

# Novel pathogen introduction rapidly alters evolved movement strategies, restructuring animal societies

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## Abstract

1  
2 Animal social interactions are the outcomes of evolved strategies that integrate the costs and benefits of  
3 being sociable. Using a novel mechanistic, evolutionary, individual-based simulation model, we examine  
4 how animals balance the risk of pathogen transmission against the benefits of social information about  
5 resource patches, and how this determines the emergent structure of socio-spatial networks. We study a  
6 scenario in which a fitness-reducing infectious pathogen is introduced into a population which has ini-  
7 tially evolved movement strategies in its absence. Within only a few generations, pathogen introduction  
8 provokes a rapid evolutionary shift in animals' social movement strategies, and the importance of social  
9 cues in movement decisions increases. Individuals undertake a dynamic social distancing approach, trad-  
10 ing more movement (and less intake) for lower infection risk. Pathogen-adapted populations disperse  
11 more widely over the landscape, and thus have less clustered social networks than their pre-introduction,  
12 pathogen-naive ancestors. Running epidemiological simulations on these emergent social networks, we  
13 show that diseases do indeed spread more slowly through pathogen-adapted animal societies. Finally, the  
14 mix of post-introduction strategies is strongly influenced by a combination of landscape productivity, the  
15 usefulness of social information, and disease cost. Our model suggests that the introduction of an infectious  
16 pathogen into a population can trigger a rapid eco-evolutionary cascade, rapidly changing animals' social  
17 movement strategies, which alters movement decisions and encounters between individuals. In turn, this  
18 changes emergent social structures, and our model informs how such change can make populations more  
19 resilient to future disease outbreaks. Overall, we offer both a modelling framework and initial predictions  
20 for the evolutionary and ecological consequences of wildlife pathogen spillover scenarios.

## Introduction

21

22 Animal societies — individual associations in a spatio-temporal context — emerge from complex interac-  
23 tions between local ecological conditions and individual behavioural strategies (Whitehead, 2008; Tanner  
24 and Jackson, 2012; Webber and Vander Wal, 2018). While such associations can yield useful social infor-  
25 mation about resource availability (Danchin et al., 2004; Dall et al., 2005; Gil et al., 2018), they also provide  
26 opportunities for the transmission of infectious pathogens (Krause and Ruxton, 2002; Weinstein et al., 2018;  
27 Romano et al., 2020; Albery et al., 2021; Cantor et al., 2021*b*; Romano et al., 2021). Individuals must there-  
28 fore balance the costs and benefits of socialising when deciding how to move. Movement strategies that  
29 incorporate social information — the presence and status of neighbours — can facilitate or reduce spatial  
30 associations, or encounters (Danchin et al., 2004; Dall et al., 2005; Nathan et al., 2008; Gil et al., 2018; Web-  
31 ber and Vander Wal, 2018; Webber et al., 2022). Movement is therefore an important mechanism linking  
32 landscape spatial structure and individual distributions with the emergent structure of animal societies.  
33 Together, they influence the dynamics of disease outbreaks in animal populations (White et al., 2018*b*; Ro-  
34 mano et al., 2020, 2021), and outbreaks may in turn cause cascading effects on landscape and community  
35 ecology (Monk et al., 2022).

36 The introduction of pathogens to animal societies often leads to rapid reductions in associations among  
37 individuals (Romano et al., 2020), due to a combination of mortality-induced decreases in population den-  
38 sity (e.g. Fereidouni et al., 2019) and adaptive behavioural responses that reduce encounter rates (Stroeymeyt  
39 et al., 2018; Romano et al., 2020; Stockmaier et al., 2021). Importantly, when a novel pathogen is first intro-  
40 duced into a population, such as during a spillover event, individuals may have no prior experience of  
41 cues that indicate infection (Power and Mitchell, 2004), making fine-tuned adaptive individual or social  
42 avoidance responses less likely. If they reduce fitness, novel pathogens spreading through host-host con-  
43 tacts may select against host social behaviour, ultimately selecting against social connectivity itself (Altizer  
44 et al., 2003; Cantor et al., 2021*b*; Romano et al., 2021; Poulin and Filion, 2021; Ashby and Farine, 2022). This  
45 selective pressure may be modulated by landscape productivity (Hutchings et al., 2006) and the benefits of  
46 grouping (Almberg et al., 2015; Ezenwa et al., 2016), especially if these can boost fitness in a way that offsets  
47 the cost of infection. Multiple animal taxa currently face novel pathogen outbreaks (Blehert et al., 2009; The  
48 Global Consortium for H5N8 and Related Influenza Viruses, 2016; Fereidouni et al., 2019; Scheele et al.,  
49 2019), and this number is likely to grow in the near future due to climate change (Sanderson and Alexan-  
50 der, 2020; Carlson et al., 2021). It is therefore especially important to know how rapid evolutionary changes

51 following pathogen introduction will be, as well as their effect on social systems and the transmission of  
52 animal culture (Cantor et al., 2021*b,a*).

53 Analytical models suggest that animal sociality evolves to balance the value of social information against  
54 the risk of pathogen transmission (Bonds et al., 2005; Prado et al., 2009; Ashby and Farine, 2022). However,  
55 these models make a number of simplifying assumptions, including homogeneous populations, and single  
56 parameters for sociality (Bonds et al., 2005; Prado et al., 2009; Ashby and Farine, 2022). In reality, sociality  
57 is an emergent outcome of spatially heterogenous environmental conditions and often substantial within-  
58 population heterogeneity in behaviour (Tanner and Jackson, 2012; Wolf and Weissing, 2012). Epidemio-  
59 logical models based on contact networks allow for heterogeneity in pairwise associations; however, these  
60 models are sensitive to the network formation process, and sampling biases in empirical data collection can  
61 complicate their parameterisation (White et al., 2017). Similar to analytical models, network models make  
62 assumptions about individuals' positions in a social network, when these positions are actually emergent  
63 outcomes of social movement – how and where to move in relation to other individuals. Mechanistic,  
64 individual-based simulation models can incorporate substantial ecological detail, including an explicit spa-  
65 tial setting (DeAngelis and Diaz, 2019), individual variation in movement strategies (Spiegel et al., 2017;  
66 Lunn et al., 2021), and realistic disease transmission (White et al., 2018*a*; Scherer et al., 2020; Lunn et al.,  
67 2021). Yet mechanistic movement-disease models thus far focus on immediate ecological outcomes, such as  
68 infection persistence, and do not have an evolutionary component (White et al., 2018*a*; Scherer et al., 2020;  
69 Lunn et al., 2021). Limiting movement-disease models to an ecological scale could miss important feed-  
70 backs between the ecological outcomes of infectious disease and the consequences for the evolution of host  
71 behaviour (Cantor et al., 2021*b*). Incorporating an evolutionary component to movement-disease models  
72 could allow predictions on the long-term consequences of wildlife disease outbreaks, such as changes in  
73 the the emergent structure of animal societies.

74 We examined the eco-evolutionary consequences of the introduction of a pathogen into a novel host  
75 population, such as during cross-species spillover, a scenario of increasing frequency and global concern  
76 (Blehert et al., 2009; The Global Consortium for H5N8 and Related Influenza Viruses, 2016; Fereidouni et al.,  
77 2019; Scheele et al., 2019; Sanderson and Alexander, 2020; Carlson et al., 2021; Kuchipudi et al., 2022). We  
78 developed a mechanistic, evolutionary, spatially-explicit, individual-based simulation model in which we  
79 introduced an infectious pathogen to populations that had already evolved movement strategies in a for-  
80 aging context (see model code, analysis code, and reference data: Gupte, 2022*b,a*; Gupte et al., 2022). In  
81 our model, the depletion of patchily distributed, discrete food items makes the use of social information

82 key to finding food (see *Supplementary Material Fig. 1 – 2*; see also Gupte et al. 2021). We investigated  
83 three questions: (i) How does the introduction of a novel pathogen affect the evolution of animals' social  
84 movement strategies? (ii) How do pathogen-adapted movement strategies affect the emergent structure  
85 of animal societies? (iii) How are evolutionary responses to pathogen introduction shaped by ecological  
86 factors, such as landscape productivity and the cost of infection? We compared how social information was  
87 used in movement strategies evolved before and after pathogen introduction, and the ecological outcomes  
88 for individual intake, movement, and associations with other foragers. We constructed proximity based  
89 social networks from individuals' movements (Whitehead, 2008; White et al., 2017; Wilber et al., 2022). We  
90 used network epidemiological models to examine whether pathogen-adapted populations were more re-  
91 silient to the spread of infectious disease than their pathogen-naive ancestors (White et al., 2017; Stroeymeyt  
92 et al., 2018; Wilber et al., 2022). We examined the effect of two important model parameters, landscape pro-  
93 ductivity ( $R$ ) and infection cost ( $\delta E$ ), by running our model over nine different combinations of  $R$  and  $\delta E$ .  
94 Overall, we provide a theoretical framework and reference implementation for the study and prediction of  
95 the evolutionary consequences of pathogen introduction for animal populations in a spatial context.

