

# What's in a resource gradient? Comparing alternative cues for foraging in dynamic environments via movement, perception, and memory

William F. Fagan ( Spin bigan@umd.edu ) University of Maryland at College Park https://orcid.org/0000-0003-2433-9052
Cole Saborio University of Maryland at College Park
Tyler Hoffman University of Maryland at College Park
Eliezer Gurarie University of Maryland at College Park
Robert Stephen Cantrell University of Miami - Coral Gables Campus: University of Miami
Chris Cosner

University of Miami - Coral Gables Campus: University of Miami

**Research Article** 

Keywords:

Posted Date: February 18th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1351426/v1

License: (c) This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

2 3 4	COMPARING ALTERNATIVE CUES FOR FORAGING IN DYNAMIC ENVIRONMENTS VIA MOVEMENT, PERCEPTION, AND MEMORY
3 4	VIA MOVEMENT, PERCEPTION, AND MEMORY
4	
5	
6	
7	William F. Fagan <sup>1,3</sup> , Cole Saborio <sup>1</sup> , Tyler Hoffman <sup>1</sup> , Eliezer Gurarie <sup>1</sup> ,
8	Robert Stephen Cantrell <sup>2</sup> , and Chris Cosner <sup>2</sup>
9	
10	<sup>1</sup> Department of Biology, University of Maryland, College Park, MD 20742
11	<sup>2</sup> Department of Mathematics, University of Miami, Coral Gables, FL 33146
12	
13	<sup>3</sup> Correspondence Author:
14	<u>bfagan@umd.edu</u>
15	301-596-9744
16 17	

18 ABSTRACT

Consumers must track and acquire resources in complex landscapes. Much discussion has 19 focused on the concept of a 'resource gradient' and the mechanisms by which consumers can 20 21 take advantage of such gradients as they navigate their landscapes in search of resources. However, the concept of tracking resource gradients means different things in different contexts. 22 23 Here we take a synthetic approach and consider six different definitions of what it means to search for resources based on density or gradients in density. These include scenarios where 24 25 consumers change their movement behavior based on the density of conspecifics, on the density of resources, and on spatial or temporal gradients in resources. We also consider scenarios 26 involving non-local perception and a form of memory. Using a continuous space, continuous 27 time model that allows consumers to switch between resource-tracking and random motion, we 28 29 investigate the relative performance of these six different strategies. Consumers' success in matching the spatiotemporal distributions of their resources differs starkly across the six 30 scenarios. Movement strategies based on perception and response to temporal (rather than 31 32 spatial) resource gradients afforded consumers with the best opportunities to match resource distributions. All scenarios would allow for optimization of resource matching in terms of the 33 underlying parameters, providing opportunities for evolutionary adaptation, and links back to 34 classical studies of foraging ecology. 35

36

### 37 INTRODUCTION

Successful acquisition of resources is essential to an individual's survival and
reproduction. The acquisition problem is especially challenging in seasonal or otherwise
dynamic landscapes where the spatial location of resources changes over time. This absence of
consistently available resources leaves consumers with several options. Consumers may track

the shifting positions of resources that themselves move across the landscape, they may move to 42 other regions to take advantage of different resources, or they may stay local but switch to 43 alternative resources. Each of these foraging strategies requires that consumers monitor resource 44 availability and respond through movement or changes in feeding style. However, many routes 45 to resource monitoring and movement decision-making exist, and different strategies are unlikely 46 47 to exhibit the same level of profitability with regard to resource acquisition (Grünbaum 1998). Historically, researchers working on foraging-related movement have sought to understand the 48 49 contributions of three elements: search strategies, behavioral changes, and cues for movement. Here, we bring together these three elements in a synthetic approach that investigates how 50 consumers' responses to alternative 'resource gradients' translate into foraging success. 51

52 As consumers seek out resources, they can employ a wide variety of search strategies. Some of these strategies operate on large scales and are long-term in nature. For example, some 53 birds and ungulates 'surf the green wave' as they time their migratory journeys to match seasonal 54 changes in the availability of palatable, nutrient-rich resources as functions of latitude or 55 elevation (Aikens et al. 2020). In other taxa, such as some Brazilian marsupials, perceptual 56 range plays a key role in determining whether the animals move randomly (when no forest was 57 58 nearby) or in a directed fashion (when they could perceive a nearby forest patch) (Prevedello et al. 2011). Similarly, Holdo et al. (2009) found that long-distance perception that allowed 59 tracking of conditions over large spatial scales was crucial to the success of wildebeests' 60 61 migratory journeys in the Serengeti and attention solely to small-scale gradients was insufficient for migratory success. In contrast, blue whales appear to rely not on perception per se, but 62 rather on spatial memory as they migrate. The whales time their patterns of space use to exploit 63

those regions in which resources have been both on average abundant and reliably available over
many years (Abrahms et al. 2019, Fagan 2019).

66 Evidence suggests that such search strategies do not exist in isolation, but rather are used 67 by consumers in different combinations, often as a function of context. With regard to switching between search strategies, a key tension is between searching for new resources and not 68 69 wandering too far. This is particularly important when resources are spatiotemporally heterogeneous. Mathematically, this tension can appear as a balance between random search 70 71 (diffusion) and range residency (movement with a central tendency) as animals switch between 72 movement modes as a function of their spatial context. A growing list of empirical examples demonstrates that such context-dependent behavioral switching between movement modes is 73 quite widespread. A few examples include mosquitoes (Rjo and DeGennaro 2017), tuna 74 (Newlands et al. 2004), opossums (Prevedello et al. 2011), elk (Morales et al. 2004), and 75 woodpeckers (Vergara et al. 2018). Moreover, robust statistical tools are increasingly available 76 77 for deconstructing empirical movement paths into alternative movement modes and identifying behavioral change points (Morales et al. 2004, Gurarie et al. 2009, 2016). Key open questions 78 center on the factors that precipitate such changes in behavior and how different forms of 79 80 context-dependent switching influence resource acquisition.

