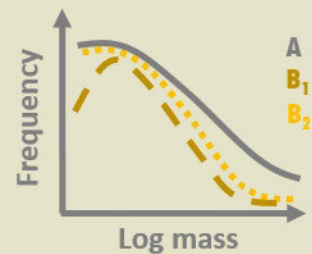
primary extinctions

Allometric Random Walk



Calculation of trait-based extinction probabilities

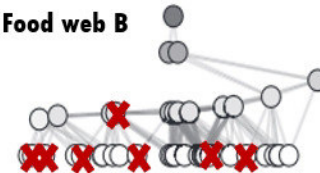
## Predicted community



Biodiversity B



Food web B



secondary extinctions

Food web C



Biodiversity C



## Outstanding Questions

- How can other important functional and behavioral traits of species (besides body mass and locomotion mode) be integrated in movement models?
- What are the consequences of functional and behavioral traits or differences in animal personalities for large-scale movement trajectories, meta-community structures and biodiversity patterns?
- How may landscape structure and heterogeneity affect movement parameters and ultimately predator-prey interactions?
- Is there an interaction between landscape structures and the movement behavior depending on the individual's functional and behavioral traits?
- What are the consequences of predator avoidance behavior for movement trajectories, individual ranges and meta-population structures?

## Highlights

- Research on movement processes and biodiversity patterns are two currently dominating ecological disciplines yet they are still difficult to link.
- This is because research on biodiversity patterns and movement trajectories mainly take place at a large landscape scale, whereas mechanistic research on movement and behavior is carried out at smaller laboratory or field-experimental scales.
- Generating trait-based movement models by including species traits (such as body mass or locomotion mode) as predictors of movement capacities will help to bridge this gap across spatial scales.



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**Author Supplementary Material**  
BridgingScales\_Supplement\_revision.docx