## 96 **Model and Analysis**

97 We implemented an individual-based simulation model to represent foraging animals ('foragers') seeking  
98 discrete, immobile, depleteable food items (as in Spiegel et al., 2017; Gupte et al., 2021, see *Supplementary*  
99 *Material Fig. 1 – 2*). Food items are distributed over a two-dimensional, continuous-space resource land-  
100 scape with wrapped boundaries (a torus). Our model, similar to previous eco-evolutionary individual  
101 based models (Getz et al., 2015; Netz et al., 2021; Gupte et al., 2021), has two distinct timescales: (1) an  
102 ecological timescale comprising of  $T$  timesteps that make up one generation ( $T = 100$  by default), and (2) an  
103 evolutionary timescale consisting of 5,000 generations ( $G$ ). At the ecological timescale, individuals sense  
104 local counts of food items and competitors, move according to inherited movement strategies, and forage  
105 for food. At the same timescale, individuals that carry an infectious, fitness-reducing pathogen, may, when  
106 in close proximity with uninfected individuals, pass on the pathogen with a small probability (see *Pathogen*  
107 *Transmission and Disease Cost*). At the evolutionary timescale, individuals reproduce and transmit their  
108 movement strategies (see *Starting Location and Inheritance of Movement Rules*) to their offspring. The num-  
109 ber of offspring is linked both to individuals' success in finding and consuming food items, and to the du-  
110 ration that they were infected by the pathogen at the ecological timescale. The model was implemented in

111 R and C++ using Rcpp (R Core Team, 2020; Eddelbuettel, 2013), using R-trees from the *Boost.Geometry* C++  
112 library for spatial computations ([www.boost.org](http://www.boost.org)), and can be found at [github.com/pratikunterwegs/pathomove](https://github.com/pratikunterwegs/pathomove).

### 113 *Distribution of Food Items*

114 Our landscape of  $60 \times 60$  units contains 1,800 discrete food items, which are clustered around 60 resource  
115 ‘kernels’, for a resource density of 0.5 items per unit<sup>2</sup> (see *Supplementary Material Fig. 1 – 2*). This prevents  
116 synchronicity in the availability and regeneration of food items. Each available food item can be sensed  
117 and harvested by foraging individuals (see below). Once harvested, another food item is regenerated at the  
118 same location after a fixed regeneration time  $R$ , which is set at 50 timesteps by default; alternative values of  
119 20 and 100 timesteps represent high and low productivity landscapes respectively. Food item regeneration  
120 is delinked from population generations. Thus the actual number of available food items is almost always  
121 in flux. In our figures and hereafter, we chose to represent  $R$  as the number of times a food item would  
122 regenerate within the timesteps in a single generation  $T$  (default = 100), resulting in  $R$  values of 1, 2, and  
123 5 for regeneration times of 100, 50 (the default), and 20 timesteps. Items that are not harvested remain on  
124 the landscape until they are picked up by a forager. Each food item must be processed, or ‘handled’, by a  
125 forager for  $T_H$  timesteps (the handling time, default = 5 timesteps) before it can be consumed (Ruxton et al.,  
126 1992; Gupte et al., 2021). The handling time dynamic is well known from natural systems in which there is  
127 a lag between finding and consuming a food item (Ruxton et al., 1992).

### 128 *Individual Foraging and Movement*

129 *Foraging.* Individuals forage in a randomised order, harvesting the first available food item within their  
130 movement and sensory range ( $d_S = d_M$ , a circle with a radius of 1 unit (see *Supplementary Material Fig. 1 –*  
131 *2*). Once harvested, the item is no longer available to other individuals, leading to exploitation competition  
132 among nearby foragers. Furthermore, the location of the item also yields no more cues to other foragers  
133 that an item will reappear there, reducing direct cues by which foragers can navigate to profitable clusters  
134 of food items. As handlers are immobilised at the location where they encountered food, they may be good  
135 indirect indicators of the location of a resource cluster (‘social information’ Danchin et al., 2004; Romano  
136 et al., 2020; Gupte et al., 2021). Once individuals finish handling a food item, they return to the non-  
137 handling, searching state.

138 *Movement.* Our model individuals move in small, discrete steps of fixed size ( $d_M = 1$  unit). Each step  
139 is chosen based on the individuals' assessment of local environmental cues, and this assessment is made  
140 using evolved movement strategies (as in Netz et al., 2021; Gupte et al., 2021). First, individuals scan their  
141 current location, and five equally spaced points around their position, at a distance of 1 unit for three cues  
142 ( $d_S$ , see *Supplementary Material Fig. 1 – 2*): the number of food items ( $F$ ), the number of foragers handling  
143 a food item ('handlers':  $H$ ) and the number of idle foragers not handling a food item ('non-handlers':  $N$ ).  
144 Individuals assign a suitability (see Netz et al., 2021; Gupte et al., 2021) to their current position and each  
145 of the five locations, using their inherited preferences for each of the cues:  $S = s_F F + s_H H + s_N N + \epsilon$ .  
146 The preferences  $s_F$ ,  $s_H$ , and  $s_N$  for each of the three cues are heritable from parents to offspring, while  $\epsilon$   
147 is a very small error term drawn for each location, to break ties among locations. The values of each of  
148 the cue preferences *relative to each other* determine individuals' movement strategies (Gupte et al., 2021) All  
149 individuals move simultaneously to the location to which they have assigned the highest suitability (akin to  
150 step-selection; Avgar et al., 2016); this may be their current location, in which case individuals are stationary  
151 for that timestep. Since individuals may differ in their inherited preferences for each of the three cues, two  
152 individuals at the same location may make quite different movement decisions based on the same local  
153 cues. Handlers, however, are considered immobile and do not make any movement decisions.

## 154 *Pathogen Transmission and Disease Cost*

155 We modelled circumstances that are expected to become increasingly common due to rapid global changes;  
156 the population evolves for 3/5<sup>th</sup> of the simulation (until  $G = 3,000$ ; of 5,000) in the absence of a pathogen,  
157 after which, a pathogen is introduced in each generation until the end of the simulation ( $G = 5,000$ ). We  
158 modelled an infectious pathogen with highly simplified dynamics, which can be transmitted from an in-  
159 fected to a susceptible individual with a low probability  $p$  (default  $p = 0.05$ ). This transmission is only  
160 possible when the two individuals are within a the transmission distance,  $d_\beta$ . For simplicity, we set  $d_\beta$  to  
161 be the movement range (1 unit). Once transmitted, the pathogen is assumed to cause a chronic disease  
162 which reduces host energy stores by a fixed amount called  $\delta E$  in every following timestep;  $\delta E$  is set to 0.25  
163 by default (alternative values: 0.1, 0.5). Since such infectious contact events can periodically re-occur in  
164 natural environments, we set up our model such that the pathogen was introduced to 4% of individuals ( $N$   
165 = 20) in each generation. This is necessary to kick-start the pathogen-movement eco-evolutionary feedback  
166 dynamics. This is also realistic, as populations may repeatedly acquire pathogens through external sources,  
167 such as infected individuals of other, spatially overlapping species (e.g. Kuchipudi et al., 2022).

## Starting Location and Inheritance of Movement Rules

168  
169 For simplicity, we considered a population of haploid individuals with discrete, non-overlapping gener-  
170 ations, and asexual inheritance. At the end of the parental generation, the net lifetime energy of each  
171 individual was determined as the difference of the total energy gained through food intake and the energy  
172 lost through infection. In *Supplementary Material Section 3.2*, we also consider an alternative implementation  
173 in which the pathogen reduces the value of each food item by a certain percentage. The parental population  
174 produced an offspring population (of the same size) as follows: to each offspring, a parent was assigned  
175 at random by a weighted lottery, with weights proportional to lifetime net energy (Netz et al., 2021; Gupte  
176 et al., 2021). This way, the expected number of offspring produced by a parent is proportional to the parent's  
177 lifetime net energy. The movement decision-making cue preferences  $s_F$ ,  $s_H$ , and  $s_N$  are subject to indepen-  
178 dent random mutations with a probability of 0.001. The mutational step size (either positive or negative) is  
179 drawn from a Cauchy distribution with a scale of 0.01 centred on zero. Thus, there can be a small number  
180 of very large mutations, while the majority of mutations are small. As in real ecological systems, individu-  
181 als in the new generation are initialised around the location of their parent (within a standard deviation of  
182 2.0), and thus successful parents give rise to local clusters of offspring (see an alternative implementation  
183 in *Supplementary Material Section 3.1*).

## Model Output

184  
185 *Social Information Use.* To understand the evolution of movement strategies, and especially how individ-  
186 uals weighed social information, we exported the population's evolved cue preferences in every second  
187 generation. We classified individuals based on how they used social information — the presence and  
188 status of competing foragers — into four social movement classes: (1) agent avoiding, if  $s_H, s_N < 0$ , (2)  
189 agent tracking, if both  $s_H, s_N > 0$ , (3) handler tracking, if  $s_H > 0, s_N < 0$ , and (4) non-handler tracking,  
190 if  $s_H < 0, s_N > 0$ . We calculated the relative importance of social cues —  $H, N$  — to each individual's  
191 movement strategy as  $SI_{imp} = (|s_H| + |s_N|) / (|s_H| + |s_N| + |s_F|)$ , with higher values indicating a greater  
192 importance of social cues.

193 *Proximity-Based Social Network.* We created a proximity-based adjacency matrix by counting the number  
194 of times each individual was within the sensory and pathogen transmission distance  $d_\beta$  ( $= d_S, d_M = 1$  unit)  
195 of another individual (Whitehead, 2008; Wilber et al., 2022). We transformed this matrix into an undirected



196 social network weighted by the number of pairwise encounters: in a pairwise encounter, both individuals  
197 were considered to have associated with each other (White et al., 2017). The strength of the connection  
198 between any pair was the number of times the pair were within  $d_\beta$  of each other over their lifetime. We  
199 logged encounters and constructed social networks after every 10% of the total generations (i.e., every 500<sup>th</sup>  
200 generation), and at the end of the simulation. We constructed adjacency matrices using Rcpp (Eddelbuettel,  
201 2013), and converted them to networks using the *igraph* (Csardi and Nepusz, 2006) and *tidygraph* (Pedersen,  
202 2020) libraries for R. We omitted ephemeral pairwise associations with a weight  $< 5$ .