To some degree, modeling studies have also explored the consequences of combining movement modes in various mixtures. Frequently, diffusion (random search) and advection (gradient following) are explored together, often with the goal of identifying optimally blended movement strategies that yield evolutionarily stable strategies (Cantrell et al. 2008, 2018, 2020; Lam and Lou 2014). Other modeling studies have directly considered switching between alternative movement modes; that is, they explored situations where, rather than simultaneously

blending two movement modes, individuals could be considered to be in either one movement 87 mode or another. Skalski and Gilliam (2003) explored how switching between slow and fast 88 movement states (which occurred independent of spatial context) influenced a population's 89 spatial distribution. More recently, Tyson et al. (2011) considered spatially independent 90 behavioral switching terms for a model where foragers had both fast-moving diffusive and slow-91 92 moving advective-diffusive states. They found that single-movement-mode models (in which the forager population was homogeneously diffusive or advective-diffusive) provided a worse fit to 93 94 data for both caribou and honeybees than did the model with behavioral switching. Different 95 types of intermittent movement (Gleiss et al. 2011), especially so-called burst-and-coast movement by fish (Kramer and McLaughlin 2001, McLaughlin and Grant 2001), provide yet 96 more examples in which animals sequentially switch between movement types. Burst movement 97 is thought to provide rapid propulsion that alternates with coast movement during which fish can 98 better perceive their surroundings. Fagan et al. (2020) analyzed a model in which switching 99 100 between movement modes depended on spatial context. They found that behavioral switching was most beneficial when an organism's gradient-following abilities were weak compared to its 101 overall capacity for movement. Moreover, they found that an organism's perceptual range was a 102 103 key determinant of whether behavioral switching was advantageous or disadvantageous in the search for resources. 104

Just as different movement strategies, and opportunities for switching between strategies, present consumers with a range of options for mobility, so too do the proximal cues on which resource-related movement decisions are based. For example, Dusenberry (1998) demonstrated that free-swimming bacteria can be differentially advantaged by using temporal gradients versus spatial gradients in their quest for resources. In that system, movements based on following

temporal gradients were especially valuable in providing superior access to resources when those 110 resources were at low densities. In another example, numerous species of tropical frugivorous 111 birds appear to track temporal changes in fruit abundance, shifting their spatial activity in 112 response to increases and decreases in fruit abundance (Loiselle and Blake 1991). In other cases, 113 following spatial rather than temporal gradients appears essential to success, and small scale 114 115 spatial gradients are particularly useful for consumers that rely on chemosensation. For example, catfish follow centimeter-scale spatial (rather than temporal) gradients in nutrient concentration 116 as they seek out resources (Johnson and Teeter 1980). Similarly, rats effectively 'smell in 117 stereo' as they respond to highly localized bilateral differences in the concentration of odorants 118 (Rajan et al. 2006), whereas moles combine serial scent detection (i.e., repeated 'sniffing') with 119 bilateral olfaction to identify the gradients that guide their search for resources (Catania 2013). 120

Here we seek to synthesize these three factors (i.e., alternative search strategies, switching between movement modes, and diverse cues for movement) into a single modeling framework to explore in detail how these features influence the abilities of consumers to track and match the spatiotemporal distribution of resources in dynamic landscapes. Intriguingly, we find that different search-movement strategies perform best under different resource situations, suggesting conditions under which alternative resource dynamics might select for the evolution of alternative foraging strategies.

128 METHODS

<u>A dynamic resource:</u> We will assume a one-dimensional binary resource landscape of habitat
 patches and non-habitat that is temporally dynamic. Fagan et al. (2017) explored how alternative
 resource functions influence the ability of consumers to match the distribution of their resources.

Here, we consider one of the resource functions studied in that paper, the Pulsed Gaussianresource:

$$m(x,t) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \sin^2(\omega t/2)$$
(1)

135 where  $\mu$  and  $\sigma$  are, respectively, the mean and standard deviation of the resource pulse and  $\omega$  is 136 the temporal frequency of the pulse. Equation (1) corresponds to a resource patch with smoothly 137 varying edges that does not change position spatially but does increase and decrease in 138 abundance over time.

We consider situations in which there either is a single resource patch that pulses in time or two identical pulsing resource patches that are shifted by half a period relative to one another. The latter scenario corresponds to a strongly seasonal landscape where there exists opportunity for migration to emerge between the two resource patches that are oscillating out-of-phase.

Consumers Switch between Random Search and Range-residency: Living on this dynamic 143 resource landscape is a population of consumers. We consider a population in which the 144 consumers can switch between two distinct modes of dispersal. Tyson et al. (2011) and Fagan et 145 al. (2019) explored scenarios in which consumers switch between a random search mode and a 146 mode in which there exists movement in response to a resource gradient. Here, motivated by 147 recent developments in the statistical analysis of animal tracking data (Fleming et al. 2014, 148 149 Noonan et al. 2019), we do something a bit different. Specifically, we consider the spatial 150 dynamics of consumers that may have home ranges, but which can switch between a random search mode and a range-resident mode. Note that this pair of movement modes is different than 151 152 the pair of modes involved in chemotaxis (Keller and Segel 1971) and area-restricted search models (Kareiva and Odell 1987). In those cases, organisms can switch between random turning 153 (employed within a resource patch) and ballistic motion (employed between resource patches). 154

Here, motivated by recent studies on some vertebrate species (Prevedello et al. 2011, Tyson et al.
2011), our foragers use random motion between resource patches and their more sophisticated
(and more spatially intensive) movement mode (here, home ranging) in the vicinity of resource
patches.

To build our model of movement, we assume that the density of the population engaged in diffusive (random search) behavior at position x and time t is denoted u(x,t), and the density engaged in range-resident behavior is denoted v(x,t). We write

$$\frac{\partial u(x,t)}{\partial t} = \overbrace{D_{\frac{\partial^2}{\partial x^2}}^{andom} central tendency}}^{random search} switching from random search (2) range residency residen$$

where the parameter *D* is the rate of diffusion undertaken by the portion of the population that is in the random search mode. The functions  $\alpha(x, t)$  and  $\beta(x, t)$ , defined below, are generic functional forms for the rates of switching between the random-search and range-resident movement modes. The term

162

167 
$$\varepsilon \frac{\partial^2}{\partial x^2} v + \theta \frac{d}{dx} (x - \mu) v$$
(3)

represents the overall movement of the portion of the population engaged in range resident behavior. In (3),  $\varepsilon \ll 1$  represents a small amount of background random movement (this is necessary for certain theorems about partial differential equations to hold true), and  $\theta$  quantifies the rate of mean reverting (home ranging) movement. The term  $\mu$  (from Eq. 1) represents the consumers' 'attractive target.' This corresponds to the center of the resource patch in scenarios

where there is only a single, fluctuating area with resources. This location  $\mu$  could also be 173 thought of as the location of a den or nest site. In more complicated scenarios,  $\mu$  could be 174 generalized to a function,  $x[\cdot]$ , that allows for more than one attractive target, and these could 175 correspond to the physical centers of multiple or temporally oscillating resource patches. In other 176 177 scenarios, where consumers are able to distinguish resource habitat from non-habitat, but where perception is limited and the physical center of a resource patch may not be detectable, the 178 179 attractive target could correspond to a location with favorable conditions inside the patch at the 180 limit of detection.

Six Scenarios for Switching Between Movement Modes: To explore the interplay between 181 182 movement modes, search strategies, and cues for movement, we focus on the switching functions  $\alpha(x, t)$  and  $\beta(x, t)$  and the impacts that these terms have on the ability of the consumers to track 183 their resources. To explore the importance of the context of behavioral switching, we simplify 184 other aspects of the model, and depart from previous treatments in Fagan et al. (2017, 2020) and 185 Gurarie et al. (2021). We consider six different scenarios, of increasing complexity, in which 186 different considerations govern the consumers' switching between random movement and home-187 ranging behavior. All six of these scenarios, which range from simple density dependence 188 through more complicated situations involving perception or spatial memory, have either been 189 190 utilized previously in theoretical studies of animal movement or discussed verbally in papers on animal movement and decision-making behavior (e.g., Noonan et al. 2019, Abrahms et al. 2019, 191 Aikens et al. 2020). 192

193 <u>Scenario 1: Switching Depends on Consumer Density.</u> In this scenario, we assume that
 194 consumers change between the random search and range resident behavior only as a function of
 195 their own density. That is, these consumers are not able to detect or react to changes in resource

availability (in space, or in time) but they can tell when they are crowded, and switch behaviorsas functions of the density of their conspecifics. We write

198 
$$\alpha_{S1}(x,t) = \begin{cases} s & \text{if } u + v > w_0 \\ 0 & \text{if } u + v \le w_0 \end{cases},$$
(4)

which means that consumers will switch from random search mode to range resident mode at rate *s* if the local total consumer density (u + v) exceeds a threshold value,  $w_0$ , and will otherwise remain in random search mode. Similarly,

202 
$$\beta_{S1}(x,t) = \begin{cases} 0 & \text{if } u + v > w_0 \\ s & \text{if } u + v \le w_0 \end{cases},$$
(5)

such that consumers will switch from range residency to random search mode at rate *s* if the local total consumer density (u + v) remains below a threshold value,  $w_0$ , and will otherwise remain in range resident mode. For simplicity, we will consider the switching rates in Equations (4-5) to be the same, but these could certainly differ as a function of the consumers' current behavioral mode, as could the threshold density for switching between movement modes.

These assumptions correspond roughly to assumptions of the 'local enhancement' 208 framework for seabirds foraging from colonies (Buckley 1997). Likewise, there are conceptual 209 connections to results described in Cvikel et al. (2015) and Egert-Berg et al. (2018), wherein bats 210 cue in on the location of their own kind in determining where to forage. However, the model 211 212 does not lead to aggregation on conspecifics per se (unless  $\theta = 0$ ). Instead, the model would be better interpreted as representing aspects of social learning with discovery. To see this, consider 213 214 the subpopulation with density u as 'uninformed about resources' and the subpopulation with density v as 'informed.' Then, note that v(x, 0) = 0 and  $u(x, 0) = u_0$  is an equilibrium if  $u_0 < 0$ 215  $w_0$ . If the model starts with v = 0 and u small everywhere, then the system will tend to stay 216 with v = 0. However, if initially, u is sufficiently large somewhere, then some u will switch to 217

218 v. As the subpopulation with density v gets concentrated near  $\mu$ , the switching rate might then

favor further increase in v and further concentrate the population near  $\mu$ . Modifying the

220 movement mechanism to include actual aggregation on the density of conspecifics

221 might produce a more concentrated population density on a smaller home range, but it is not

clear that it can produce home ranging behavior in the absence of other movement components.