## 203 *Model Analysis*

204 We plotted the mix of social information-based movement strategies evolved across generations in each  
205 parameter combination. Focusing on our default scenario ( $\delta E = 0.25$ ,  $R = 2$ ), we visualised the mean per-  
206 capita distance moved, mean per-capita intake, and mean per-capita encounters with other foragers. We  
207 examined how the three main social movement strategies — agent avoidance, agent tracking, and han-  
208 dler tracking — changed in frequency over generations. We also examined differences among strategies  
209 in the movement distance, associations with other agents, and frequency of infection, in the generations  
210 after pathogen introduction ( $3,000 < G < 3,500$ ). We visualised the proximity based social networks of  
211 populations in a representative scenario ( $\delta E = 0.25$ ,  $R = 2$ ), focusing on the generations just before and after  
212 the pathogen introduction events begin (pre-introduction:  $G = 3,000$ ; post-introduction:  $G = 3,500$ ). We  
213 compared the time taken for diseases to spread across these social networks by running simple network  
214 epidemiological models on the emergent networks (Bailey, 1975; White et al., 2017; Stroeymeyt et al., 2018)  
215 using the *igraph* (Csardi and Nepusz, 2006) library.

## 216 **Results**

### 217 *Rapid evolutionary shift in social movement strategies following pathogen* 218 *introduction*

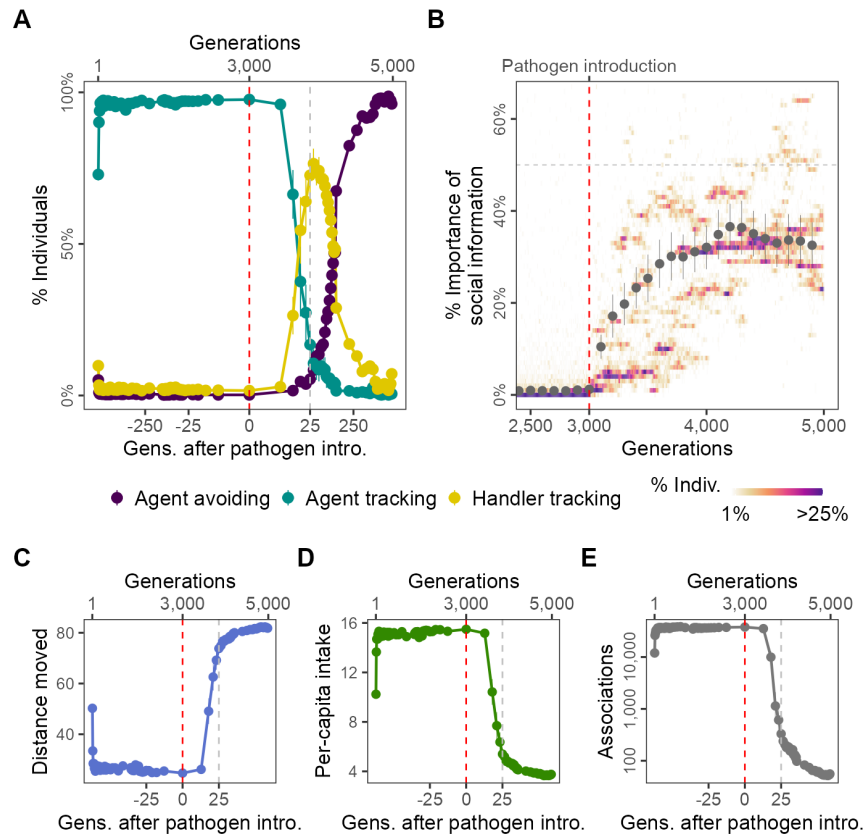
219 In our model, individuals move on a landscape with patchily distributed food items, and select where  
220 next to move in their vicinity, based on inherited preferences for environmental cues — food items, and  
221 other individuals (see *Supplementary Material Fig. 1*). Food items, once consumed, regenerate at a rate  $R$ ,

222 and pathogen infection imposes a per-timestep cost  $\delta E$ . We classified individuals' social movement strate-  
223 gies in our model by the sign of their preferences for successful foragers handling a food item ('handlers',  
224 preference  $s_H$ ), and for unsuccessful foragers still searching for food ('non-handlers', preference  $s_N$ ). In  
225 our default scenario,  $R = 2$ , food regenerates twice per generation, and  $\delta E = 0.25$ , i.e., consuming 1 food  
226 item offsets 4 timesteps of infection. Before the introduction of the pathogen, populations's social move-  
227 ment strategy was primarily to prefer moving towards both handlers and non-handlers ('agent tracking';  
228  $s_H, s_N > 0$ ; but see below) (Fig. 1A). The introduction of the infectious pathogen leads to a remarkably rapid  
229 evolutionary shift — within only 25 generations of pathogen introduction — in how social information is  
230 incorporated into agents' movement strategies. There is a marked increase in the frequency of individuals  
231 that track successful foragers, but avoid non-handlers ('handler tracking';  $s_H > 0$ , but  $s_N < 0$ ) (Fig. 1A;  
232  $3,000 < G < 3,025$ ). Surprisingly, after a brief period (in evolutionary terms) of handler tracking being  
233 the most common strategy, a third strategy emerges: avoiding both handlers and non-handlers ('agent  
234 avoiding';  $s_H, s_N < 0$ ). Agent avoiding rapidly becomes the commonest strategy within 100 generations of  
235 pathogen introduction, and remains so until the end of the simulation (a further 2,000 generations; Fig. 1A).

236 In addition to qualitative changes in social movement strategies, pathogen introduction also leads to  
237 social information becoming more important to movement decisions. Prior to pathogen introduction ( $G <$   
238  $3,000$ ), individuals' handler- and non-handler preferences ( $|s_H| + |s_N|$ ; taken together, social information)  
239 barely influence their movement strategies (Fig. 1B); these are instead guided primarily by the preference  
240 for food items ( $s_F$ ; see *Model and Analysis*; see also *Supplementary Material Fig. 1*). Social movement decisions  
241 are joint outcomes of individual preferences for social cues and the cue value: consequently, in clustered  
242 populations (see below), even small positive values of  $s_H$  and  $s_N$  lead to strong emergent sociality. After  
243 pathogen introduction, there is a substantial increase in the average importance of individuals' preferences  
244 (or aversions) for the presence of other foragers (Fig. 1B). There is also significant variation among individ-  
245 uals in the importance of social information to their movement strategies, with distinct evolved polymor-  
246 phisms: for example, at  $G = 4,000$ , social information comprises about 30% of most individual's movement  
247 decisions, but for some individuals, that may be  $>40\%$ , or only about 20% (Fig. 1B).

### 248 *Ecological-scale consequences of shift in movement strategies*

249 In our default scenario ( $R = 2$ ,  $\delta E = 0.25$ ) the ecological and behavioural consequences of the evolutionary  
250 shift in movement strategies are drastic and similarly rapid (Fig. 1C – E; see *Supplementary Material Fig. 3* for  
251 other scenarios). There is a sharp increase in mean distance moved by individuals; while pre-introduction



**Figure 1: Pathogen introduction leads to rapid evolutionary changes in social information use, with cascading effects on population ecological outcomes.** (A) Before pathogen introduction in the default scenario ( $R = 2$ ,  $\delta E = 0.25$ ), populations rapidly evolve a social movement strategy that tracks all other individuals (‘agent tracking’;  $G \leq 3,000$ ) — however, their overall movement strategy is primarily guided by the presence of food items (B). Pathogen introduction leads to the rapid replacement, within 25 generations, of agent tracking with ‘handler tracking’ (preference for successful foragers;  $3,000 < G < 3,025$ ), and within 250 generations, with ‘agent avoidance’ (avoidance of both successful and unsuccessful foragers;  $G > 3,250$ ). (B) After pathogen introduction ( $G > 3,000$ ), the importance of social cues (the presence of other individuals; the sum of the absolute, normalised preferences  $sH, sN$ ) increases substantially on average (grey points). Additionally, there is significant variation in the importance of social cues to individuals (shaded regions), which is not captured by the mean or standard error. At  $G = 4,000$ , for example, social information comprises  $\approx 30\%$  of most individuals’ movement strategies, but has both higher ( $> 40\%$ ) and lower weightage ( $\approx 20\%$ ) for some individuals. The rapid change in social movement strategies following pathogen introduction is reflected in ecological outcomes. Individuals, which have evolved strong aversions to other foragers, (C) move more on average, (D) have a mean per-capita intake of only 25% of the pre-pathogen average, and (E) reduce associations with other individuals 100-fold. All panels show data averaged over 10 replicates, but shaded region in panel B shows only a single replicate for clarity.