223 <u>Scenario 2: Switching Depends on Resource Density.</u> Here, consumers change their movement 224 behavior as a function of the density of resources instantaneously available at their immediate 225 location. This kind of temporal tracking of resource density is at the heart of the marginal value 226 theorem from optimal foraging theory (e.g., Charnov 1976, McNair 1982), but in that case 227 (unlike here) such temporal tracking is tied to globally omniscient knowledge of resource 228 conditions elsewhere. Assuming a threshold resource density,  $m_0$ , to which the consumers 229 respond by switching their movement mode, we write

230 
$$\alpha_{S2}(x,t) = \begin{cases} s & \text{if } m(x,t) > m_0 \\ 0 & \text{if } m(x,t) \le m_0 \end{cases},$$
(6)

which means that consumers will switch from random search mode to range resident mode at rate *s* if the resource density and position *x* and time *t* exceeds a threshold value,  $m_0$ , and will otherwise remain in random search mode. Similarly,

234 
$$\beta_{S2}(x,t) = \begin{cases} 0 & \text{if } m(x,t) > m_0 \\ s & \text{if } m(x,t) \le m_0 \end{cases},$$
(7)

such that consumers will switch from range residency to random search mode at rate *s* as
resource availability deteriorates below the threshold density. Note that the structure of
Equations (6-7) effectively creates an aggregative response to areas of abundant resources.

238 <u>Scenario 3: Switching Depends on Spatial Changes in Resource Density.</u> Whereas Scenario 2

focused on resource density *per se*, in this scenario, consumers change their movement behavior

as a function of the magnitude of the spatial gradient in the resources available,  $\left|\frac{\partial m(x,t)}{\partial x}\right|$ . We

241 write

242 
$$\alpha_{S3}(x,t) = \begin{cases} s & \text{if } \left| \frac{\partial m(x,t)}{\partial x} \right| > \varphi_0 \\ 0 & \text{if } \left| \frac{\partial m(x,t)}{\partial x} \right| \le \varphi_0 \end{cases}, \tag{8}$$

where the rate of switching is *s* if the spatial gradient in resource availability is greater than the threshold magnitude  $\varphi_0$ , and zero otherwise. Similarly,

245 
$$\beta_{S3}(x,t) = \begin{cases} 0 & \text{if } \left| \frac{\partial m(x,t)}{\partial x} \right| > \varphi_0 \\ s & \text{if } \left| \frac{\partial m(x,t)}{\partial x} \right| \le \varphi_0 \end{cases}, \tag{9}$$

such that consumers will switch from range residency to random search mode at rate *s* as thespatial gradient in resource availability weakens.

### 248 Scenario 4: Switching Depends on Perceived Spatial Changes in Resource Density. Here,

249 consumers again change their movement behavior as a function of the spatial gradient in the

resources available, but we augment their perceptual abilities to detect those spatial gradients.

251 Specifically, we assume that the consumers possess a perceptual range, *R* (Zollner and Lima

1997, Mech and Zollner 2002, Fagan et al. 2017). Thus, for a distance |x - y| from position x the

253 consumers can perceive the existence of resources according to a detection function

254 
$$g(x, y, R) = \begin{cases} 1 & -R \le x - y \le R \\ 0 & else \end{cases}$$
 (10)

255 The perceived resource function, h(x), is then written

256 
$$h(x,t) = \frac{1}{2R} \int_{x-R}^{x+R} \underbrace{\prod_{resources}^{available}}_{x-R} \underbrace{\prod_{y=R}^{available}}_{g(x,y,R)} \frac{\prod_{resources}^{available}}{g(x,y,R)} dy$$

which in the case of g(x, y, R) from Eq. 10 simplifies to

$$h(x,t) = \frac{1}{2R} \int_{x-R}^{x+R} m(y,t) dy$$
(11)

We make these choices of g(x, y, R) and h(x) to simplify comparisons with the other scenarios developed in this paper. The consequences of choosing different functional forms for g(x, y, R)are explored extensively in Fagan et al. (2017).

To model the effects of switching movement modes as a function of <u>perceived</u> spatial resource
 gradients, we write

264 
$$\alpha_{S4}(x,t) = \begin{cases} s & \text{if } \left| \frac{\partial h(x,t)}{\partial x} \right| > \varphi_0 \\ 0 & \text{if } \left| \frac{\partial h(x,t)}{\partial x} \right| \le \varphi_0 \end{cases},$$
(12)

where the rate of switching is *s* if the spatial gradient in resource availability is greater than the threshold magnitude  $\varphi_0$ , and zero otherwise. Similarly,

267 
$$\beta_{S4}(x,t) = \begin{cases} 0 & \text{if} \quad \left|\frac{\partial h(x,t)}{\partial x}\right| > \varphi_0\\ s & \text{if} \quad \left|\frac{\partial h(x,t)}{\partial x}\right| \le \varphi_0 \end{cases},$$
(13)

such that consumers will switch from range residency to random search mode at rate *s* when the spatial gradient in resource availability is sufficiently weak. Note that because of our choices of g(x, y, R) and h(x, t) in Eqs. 10-11 we can use the same threshold magnitude,  $\varphi_0$ , in Eqs. 12-13 as in Scenario 3 (Eqs. 8-9).

Scenario 5: Switching Depends on Temporal Changes in Resource Density. In this penultimate
scenario, we depart from the previous two scenarios that focused on reaction to spatial gradients,
and instead assume that the consumers have some modest ability to detect and respond to
temporal changes in resource density at their specific spatial location (e.g., Loiselle and Blake
1991, Dusenberry 1998). The assumptions in this scenario of our model mean that consumers
are able to identify whether their access to immediately local resources is instantaneously getting
better or worse, but they have no knowledge of long-term trends in resource availability nor any

information about trends beyond their current location. Mathematically, we can write this

280 detection of immediate trends in terms of the temporal gradient of the resource,  $\frac{\partial m}{\partial t}$ , such that

281 
$$\alpha_{S5}(x,t) = \begin{cases} s & \text{if } \frac{\partial m(x,t)}{\partial t} > \delta_0 \\ 0 & \text{if } \frac{\partial m(x,t)}{\partial t} \le \delta_0 \end{cases}$$
(14)

where the rate of switching is s if the temporal gradient in resource availability is greater than the 282 threshold magnitude  $\delta_0$ , and zero otherwise. This means that the consumers only switch from 283 284 random search mode into range resident mode if resource density is improving sufficiently quickly. Note that we must use a different threshold,  $\delta_0$ , and not  $\varphi_0$ , because we are dealing with 285 a temporal rather than a spatial gradient in resource density. However, because of our choices of 286 m(x,t) and q(x,t), we can, under some circumstances, use the same magnitude for these 287 288 thresholds and just allow the dimensional units to differ. More specifically, because the resource equation for m(x,t) (and by extension for h(x,t)) has a natural time scale of  $4\pi/\omega$  and a 289 natural spatial scale of  $\sigma$  built into it (Eq. 1), we can equate the thresholds  $\delta_0$  and  $\varphi_0$  if we 290 291 equate the magnitudes of the two intrinsic scales. With different choices for these intrinsic scales, we can make the same transition from spatial to temporal gradients with a rescaling coefficient. 292 Scenario 6: Switching Depends on Consumers' Memory of Resource Density. Here, we assume 293 that the consumers possess a simple, but spatially detailed form of memory that allows them to 294 keep track of the long-term resource dynamics of an area. If we were building models of 295 296 movement trajectories for individual animals, we would want to structure each consumer's memory around the resources encountered along those trajectories (Schlaegel and Lewis 2014, 297 Bracis et al. 2015, Abrahms et al. 2019, Lin et al. 2020). However, because we are working 298 within a PDE modeling framework, and need to characterize the collective memory of a group of 299 organisms, we need a different approach. 300

To do this, we consider a situation in which the consumers base their decisions to switch between movement modes on how much they can remember of the resource cycle and where they are within that cycle. From Equation (1), the temporally dynamic resource has period  $1/\omega$ and repeats endlessly for any given spatial location. We use the parameter Q, where  $Q \le 1/\omega$ , to represent the memory length, i.e.,  $Q\omega$  is the proportion of the full resource cycle that the consumers can remember. The consumers' memory, M, of the resource conditions leading up to time *t* can thus be written

308 
$$M = \frac{\int_{t-Q}^{t} m(x,t)dt}{Q} .$$
 (16)

Note that a given value of Q will yield a different memory depending on what point in the resource cycle the system is in. We then base the movement switching rates on this memory by writing

312 
$$\alpha_{S6}(x,t) = \begin{cases} s & \text{if } M > M_0 \\ 0 & \text{if } M \le M_0 \end{cases},$$
(17)

where the rate of switching is *s* if the consumers' memory of resource availability at location *x* exceeds the threshold magnitude  $M_0$ , and zero otherwise. This means that the consumers only switch from random search mode into range resident mode if their memory of a location, at a particular time, is sufficiently positive. Similarly,

317 
$$\beta_{S6}(x,t) = \begin{cases} 0 & \text{if } M > M_0 \\ s & \text{if } M \le M_0 \end{cases},$$
(18)

such that consumers switch from range-resident mode into random search mode if their memory
of a location, at a particular time, is sufficiently unfavorable, but remain in range resident mode
otherwise.

#### 321 <u>Summary of Modeling Effort</u>

322 Table 1 provides a summary of the different scenarios and the functions and parameters

323 involved.

324

Table 1. Summary of the six modeling scenarios and a listing of functions and parameters.

326 Scenarios are listed in a 2 x 3 array that matches the presentation style of figures in Results.

327 Entries are to be read as "Switching depends on ...".

## Scenario Summary

Scenario 1	Scenario 2	Scenario 3
conspecific density	resource density	spatial gradient of resource
Scenario 4	Scenario 5	Scenario 6
perceived spatial gradient of resource	temporal gradient of resource	memory of resource

# **Function Summary**

m(x,t)	Spatiotemporal distribution of resources
v(x,t)	Population density engaged in diffusive movement
u(x, t)	Deputation density angegoed in range resident meyoment
u(x,t)	ropulation density engaged in range-resident movement
$\alpha(x,t)$	Rate of switching from diffusive to range-resident movement
$\beta(x,t)$	Rate of switching from range-resident to diffusive movement
g(x, y, R)	Resource detection function for foragers with perceptual range R
m(x,t)	Perceived spatiotemporal distribution of resources

# Parameter Summary

μ	Mean of the Gaussian resource pulse
$\sigma$	Standard deviation of the Gaussian resource pulse
ω	Temporal frequency of the Gaussian resource pulse
D	Diffusion rate
ε	Small background rate of random movement in range-resident movement mode
θ	Rate of home-ranging (mean-reverting) movement
S	Rate of switching between diffusive and range-resident movement modes