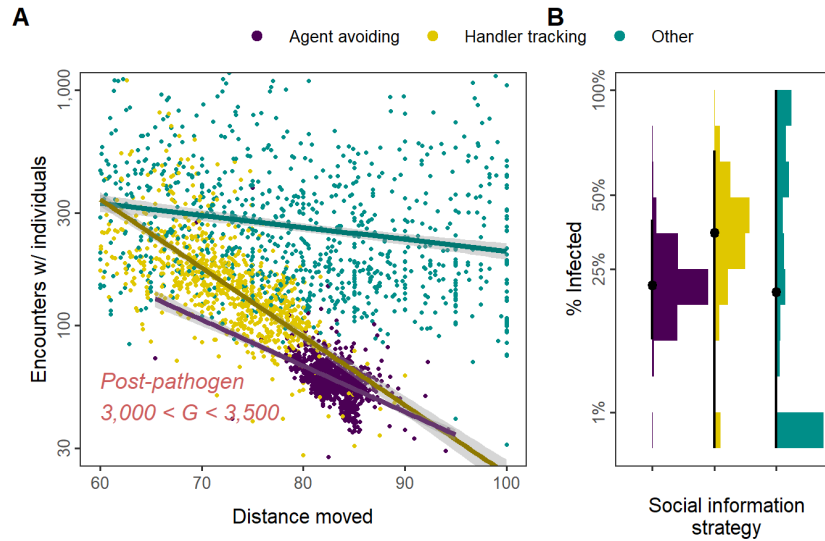
252 individuals moved 55% of their lifetimes on average (i.e., 55 timesteps; handling for the remainder), post-  
 253 introduction, individuals move for 80% of their lifetimes (i.e., 80 timesteps; Fig. 1C). One reason individu-  
 254 als move more post-introduction is that their strategy of avoiding searching foragers (or all foragers) likely

255 leads them to mostly move away from other individuals. Since individuals are most likely to be found on  
256 or near resource clusters, this possibly leads to movement away from productive areas of the landscape.  
257 This idea is supported by the rapid, four-fold drop in mean per-capita intake after pathogen introduction  
258 (Fig. 1D). The near 100-fold drop in encounters between individuals after pathogen introduction (Fig. 1E)  
259 also supports this idea and suggests that most encounters were likely taking place on or near resource  
260 clusters. These reductions in intake are equivalent to those expected from halving landscape productiv-  
261 ity (*Supplementary Material Fig. 3*). Thus our model suggests that in addition to direct disease costs ( $\delta E$ ),  
262 pathogen introduction, by influencing the evolution of movement strategies, may also have substantial  
263 indirect ecological effects.

### 264 *Individual differences in social movement strategies affect population-level social* 265 *structure*

266 The relationship between movement and avoiding associations (and further, infection) is mediated by indi-  
267 vidual differences in how exactly social information is incorporated into movement strategies. Individuals  
268 using the agent avoiding strategy move more than handler tracking ones (Fig. 2A), about 85% of their life-  
269 time (default scenario:  $R = 2$ ;  $\delta E = 0.25$ ). At this limit, every step moved allows them to avoid approximately  
270 2 encounters with other individuals. Handler tracking individuals move much less ( $\sim 60\% - 80\%$ ), but are  
271 able to avoid approximately 20 encounters with other individuals with every extra step. These differences  
272 may explain why agent avoiding and handler tracking individuals have very similar mean infection rates, at  
273  $\sim 25\%$  and  $\sim 33\%$  respectively (Fig. 2B). All other strategies, including the agent tracking strategy common  
274 in pre-introduction populations, are barely able to translate increased movement into fewer associations  
275 (Fig. 2A). These strategies have a wide range of infection rates (Fig. 2B), potentially because they are very  
276 rare — these likely represent mutants that do not give rise to persistent lineages.

277 Following pathogen introduction, the mixture of individual-level movement strategies experiences a  
278 substantial re-organisation of emergent spatial and social structure at the population level (default scenario:  
279  $R = 2$ ;  $\delta E = 0.25$ ). Pre-introduction populations are strongly clustered in space (Fig. 3A), due to movement  
280 strategies that favour following most other foragers. This spatial proximity means that most individuals  
281 encounter each other at least once, leading to numerous unique partners (the ‘degree’) for each forager  
282 (Fig. 3 inset A). In contrast, post-introduction populations are much more dispersed across the landscape  
283 (Fig. 3B), reflecting movement strategies which lead to near-perpetual movement to avoid associations; a

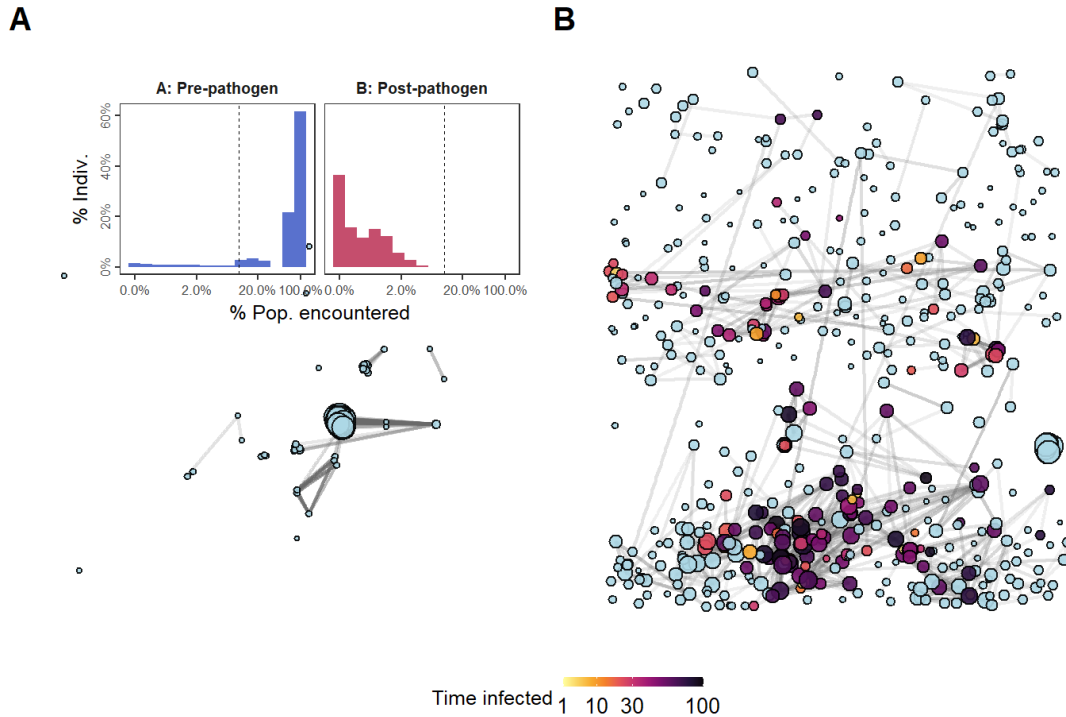


**Figure 2: Social movement strategies trade movement for associations through dynamic social distancing, leading to differences in infection rates.** In post-introduction populations ( $3,000 < G < 3,500$ ), **(A)** both agent avoiding and handler tracking individuals can reduce encounters with other individuals by moving to avoid other foragers (dynamic social distancing). Handler tracking individuals have many more encounters than agent avoiding individuals, but surprisingly, are better able to reduce encounters through increased movement. Individuals using other strategies (mostly agent tracking) have a wider range of movement distances, but cannot efficiently avoid other foragers by moving more. **(B)** Avoiding all other foragers leads to marginally lower infection rates than tracking successful foragers (and avoiding unsuccessful ones; handler tracking). Surprisingly, rare pre-introduction strategies such as following any nearby individuals (agent tracking) may also have low infection rates, potentially due to their rarity. Panel A shows linear model fits with a log scale Y-axis; panel B shows infection rates; all data represent generation- and replicate-specific means ( $3,000 < G < 3,500$ ;  $R = 2$ ,  $\delta E = 0.25$ ).

284 sort of dynamic social distancing (Pusceddu et al., 2021). This dispersed population structure means that  
285 most foragers encounter fewer than 10% of the population over their lifetime (Fig. 3 inset B).

286 *Pathogen-adapted movement strategies make animal societies more resilient to*  
287 *the spread of disease*

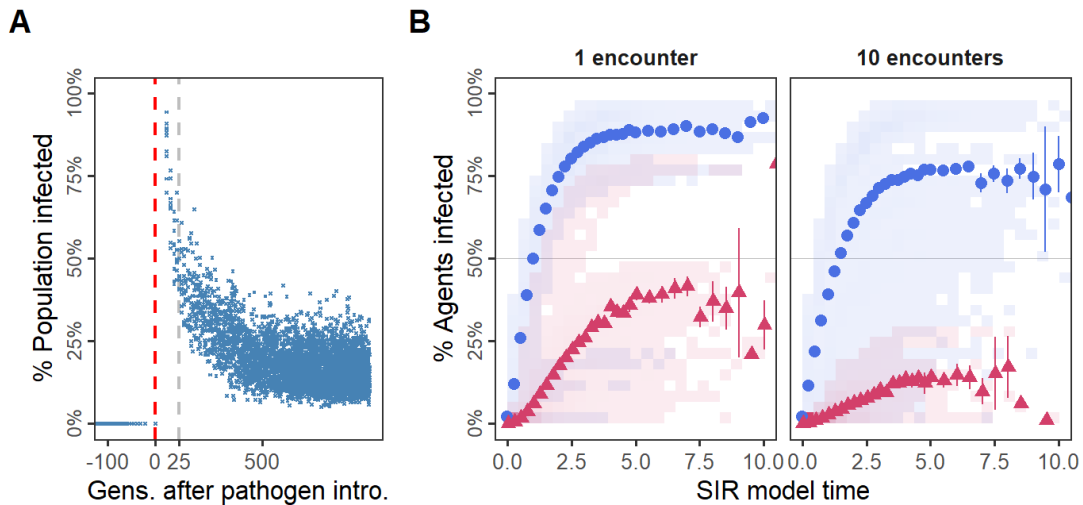
288 Nearly every individual in the generations just after pathogen introduction was infected. However, track-  
289 ing the evolutionary change in movement strategies, the number of infected individuals fell to just about  
290 50% within 25 generations (Fig. 4A). To examine potential pathogen spread in pre-introduction populations,  
291 we ran a simple epidemiological model on the social networks emerging from individuals' movements be-  
292 fore and after pathogen introduction (pre-introduction:  $G = 3,000$ ; post-introduction:  $G = 3,500$ ). We