<i>w</i> <sub>0</sub>	Threshold forager density determining whether switching of movement modes occurs in Scenario 1
$m_0$	Threshold resource density determining whether switching of movement modes occurs in Scenario 2
$arphi_0$	Threshold resource gradient determining whether switching of movement modes occurs in Scenarios 3 and 4
$\delta_0$	Threshold temporal resource gradient determining whether switching of movement modes occurs in Scenario 5
M <sub>0</sub>	Threshold memory of available resources determining whether switching of movement modes occurs in Scenario 6
R	Perceptual range in Scenario 4
М	Integrated memory of resources in Scenario 6
Q	Memory duration in Scenario 6
Ω	Degree of spatiotemporal matching between foragers and their resources

<u>Quantifying Foraging Success</u> To quantify the consumers' ability to track the distribution of
their resources over space and time, we use the continuous form of the Bhattacharyya Coefficient
(BC; Bhattacharyya 1943) for quantifying the overlap between two distributions. Because the
BC was initially formulated for use with probability distributions, we use a normalized form.
Specifically, we have

334 
$$\Omega = \frac{\int_{t'}^{t_{max}} \int_{0}^{100} \sqrt{[u(x,t)+v(x,t)]m(x,t)} dx dt}}{\sqrt{\int_{t'}^{t_{max}} \int_{0}^{100} [u(x,t)+v(x,t)] dx dt} \sqrt{\int_{t'}^{t_{max}} \int_{0}^{100} m(x,t) dx dt}} \leq 1 \quad . (19)$$

The timeframe t' to  $t_{max}$  represents some period after transient behaviors have settled down. For static resource distributions, which (with appropriate boundary conditions of mass conservation) always exhibit an equilibrium solution, the integral is only over space (Fagan et al. 2020). For dynamic landscapes, such as periodically fluctuating landscapes on which we focus, the time integral needs to be taken over a long enough period to discount the transient behaviors and instead capture long-term variation (Fagan et al. 2017). This metric of foraging
success differs a bit from that used in Fagan et al. (2017, 2020), but the change is necessary to
accommodate comparison across all six of the scenarios we consider here.

343 Equation (19) quantifies 'resource matching' in the sense that foragers must spatially and temporally overlap with resources to be successful. We do not consider mutual interference or 344 345 resource depletion because we want to focus only on animal movement behavior and not population growth or decay. This is a reasonable assumption when population density is low 346 (i.e., sparsely populated regions) and resources are ephemeral (i.e., resources degrade before 347 their density can be reduced much by the foragers). In these systems, the question is more about 348 capitalizing on transient resources, as opposed to avoiding competition. Such transient resource 349 dynamics characterize, for example, the Eastern steppes of Mongolia that have motivated much 350 earlier work on animal movement (Mueller and Fagan 2008, Mueller et al. 2011, Martínez-351

352 Garcia et al. 2013, Fleming et al. 2014).

Throughout, we solved the initial-boundary value problem numerically using the method 353 of lines by discretizing in space over the domain x = [0, 100] and solving the system of ordinary 354 differential equations in time. We implemented a different scheme for the components of Eq. 2 355 as required by their respective structure. For example, for the random search equation, we used a 356 simple forward-time, centered-space scheme, whereas for the gradient following equation, we 357 358 used the Lax-Wendroff method, accounting for the method's natural dispersion error in the term  $\varepsilon \frac{\partial^2}{\partial x^2} v$ . To solve the resulting coupled system of ODEs, we used the variable-step, variable-order 359 differential algebraic equation solver ODE15S (Shampine and Reichalt, 1997). 360

For initial conditions, all the numerical experiments had *u* and *v* distributed uniformly with population density 1 / *L*. Thus, at any time the total population u + v would integrate to 2 over space, while the total population in the individual *u* and *v* components varied with time. We used zero flux boundary conditions on the rectangular domain  $(x, t) \in [0, 100] \times [0,\infty)$ . For all of the simulations, we considered the pulsed Gaussian resource function detailed in Eq. 1.

366 RESULTS

Figure 1 shows the dynamic (pulsed Gaussian) resource landscapes on which the forager populations are moving. In both the single patch and two patch landscapes, resources are highly transient but are predictable with regard to their location and timing.





- 375
- The six advection scenarios involve starkly different locations and times at which the
- 377 consumers are switching from the diffusive foraging mode to the home ranging mode (Figure 2).
- 378 For example, in Scenario 1, switching into the home ranging mode is constant after the

population equilibrates, with no influence from the underlying periodicity in resource 379 availability. In contrast, the resource conditions that favor switching to home ranging are 380 strongest at the time and location of the resource peak in Scenario 2 (tracking the resource 381 density, Fig. 2 b) whereas the resource conditions that favor switching are strongest on the 382 'shoulders' of the resource peak in Scenarios 3 and 4 (tracking changes and perceived spatial 383 384 changes in resource density, respectively) (Fig. 2c,d). Provided R in Equation 10 (perception scenario) is sufficiently small, the resource conditions favoring switching regions for scenario 4 385 are nearly identical to those of scenario 3 for low R (Supp. Fig. F). Different still are the resource 386 387 conditions that promote the switching behavior in Scenario 5 (tracking temporal changes in resource density) where the switching behavior is greatest as the resource begins to increase in 388 density (Fig. 2e). Provided Q in Eq. 16 (memory scenario) is sufficiently large, resource 389 conditions will lead to some portion of the consumer population constantly switching into the 390 diffusive foraging mode regardless of what part of the seasonal cycle the system is in (Fig. 2f). 391 392 In contrast, for sufficiently small Q, the resource conditions promoting this constancy of switching disappears and the results from Scenario 6 converge on those from Scenario 2 (Supp. 393 Fig. G). Resource conditions that promote switching from home ranging to diffusive foraging 394 395 mode are largely complementary to these results for all six scenarios for switching from diffusive to home ranging. 396



398

**Figure 2.** Location and timing of the resource conditions that promote the consumer population actively switching into home ranging mode for the landscape with a single resource patch (see Fig. 1a). Note how the intensity of the resource conditions that promote switching behavior as well as the timing and location of those favorable locations vary strongly depending on how the gradient of the resource is defined (labeled as scenarios 1 - 6). Fixed parameters:  $\theta = 0.01$ , D =0.1; Scenario 1:  $\theta = 0.01$ , D = 0.1,  $w_0 = 0.01$ ; Scenario 2:  $m_0 = 0.035$ ; Scenario 3:  $\varphi_0 = 0.0037$ ; Scenario 4:  $\varphi_0 = 0.0018$ , R = 10; Scenario 5:  $\delta_0 = 0.0014$ , Scenario 6:  $M_0 = 0.02$ , Q = 20.9.