**Figure 3: Reduced spatial-social clustering in the presence of an infectious pathogen.** Pre-introduction populations (**A**;  $G = 3,000$ ) are substantially more spatially clustered than post-introduction populations (**B**;  $G = 3,500$ ). This clustering means that pre-introduction individuals encounter many more unique neighbours (**inset A**) than do post-introduction individuals (**inset B**). Dashed grey line represents 10% of individuals encountered ( $N = 50$ ). The more spread-out networks in post-introduction populations suggest that most foragers move substantially from their initial locations over their lifetime, leading to associations with foragers from all over the landscape. Main panels show social networks from a single replicate of the default scenario ( $R = 2$ ,  $\delta E = 0.25$ ); (**A**) shows all 500 individuals, which are extremely spatially clustered. Nodes representing individuals, connections representing pairwise encounters, and node size representing the total number of encounters (larger circles = more encounters). In main panels, colours indicate how long individuals have been infected: darker colours indicate longer infection, light blue indicates no infection. Main panels show a single unique simulation run; inset shows degree distributions from 10 simulation replicates, and the X-axis is log-scaled.

293 modelled two diseases, (*i*) first, a disease requiring one encounter, and (*ii*) second, a disease requiring ten  
 294 encounters between individuals for a potential transmission event (transmission rate  $\beta = 5.0$ , recovery rate  
 295  $\gamma = 1.0$ ). Both the single encounter and multiple encounter diseases would infect 75% – 80% of individuals  
 296 when spreading through the networks of pre-introduction populations (Fig. 4B). Pathogen-adapted popu-  
 297 lations' social networks are more resilient to both the single encounter and multiple encounter disease, com-  
 298 pared to their pre-introduction, pathogen-naive ancestors (Fig. 4B). Less than 50% of post-introduction popu-  
 299 lations were finally infected by the single encounter disease, compared with  $> 75\%$  of pre-introduction,  
 300 pathogen-naive ancestors. In pathogen-adapted populations, the spread of the multiple encounter disease

301 was even slower (ever infected:  $\approx 20\%$ ), as these social networks are sparser and individuals are more  
302 weakly connected (Fig. 4B; see Fig. 3B).



**Figure 4: The spread of disease is slowed in populations adapted to the presence of an infectious pathogen.** (A) In the first generations following pathogen introduction, nearly every single individual in the population is infected (default scenario:  $R = 2$ ,  $\delta E = 0.25$ ). However, within 25 generations, tracking the evolutionary shift towards movement strategies that avoid some or all other individuals, only about 50% of individuals are ever infected; this drops further to a stable  $\approx 20\%$  within 500 generations after pathogen introduction. (B) The progression of two hypothetical diseases (transmission rate  $\beta = 5.0$ , recovery rate  $\gamma = 1.0$ ), requiring a single encounter, or 10 encounters for a potential transmission. A simple SIR model on the emergent social networks of pre- (blue dots) and post-introduction (red triangles) populations ( $G = 3,000$ , and  $G = 3,500$ ) shows that the transmission of both diseases is reduced in populations with disease-adapted movement strategies. Panels show means of 25 SIR model replicates, run on emergent social networks from each of 10 simulation replicates in the default scenario ( $R = 2$ ,  $\delta E = 0.25$ ).

303 *Landscape productivity and infection cost influence which social movement*

304 *strategies evolve*

305 We ran our model with nine different combinations of landscape productivity ( $R \in 1, 2, 5$ ) and infection  
306 cost per timestep ( $\delta E \in 0.1, 0.25, 0.5$ ). Initially, in the absence of the pathogen, landscape productivity alone  
307 determines the benefits of social information, and thus which social movement strategies evolve (Fig. 5). On  
308 low-productivity landscapes ( $R = 1$ ), social information is valuable as direct resource cues are scarce; here,  
309 the handler-tracking strategy persists. On high-productivity landscapes ( $R \in 2, 5$ ), social information is less  
310 valuable as individuals can directly detect food items more often; here, the agent tracking strategy is most

311 common. Across scenarios, the introduction of the infectious pathogen leads to a rapid evolutionary shift in  
312 social movement strategies. The benefits of social information (mediated by landscape productivity), and  
313 infection cost jointly determine how pathogen introduction alters the mix of social movement strategies.  
314 When the benefit of social information balances the cost of infection, the handler tracking strategy is com-  
315 mon ( $R = 1, \delta E = 0.1$ ;  $R = 5, \delta E = 0.25$ ). When social information benefits are lower than infection costs (e.g.  
316  $\delta E = 0.5$ ), the agent avoiding strategy is common. Landscape productivity can also directly balance infection  
317 costs: on high-productivity landscapes with low infection costs ( $R \in 2, 5, \delta E = 0.1$ ), pathogen introduction  
318 does not cause a shift in movement strategies, and the agent tracking strategy remains prevalent.

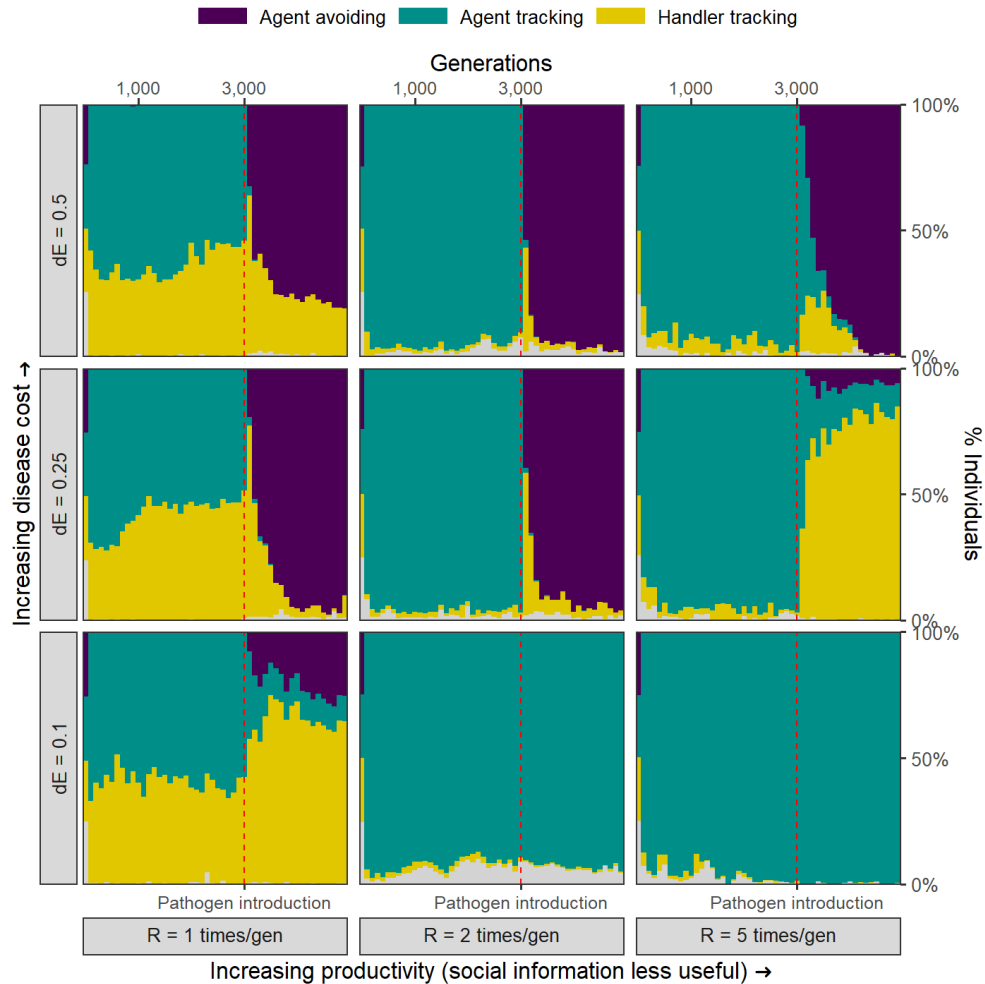
319

## Discussion

320 Our model is among the first to demonstrate the tension inherent to sociality under the risk of an infectious  
321 pathogen, in an explicitly spatial context. We show how populations, initially evolved to find patchily  
322 distributed food using social information, rapidly evolve to eschew social encounters when an infectious  
323 pathogen is introduced. Our work shows how qualitatively and quantitatively different social movement  
324 strategies — each making a different trade-off between social information and infection risk — can co-exist  
325 in a single population.

326 We expected that prior to pathogen introduction, exploitation competition should promote the use of  
327 high-quality social information, and the avoidance of potential competitors (handler tracking; Gupte et al.,  
328 2021). We found that the usefulness of social information affected this outcome quite strongly, as handler  
329 tracking was most common on low-productivity landscapes ( $R = 1$ ), where social information is crucial  
330 to finding resources (see *Model and Analysis*). Our current model's landscape clusters are more sparsely  
331 and irregularly distributed than in our previous work (Gupte et al., 2021), and individuals are initialised  
332 near their parent's final location (see *Supplementary Material Fig. 2, 4*). This leads to 'ecological inheritance'  
333 whereby successful individuals on or near resource clusters pass their favourable positions on to their off-  
334 spring (Badyaev and Uller, 2009). Avoiding potential competitors thus correlates with avoiding profitable  
335 areas. This leads to the persistence of the indiscriminately social agent tracking strategy, despite the evident  
336 costs of exploitation competition (see *Supplementary Material Section 3.2* for an alternative implementation).  
337 We found an unexpectedly rapid evolutionary shift, within 25 generations, in individual movement strate-  
338 gies following pathogen introduction. This is much more rapid than the timescales usually associated with  
339 the evolution of complex traits such as sociality. This change actually occurs over fewer generations than





**Figure 5: The balance of infection cost and the usefulness of social information together shape the rapid evolutionary change in movement strategies triggered by pathogen introduction.** Pre-introduction ( $G = 3,000$ ; dashed line) populations contain a mix of individuals that either track all foragers (agent tracking), or only successful foragers (handler tracking). Handler tracking is more common on low-productivity landscapes ( $R = 1$ ), where social information is more useful to find patchily distributed resources. After pathogen introduction, the agent avoidance (avoiding both successful and unsuccessful foragers) emerges and rapidly becomes the most common strategy when infection costs are high ( $\delta E \geq 0.25$ ), and on low-productivity landscapes. When the benefit of social information outweighs the costs of infection, the handler tracking strategy is common. This occurs both when productivity is low ( $R = 1$ ) and infection costs are low ( $\delta E = 0.1$ ), but also when productivity is high ( $R = 5$ ) with intermediate infection costs ( $\delta E = 0.25$ ). In scenarios of high landscape productivity combined with low infection costs (e.g.  $R = 5$ ,  $\delta E = 0.1$ ), the agent tracking strategy persists beyond pathogen introduction. All panels show mean frequencies over 10 replicate simulations in 100 generation bins; frequencies are stacked. Grey areas show the relatively uncommon ‘non-handler’ tracking strategy.

340 over which key aspects of animal culture and ecology, such as migration routes, are established through  
 341 social learning (Jesmer et al., 2018; Cantor et al., 2021b). Current and expected cross-species transmissions

342 of novel pathogens (Carlson et al., 2021; Pusceddu et al., 2021) should thus prompt concern that the evolu-  
343 tionary consequences of pathogen introduction could slow the transmission of, and erode, animal culture  
344 (Cantor et al., 2021b).

345 Avoiding potentially infectious individuals is a key component of navigating the ‘landscape of disgust’  
346 (Weinstein et al., 2018). To navigate this landscape effectively, animals must first be sensitive, or become  
347 more sensitive, to cues of high transmission risk. Our results show that such sensitivity can rapidly evolve  
348 following the introduction of a novel pathogen, leading to strong qualitative changes in movement strate-  
349 gies within 100 generations. Furthermore, on average, individuals’ sensitivity to social movement cues  
350 actually increases after pathogen introduction. However, there was substantial between-individual varia-  
351 tion in the importance of social cues overall, even after a specific movement strategy had become dominant.  
352 A mix of individuals with different sensitivities to social cues, relative to resource cues, is key to the evolu-  
353 tion of large-scale collective behaviours, such as migration (Guttal and Couzin, 2010). Our work suggests  
354 how in the long term (about 500 generations), by leading to the necessary diversity in social movement  
355 strategies, a novel pathogen may actually lay the groundwork for the evolution of more complex collective  
356 behaviour. The emergence of individual variation in social movement strategies, and especially the trade-  
357 off between movement, associations, and infection risk also suggests a clear mechanism by which sociality  
358 could evolve as a personality trait (Gartland et al., 2021).

359 The evolutionary changes triggered by pathogen introduction were strongly and predictably controlled  
360 by the combination of landscape productivity ( $R$ ) and infection cost ( $\delta E$ ). Productivity can be seen in an-  
361 other context: as a proxy for the usefulness of social information. The benefits of grouping, relative to  
362 the costs of infection, can also influence sociality in the context of disease (Almberg et al., 2015; Ezenwa  
363 et al., 2016). Social information benefits in a disease context are often modelled as a single parameter,  
364 with no mechanistic relationship with the subject of the information (e.g. food, predators; see e.g. Ashby  
365 and Farine 2022). In contrast, social information benefits in our model are emergent outcomes of animal  
366 movement and foraging mechanisms. Our model’s predictions may help explain intra- and inter-specific  
367 diversity in social systems across contexts that differ in the usefulness of social information and disease risk  
368 (Lott, 1991; Sah et al., 2018). At the population level, this suggests one pathway by which gregarious, clus-  
369 tered species, which are expected to be more at risk from transmissible pathogens (Sah et al., 2018), could  
370 transition to a more solitary social organisation over evolutionary timescales. More positively, our results  
371 show that animals may be able to adapt relatively quickly to the spillover and eventual persistence of in-  
372 fectious pathogens, even when they cannot specifically detect and avoid infected individuals (Stroeymeyt

373 et al., 2018).

374 Ecological models expect even isolated pathogen outbreaks, such as that of swine fever in wild boar, to  
375 last over a decade due to interacting effects of host movement and landscape structure (Scherer et al., 2020).  
376 These outbreaks are expected to have substantial cascading effects for landscape and community ecology  
377 (Monk et al., 2022). Our model shows that rapid, disease-dominated ecological cascades — individuals  
378 have less intake, exerting less top-down pressure on their resource — can occur even without mortality ef-  
379 fects, due to evolutionary shifts in movement alone. Furthermore, our results suggest that selection against  
380 sociality (usually held constant in ecological models) could bring infection outbreaks under control more  
381 swiftly than predicted, as the population shifts from gregarious to solitary. Nonetheless, the altered eco-  
382 logical state (here, less resource consumption, as in Monk et al. 2022) may be maintained long after — and  
383 indeed because — a population has adapted to be less social in the presence of a pathogen. Our network  
384 epidemiological models suggest that the spread of pathogens and parasites that are better transmitted by  
385 actual social contact (e.g. helminths), rather than simply proximity (e.g. viruses) (Rimback et al., 2015),  
386 may be lower in pathogen-adapted populations. On one hand, this could reduce the prevalence and dis-  
387 ease burden of previous endemic pathogens adapted to a more social host. On the other hand, increased  
388 dispersal over the landscape may make animals more likely to widely transmit certain pathogens to their  
389 environment, and pick up these pathogens in turn (Rimback et al., 2015; Weinstein et al., 2018; Scherer et al.,  
390 2020).

391 Our infectious pathogen is easily transmitted through proximity, and causes a chronic yet non-fatal dis-  
392 ease; though realistic, these assumptions cannot capture the full diversity of pathogens and their dynamics  
393 (White et al., 2018a; Scherer et al., 2020; Lunn et al., 2021). More detailed mechanistic modelling would  
394 have to account for the differential effects of proximity and actual social contacts on transmission (Rimback  
395 et al., 2015). The most pressing epizootics are fatal, causing mass mortality in mammals (Blehert et al., 2009;  
396 Fereidouni et al., 2019) and amphibians (Scheele et al., 2019; Sanderson and Alexander, 2020). Whether  
397 such sharp, temporally restricted outbreaks result in substantial evolutionary pressure against sociality is  
398 unclear. Comparing sociality before and after an unexpected pathogen spillover (as in Kuchipudi et al.,  
399 2022) is likely to be challenging, not least because data on past and ongoing host-pathogen introduction  
400 events is sparse. Our model then is especially suited to longer-term outbreaks in which populations are  
401 repeatedly exposed to novel pathogens (or strains), such as wild boar swine fever outbreaks (Scherer et al.,  
402 2020), avian influenza in Arctic migratory birds (The Global Consortium for H5N8 and Related Influenza  
403 Viruses, 2016), or the recent introduction of Covid-19 to deer (Kuchipudi et al., 2022).

404 Pathogens also typically have much shorter generation times than their hosts. Analytical models expect  
405 pathogen attributes to rapidly co-evolve to match host population attributes (e.g. sociality and immune  
406 resistance) (Bonds et al., 2005; Prado et al., 2009; Ashby and Farine, 2022). Such models treat pathogens  
407 — just as they do host animals — in relatively simple, non-mechanistic ways. Pathogens are primarily  
408 expected to evolve to a virulence that promotes between-host transmission (Bonds et al., 2005). Our mech-  
409 anistic model does not explicitly consider host-pathogen co-evolutionary dynamics, as this complexity was  
410 beyond the scope of our general, conceptual model. Adding pathogen evolutionary dynamics to a mech-  
411 anistic individual-based model would require careful consideration of (i) the costs the pathogen imposes  
412 on its hosts, and (ii) how it transmits between hosts, both within and between generations. We expect that  
413 multiple pathogen strategies could coexist in a host population that itself has multiple social movement  
414 strategies.