407 The differences in switching behavior among Scenarios alter the consumers' movement behaviors and thus translate into differences in the location and timing of the consumer 408 409 population densities. Scenario 1 (tracking conspecific density) shows a concentration of 410 consumers to the location of the resource peak regardless of whether the resource is at high or 411 low density. In contrast, Scenario 2 (tracking resource density) shows periodicity in the 412 consumer population density, indicating a degree of matching of the consumers to both the 413 location and timing of the resource peak. Scenario 3 (tracking spatial changes in resource 414 density) shows the consumers concentrating on the shoulders of the resource peak, but not on the resource peak itself. In contrast, scenario 4 (tracking perceived spatial changes in resource 415 416 density) shows advection occurring over a much broader area. In scenarios 5 (tracking temporal

changes in resource density) and 6 (memory), the density of the advecting consumers is greatest
on the resource peak. Both of these scenarios also feature a limited degree of oscillation in
population density that mirrors the temporally dynamic nature of the resources. Supplementary
Figure A provides the corresponding densities for the diffusive component of the populations.





### 423

Figure 3. Densities of the home ranging component of the consumer population across the six 424 switching scenarios for the landscape with a single resource peak. Scenarios differ with regard to 425 both the timing and location of the density of the portion of the consumer population that is in 426 the home ranging mode. Note that densities fluctuate strongly in time in Scenarios 2 and 3. Note 427 also that densities are concentrated on the 'shoulders' of the resource distribution in Scenario 3 428 and over a much broader area in Scenario 4. Fixed parameters:  $\theta = 0.01$ , D = 0.1; Scenario 1: 429 430  $w_0 = 0.01$ ; Scenario 2:  $m_0 = 0.035$ ; Scenario 3:  $\varphi_0 = 0.0037$ ; Scenario 4:  $\varphi_0 = 0.0018$ , R = 10; Scenario 5:  $\delta_0 = -0.0014$ , in Scenario 6  $M_0 = 0.02$ , Q = 20.9. 431 432



In the case of a single resource patch, considerable differences exist in  $\Omega$  across

434 scenarios, indicating that the different movement strategies allow for very different degrees of

- 435 resource matching. Resource matching success ( $\Omega$ ) is clearly greatest in Scenario 5 where
- 436 switching between diffusive and home ranging movement types depends on the temporal
- 437 resource gradient, but only when the threshold for switching between movement behaviors is

very small (Figure 4). Peak  $\Omega$  values (broad to concentrated in parametric extent) exist within 438 each scenario, and the location of these  $\Omega$  peaks differs across scenarios. Collectively, these 439 results indicate that, within a given movement strategy, resource matching could potentially be 440 optimized, but that the degree of switching and the switching thresholds that are necessary to 441 provide optimal matching differs among scenarios. For example, in Figure 4, low levels of 442 switching provide marginally better resource matching in Scenarios 1 and 2, but switching needs 443 to occur at a faster rate when it occurs in conjunction with temporal resource gradients (Scenario 444 5). 445

446



- 453
- 454

<sup>449</sup> Figure 4. Resource matching success  $(\Omega)$  for foragers in a landscape with a single periodic

<sup>450</sup> resource peak. Results for all scenarios are plotted as functions of switching rates (x axes) and

<sup>451</sup> scenario-specific parameters (y-axes). Fixed parameters  $\theta = 0.01$ , D = 0.1: Scenario 4: R=10;

<sup>452</sup> Scenario 6: *Q*=20.9.

In the case of two resource patches, the location and timing of the consumer population 455 switching into home ranging mode becomes more complicated, reflecting the greater complexity 456 of the resource conditions favoring such changes in behavior (Figure 5). The timing and location 457 of such switching vary strongly across scenarios depending how the gradient of the resource is 458 defined. For example, switching to advection is consistently concentrated in the vicinity of the 459 460 resource peaks in Scenario 1 even though the resource is periodic in time. Switching to advection occurs on the 'shoulders' of the double-peaked resource distributions in Scenarios 3 and 4, but 461 occurs in the vicinity of, but in advance of, the resource peaks in Scenario 5 (excluding only the 462 463 spatiotemporal region where the resource is most strongly waning in abundance). In Scenario 6, switching to advection again reflects the periodic nature of the resource, but, due to the effects of 464 memory, there exists a lingering degree of switching near the centers of the resource peaks even 465 though the resources are least abundant at these times (Figure 5). Density plots for the 466 component of the consumer population in the home ranging mode appear in Supplementary 467 Figure B. A counterpart to Figure 5 that shows the location and timing of the population 468 switching from foraging mode into diffusive mode appears in Supplementary Figure C. 469 470



**Figure 5.** Location and timing of the consumer population switching into home ranging foraging mode for the landscape with two in-phase resource peaks (see Fig. 1b). Compare results with Figure 2. Fixed parameters:  $\theta = 0.01$ , D = 0.1; Scenario 1:  $w_0 = 0.01$ ; Scenario 2:  $m_0 = 0.035$ ; Scenario 3:  $\varphi_0 = 0.0037$ ; Scenario 4:  $\varphi_0 = 0.0018$ , R = 10; Scenario 5:  $\delta_0 = 0.0014$ ; Scenario 6  $M_0$ = 0.02, Q = 20.9.