415 Our mechanistic model, combining animal movement and plausible disease transmission, extends cur-  
416 rent understanding of the evolutionary consequences of individual spatial-social ecology (Webber and Van-  
417 der Wal, 2018; Albery et al., 2021; Webber et al., 2022). We generate consistent predictions of marked and  
418 swift evolutionary shifts in social movement strategies that could plausibly be tested over the timescales  
419 of some long-term animal tracking studies (Wilber et al., 2022). Our social information-based movement  
420 strategies are made up of continuous values that place individuals on a two-dimensional trait space of rel-  
421 ative preferences (or aversions) for successful and unsuccessful foragers (see *Model and Analysis*; see also  
422 Gupte et al. 2021). Such social movement strategies could already be revealed for free-living animals using  
423 newer step-selection approaches (Avgar et al., 2016), combined with the simultaneous, high-throughput  
424 tracking of many hundreds of animals in an area (Nathan et al., 2022). More immediately, studying the  
425 movement ecology of animals across a cline of pathogen prevalence could help test the predictions of this  
426 and similar models (Wilber et al., 2022). Given that infection patterns can change rapidly in space even in  
427 small, well-mixed populations (Albery et al., 2022), the systems that could be used to test these phenomena  
428 may be widespread and easily available. Finally, our general modelling framework, correctly parame-  
429 terised to suit specific animal systems, could provide useful insights in the future to guide the long-term  
430 management of wildlife populations.

### 431 *Data and Code Availability*

432 The *Pathomove* simulation model code is available on Zenodo at <https://zenodo.org/record/6331816>, and  
433 on Github at [github.com/pratikunterwegs/pathomove](https://github.com/pratikunterwegs/pathomove). A reference dataset with 10 replicates of the pa-

434 parameter combinations presented here is archived on Zenodo at: <https://zenodo.org/record/6331757>. Code  
435 to run the simulations and analyse the output is on Zenodo at <https://zenodo.org/record/6341440>, and on  
436 Github at: [github.com/pratikunterwegs/patho-move-evol](https://github.com/pratikunterwegs/patho-move-evol).

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## 445 **Literature Cited**

- 446 Albery, G. F., L. Kirkpatrick, J. A. Firth, and S. Bansal. 2021. Unifying spatial and social network analysis in  
447 disease ecology. *Journal of Animal Ecology* 90:45–61.
- 448 Albery, G. F., A. R. Sweeny, D. J. Becker, and S. Bansal. 2022. Fine-scale spatial patterns of wildlife disease  
449 are common and understudied. *Functional Ecology* 36:214–225.
- 450 Almberg, E. S., P. C. Cross, A. P. Dobson, D. W. Smith, M. C. Metz, D. R. Stahler, and P. J. Hudson. 2015.  
451 Social living mitigates the costs of a chronic illness in a cooperative carnivore. *Ecology Letters* 18:660–667.
- 452 Altizer, S., C. L. Nunn, P. H. Thrall, J. L. Gittleman, J. Antonovics, A. A. Cunningham, A. P. Dobson,  
453 V. Ezenwa, K. E. Jones, A. B. Pedersen, M. Poss, and J. R. Pulliam. 2003. Social Organization and Parasite  
454 Risk in Mammals: Integrating Theory and Empirical Studies. *Annual Review of Ecology, Evolution, and*  
455 *Systematics* 34:517–547.
- 456 Ashby, B., and D. R. Farine. 2022. Social information use shapes the coevolution of sociality and virulence.  
457 *bioRxiv* : the preprint server for biology .
- 458 Avgar, T., J. R. Potts, M. A. Lewis, and M. S. Boyce. 2016. Integrated step selection analysis: Bridging the  
459 gap between resource selection and animal movement. *Methods in Ecology and Evolution* 7:619–630.
- 460 Badyaev, A. V., and T. Uller. 2009. Parental effects in ecology and evolution: Mechanisms, processes and  
461 implications. *Philosophical Transactions of the Royal Society B: Biological Sciences* 364:1169–1177.
- 462 Bailey, N. T. J. 1975. *The Mathematical Theory of Infectious Diseases and Its Applications*. 2nd ed. Griffin,  
463 London.
- 464 Blehert, D. S., A. C. Hicks, M. Behr, C. U. Meteyer, B. M. Berlowski-Zier, E. L. Buckles, J. T. H. Coleman,  
465 S. R. Darling, A. Gargas, R. Niver, J. C. Okoniewski, R. J. Rudd, and W. B. Stone. 2009. Bat white-nose  
466 syndrome: An emerging fungal pathogen? *Science (New York, N.Y.)* 323:227.

- 467 Bonds, M. H., D. D. Keenan, A. J. Leidner, and P. Rohani. 2005. Higher Disease Prevalence Can Induce  
468 Greater Sociality: A Game Theoretic Coevolutionary Model. *Evolution* 59:1859–1866.
- 469 Cantor, M., M. Chimento, S. Q. Smeele, P. He, D. Papageorgiou, L. M. Aplin, and D. R. Farine. 2021a. Social  
470 network architecture and the tempo of cumulative cultural evolution. *Proceedings of the Royal Society*  
471 *B: Biological Sciences* 288:20203107.
- 472 Cantor, M., A. A. Maldonado-Chaparro, K. B. Beck, H. B. Brandl, G. G. Carter, P. He, F. Hillemann, J. A.  
473 Klarevas-Irby, M. Ogino, D. Papageorgiou, L. Prox, and D. R. Farine. 2021b. The importance of individual-  
474 to-society feedbacks in animal ecology and evolution. *Journal of Animal Ecology* 90:27–44.
- 475 Carlson, C. J., G. F. Albery, C. Merow, C. H. Trisos, C. M. Zipfel, E. A. Eskew, K. J. Olival, N. Ross, and  
476 S. Bansal. 2021. Climate change will drive novel cross-species viral transmission.
- 477 Csardi, G., and T. Nepusz. 2006. The igraph software package for complex network research. *InterJournal*  
478 *Complex Systems*:1695.
- 479 Dall, S. R. X., L.-A. Giraldeau, O. Olsson, J. M. McNamara, and D. W. Stephens. 2005. Information and its  
480 use by animals in evolutionary ecology. *Trends in Ecology & Evolution* 20:187–193.
- 481 Danchin, É., L.-A. Giraldeau, T. J. Valone, and R. H. Wagner. 2004. Public information: From nosy neighbors  
482 to cultural evolution. *Science* 305:487–491.
- 483 DeAngelis, D. L., and S. G. Diaz. 2019. Decision-making in agent-based modeling: A current review and  
484 future prospectus. *Frontiers in Ecology and Evolution* 6.
- 485 Eddelbuettel, D. 2013. *Seamless R and C++ Integration with Rcpp*. Use R! Springer-Verlag, New York.
- 486 Ezenwa, V. O., R. R. Ghai, A. F. McKay, and A. E. Williams. 2016. Group living and pathogen infection  
487 revisited. *Current Opinion in Behavioral Sciences* 12:66–72.
- 488 Fereidouni, S., G. L. Freimanis, M. Orynbayev, P. Ribeca, J. Flannery, D. P. King, S. Zuther, M. Beer, D. Höper,  
489 A. Kydyrmanov, K. Karamendin, and R. Kock. 2019. Mass Die-Off of Saiga Antelopes, Kazakhstan, 2015.  
490 *Emerging Infectious Diseases* 25:1169–1176.
- 491 Gartland, L. A., J. A. Firth, K. L. Laskowski, R. Jeanson, and C. C. Ioannou. 2021. Sociability as a personality  
492 trait in animals: Methods, causes and consequences. *Biological Reviews* n/a.
- 493 Getz, W. M., R. Salter, A. J. Lyons, and N. Sippel-Swezey. 2015. Panmictic and clonal evolution on a single  
494 patchy resource produces polymorphic foraging guilds. *PLOS ONE* 10:e0133732–e0133732.
- 495 Gil, M. A., A. M. Hein, O. Spiegel, M. L. Baskett, and A. Sih. 2018. Social Information Links Individual  
496 Behavior to Population and Community Dynamics. *Trends in Ecology & Evolution* 33:535–548.
- 497 Gupte, P. R. 2022a. Reference data from the Pathomove simulation, for the manuscript "Novel pathogen  
498 introduction rapidly alters the evolution of movement, restructuring animal societies".
- 499 ———. 2022b. Source code for Pathomove, an individual-based model for the evolution of animal move-  
500 ment strategies under the risk of pathogen transmission. Zenodo.
- 501 Gupte, P. R., G. F. Albery, J. Gismann, A. R. Sweeny, and F. J. Weissing. 2022. Source Code and Supplemen-  
502 tary Material for "Novel pathogen introduction rapidly alters the evolution of movement, restructuring  
503 animal societies". Zenodo.
- 504 Gupte, P. R., C. F. G. Netz, and F. J. Weissing. 2021. The joint evolution of animal movement and competition  
505 strategies. *bioRxiv : the preprint server for biology* .

- 506 Guttal, V., and I. D. Couzin. 2010. Social interactions, information use, and the evolution of collective  
507 migration. *Proceedings of the National Academy of Sciences* 107:16172.
- 508 Hutchings, M. R., J. Judge, I. J. Gordon, S. Athanasiadou, and I. Kyriazakis. 2006. Use of trade-off theory to  
509 advance understanding of herbivore–parasite interactions. *Mammal Review* 36:1–16.
- 510 Jesmer, B. R., J. A. Merkle, J. R. Goheen, E. O. Aikens, J. L. Beck, A. B. Courtemanch, M. A. Hurley, D. E.  
511 McWhirter, H. M. Miyasaki, K. L. Monteith, and M. J. Kauffman. 2018. Is ungulate migration culturally  
512 transmitted? Evidence of social learning from translocated animals. *Science* 361:1023–1025.
- 513 Krause, J., and G. D. Ruxton. 2002. *Living in Groups*. Oxford University Press.
- 514 Kuchipudi, S. V., M. Surendran-Nair, R. M. Ruden, M. Yon, R. H. Nissly, K. J. Vandegrift, R. K. Nelli, L. Li,  
515 B. M. Jayarao, C. D. Maranas, N. Levine, K. Willgert, A. J. K. Conlan, R. J. Olsen, J. J. Davis, J. M. Musser,  
516 P. J. Hudson, and V. Kapur. 2022. Multiple spillovers from humans and onward transmission of SARS-  
517 CoV-2 in white-tailed deer. *Proceedings of the National Academy of Sciences* 119.
- 518 Lott, D. F. 1991. *Intraspecific Variation in the Social Systems of Wild Vertebrates*, vol. 2. Cambridge Univer-  
519 sity Press.
- 520 Lunn, T. J., A. J. Peel, H. McCallum, P. Eby, M. K. Kessler, R. K. Plowright, and O. Restif. 2021. Spatial  
521 dynamics of pathogen transmission in communally roosting species: Impacts of changing habitats on  
522 bat-virus dynamics. *Journal of Animal Ecology* n/a.
- 523 Monk, J. D., J. A. Smith, E. Donadío, P. L. Perrig, R. D. Crego, M. Fileni, O. Bidder, S. A. Lambertucci, J. N.  
524 Pauli, O. J. Schmitz, and A. D. Middleton. 2022. Cascading effects of a disease outbreak in a remote  
525 protected area. *Ecology Letters* n/a.
- 526 Nathan, R., W. M. Getz, E. Revilla, M. Holyoak, R. Kadmon, D. Saltz, and P. E. Smouse. 2008. A movement  
527 ecology paradigm for unifying organismal movement research. *Proceedings of the National Academy of*  
528 *Sciences* 105:19052–19059.
- 529 Nathan, R., C. T. Monk, R. Arlinghaus, T. Adam, J. Alós, M. Assaf, H. Baktoft, C. E. Beardsworth, M. G.  
530 Bertram, A. I. Bijleveld, T. Brodin, J. L. Brooks, A. Campos-Candela, S. J. Cooke, K. Ø. Gjelland, P. R.  
531 Gupte, R. Harel, G. Hellström, F. Jeltsch, S. S. Killen, T. Klefoth, R. Langrock, R. J. Lennox, E. Lourie, J. R.  
532 Madden, Y. Orchan, I. S. Pauwels, M. Říha, M. Roeleke, U. E. Schlägel, D. Shohami, J. Signer, S. Toledo,  
533 O. Vilk, S. Westrelin, M. A. Whiteside, and I. Jarić. 2022. Big-data approaches lead to an increased under-  
534 standing of the ecology of animal movement. *Science* 375:eabg1780.
- 535 Netz, C., H. Hildenbrandt, and F. J. Weissing. 2021. Complex eco-evolutionary dynamics induced by the  
536 coevolution of predator–prey movement strategies. *Evolutionary Ecology* .
- 537 Pedersen, T. L. 2020. *Tidygraph: A Tidy API for Graph Manipulation*.
- 538 Poulin, R., and A. Fillion. 2021. Evolution of social behaviour in an infectious world: Comparative analysis  
539 of social network structure versus parasite richness. *Behavioral Ecology and Sociobiology* 75:105.
- 540 Power, A. G., and C. E. Mitchell. 2004. Pathogen Spillover in Disease Epidemics. *The American Naturalist*  
541 164:S79–S89.
- 542 Prado, F., A. Sheih, J. D. West, and B. Kerr. 2009. Coevolutionary cycling of host sociality and pathogen  
543 virulence in contact networks. *Journal of Theoretical Biology* 261:561–569.
- 544 Pusceddu, M., A. Cini, S. Alberti, E. Salaris, P. Theodorou, I. Floris, and A. Satta. 2021. Honey bees increase  
545 social distancing when facing the ectoparasite *Varroa destructor*. *Science Advances* 7:eabj1398.
- 546 R Core Team. 2020. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical  
547 Computing, Vienna, Austria.

- 548 Rimbach, R., D. Bisanzio, N. Galvis, A. Link, A. Di Fiore, and T. R. Gillespie. 2015. Brown spider mon-  
549 keys (*Ateles hybridus*): A model for differentiating the role of social networks and physical contact on  
550 parasite transmission dynamics. *Philosophical Transactions of the Royal Society B: Biological Sciences*  
551 370:20140110.
- 552 Romano, V., A. J. J. MacIntosh, and C. Sueur. 2020. Stemming the Flow: Information, Infection, and Social  
553 Evolution. *Trends in Ecology & Evolution* 35:849–853.
- 554 Romano, V., C. Sueur, and A. J. J. MacIntosh. 2021. The tradeoff between information and pathogen trans-  
555 mission in animal societies. *Oikos* n/a.
- 556 Ruxton, G. D., W. S. C. Gurney, and A. M. de Roos. 1992. Interference and generation cycles. *Theoretical*  
557 *Population Biology* 42:235–253.
- 558 Sah, P., J. Mann, and S. Bansal. 2018. Disease implications of animal social network structure: A synthesis  
559 across social systems. *Journal of Animal Ecology* 87:546–558.
- 560 Sanderson, C. E., and K. A. Alexander. 2020. Uncharted waters: Climate change likely to intensify in-  
561 fectious disease outbreaks causing mass mortality events in marine mammals. *Global Change Biology*  
562 26:4284–4301.
- 563 Scheele, B. C., F. Pasmans, L. F. Skerratt, L. Berger, A. Martel, W. Beukema, A. A. Acevedo, P. A. Burrowes,  
564 T. Carvalho, A. Catenazzi, I. De la Riva, M. C. Fisher, S. V. Flechas, C. N. Foster, P. Frías-Álvarez, T. W. J.  
565 Garner, B. Gratwicke, J. M. Guayasamin, M. Hirschfeld, J. E. Kolby, T. A. Kosch, E. La Marca, D. B.  
566 Lindenmayer, K. R. Lips, A. V. Longo, R. Maneyro, C. A. McDonald, J. Mendelson, P. Palacios-Rodriguez,  
567 G. Parra-Olea, C. L. Richards-Zawacki, M.-O. Rödel, S. M. Rovito, C. Soto-Azat, L. F. Toledo, J. Voyles,  
568 C. Weldon, S. M. Whitfield, M. Wilkinson, K. R. Zamudio, and S. Canessa. 2019. Amphibian fungal  
569 panzootic causes catastrophic and ongoing loss of biodiversity. *Science (New York, N.Y.)* 363:1459–1463.
- 570 Scherer, C., V. Radchuk, M. Franz, H.-H. Thulke, M. Lange, V. Grimm, and S. Kramer-Schadt. 2020. Moving  
571 infections: Individual movement decisions drive disease persistence in spatially structured landscapes.  
572 *Oikos* 129:651–667.
- 573 Spiegel, O., S. T. Leu, C. M. Bull, and A. Sih. 2017. What’s your move? Movement as a link between  
574 personality and spatial dynamics in animal populations. *Ecology Letters* 20:3–18.
- 575 Stockmaier, S., N. Stroeymeyt, E. C. Shattuck, D. M. Hawley, L. A. Meyers, and D. I. Bolnick. 2021. Infectious  
576 diseases and social distancing in nature. *Science* 371:eabc8881.
- 577 Stroeymeyt, N., A. V. Grasse, A. Crespi, D. P. Mersch, S. Cremer, and L. Keller. 2018. Social network plastic-  
578 ity decreases disease transmission in a eusocial insect. *Science (New York, N.Y.)* 362:941–945.
- 579 Tanner, C. J., and A. L. Jackson. 2012. Social structure emerges via the interaction between local ecology  
580 and individual behaviour. *Journal of Animal Ecology* 81:260–267.
- 581 The Global Consortium for H5N8 and Related Influenza Viruses. 2016. Role for migratory wild birds in the  
582 global spread of avian influenza H5N8. *Science* 354:213–217.
- 583 Webber, Q., G. Albery, D. R. Farine, N. Pinter-Wollman, N. Sharma, O. Spiegel, E. V. Wal, and K. Manlove.  
584 2022. Behavioural ecology at the spatial-social interface.
- 585 Webber, Q. M. R., and E. Vander Wal. 2018. An evolutionary framework outlining the integration of indi-  
586 vidual social and spatial ecology. *Journal of Animal Ecology* 87:113–127.
- 587 Weinstein, S. B., J. C. Buck, and H. S. Young. 2018. A landscape of disgust. *Science* .
- 588 White, L. A., J. D. Forester, and M. E. Craft. 2017. Using contact networks to explore mechanisms of parasite  
589 transmission in wildlife. *Biological Reviews* 92:389–409.



- 590 ———. 2018*a*. Disease outbreak thresholds emerge from interactions between movement behavior, land-  
591     scape structure, and epidemiology. *Proceedings of the National Academy of Sciences* 115:7374–7379.
- 592 ———. 2018*b*. Dynamic, spatial models of parasite transmission in wildlife: Their structure, applications  
593     and remaining challenges. *Journal of Animal Ecology* 87:559–580.
- 594 Whitehead, H. 2008. *Analyzing Animal Societies: Quantitative Methods for Vertebrate Social Analysis*.  
595     University of Chicago Press.
- 596 Wilber, M. Q., A. Yang, R. Boughton, K. R. Manlove, R. S. Miller, K. M. Pepin, and G. Wittemyer. 2022.  
597     A model for leveraging animal movement to understand spatio-temporal disease dynamics. *Ecology*  
598     Letters n/a.
- 599 Wolf, M., and F. J. Weissing. 2012. Animal personalities: Consequences for ecology and evolution. *Trends*  
600     in *Ecology & Evolution* 27:452–461.