Compared to Figure 4, resource matching success is generally higher in the two patch 478 case because the resources are better distributed within the landscape and easier to find with a 479 given level of mobility (Figure 6). This is especially true for Scenario 3 (spatial gradient) and 480 Scenario 4 (spatial gradient with non-local perception) where resource matching success is now 481 on par with the best performing parameters from Scenario 5 (following a temporal resource 482 gradient). High levels of switching between diffusion and advection are generally deleterious 483 unless the thresholds for undertaking such switches are sufficiently high. The thresholds at 484 which optimal resource matching is reached tend to be higher in this two resource patch case 485 486 than in the single resource patch.



Figure 6. Resource matching in the case of two in-phase resource patches. Compare results with Figure 4. Fixed parameters  $\theta = 0.01$ , D = 0.1: Scenario 4: R=10; Scenario 6: Q=20.9.

The home ranging parameter,  $\theta$ , also influences the degree of resource matching success. 491 Supplementary Figure D gives resource matching success in the case of one resource path 492 (comparable to Figure 4), except that  $\theta$  is increased and, separately, decreased from the baseline 493 level. For a fixed rate of diffusion, increasing  $\theta$  affords greater resource matching success for 494 almost all scenarios and decreasing  $\theta$  has the opposite effect. Scenario 1 (advection on 495 conspecifics) clearly differs in that increasing  $\theta$  leads to a decrease in resource matching. For the 496 case of two resource peaks (Supp. Figure E, compare with Fig. 6),  $\theta$  has a different effect in that 497 increasing the degree of home ranging tends to decrease  $\Omega$ , at least somewhat, except in 498 Scenarios 3 and 4. In these scenarios, where the behavioral switching depends upon a form of 499 500 spatial resource gradient, resource matching clearly increases with increasing  $\theta$ .

Perceptual range (R) plays an important role in the degree of resource matching success 501 afforded by Scenario 4 by shifting the timing and location of the behavioral switching into the 502 home ranging mode (Supplementary Figure F). For sufficiently small R, results from Scenario 4 503 converge on those of Scenario 3. For sufficiently large R, the switching regions become more 504 refined as the organisms' increased perceptual radius affords more information on the full 505 506 distribution of resources across the domain and the ideal times and locations to switch behaviors. Note that for R=15, which is exactly half the distance between the centers of the two resource 507 pulses, the switching regions turn on and off centered at x = 50 (Supplementary Figure F). 508 509 Likewise, the duration of memory in Scenario 6 can also influence the timing and location of behavioral switching (Supplementary Figure G). As memory duration, Q, increases, 510 the lingering effects of memory tend to link the switching responses to consecutive resource 511 peaks so that switching to advection occurs in a consistent location, even though the underlying 512 resource is periodic in time. For sufficiently small Q, switching behavior of Scenario 6 converges 513 on that of Scenario 2. 514

### 515 **DISCUSSION**

This synthetic overview makes clear that the ecological concept of 'consumers tracking resource gradients' can mean very different things in practice when implemented in movement models with continuous space. Furthermore, the detailed assumptions of how consumers actually track their resources can translate into radically different levels of success for consumers attempting to match the spatiotemporal distributions of their resources.

521 Overall, we found that Scenarios 3 (tracking spatial gradients), 4 (tracking spatial 522 gradients with the benefit of non-local perception), and 5 (tracking temporal gradients) provided 523 the highest level of resource matching for consumers. To some extent these advantages may

change with the distribution of resources. For example, if one considers a resource distribution 524 function which is very flat around its global maximum point but peaked around a local maximum 525 point, Scenario 3 would likely provide very poor resource matching levels. In this scenario, 526 tracking perceived spatial gradients (Scenario 4) should perform better than tracking the 527 immediately local gradients (Scenario 3). Results in Fagan et al. (2020), where we considered 528 529 step functions for the resources, support this contention. Perception (Scenario 4) afforded good resource matching success, comparable to the highest levels of resource matching that were 530 obtained through Scenario 5 (tracking temporal gradients). The utility of perception, which was 531 especially true in more complex two patch resource landscapes, is in line with earlier studies 532 suggesting the benefits of non-local information gathering in temporally variable resource 533 landscapes (Fagan et al. 2017). 534

The general superiority of Scenario 5 (tracking temporal gradients) may be, in part, due 535 to the mathematical model of movement that we explored. For example, because  $\mu$ , the spatial 536 location of resources, is built into the range-resident dispersal mode, there is spatial information 537 built into that mode, but no temporal information. Then, adding temporal information via 538 tracking of temporal gradients (Scenario 5) would add relatively more to an organism's overall 539 540 information about the environment than using additional spatial information, because there is already some spatial information implicitly available in the OU mode. The observation that 541 542 Scenarios 3 and 4, especially 4, perform relatively better when there are two resource patches 543 than where there is only one supports this argument, because with two resource locations getting extra spatial information might be more valuable. 544

In contrast to the more successful strategies (Scenarios 3, 4, and 5), other scenarios
involving tracking the density of conspecifics (Scenario 1), tracking the abundance (rather than

the gradient) of resources (Scenario 2), or employing a particular form of memory (Scenario 6) 547 provided poorer spatiotemporal matches to resources. Consumers that switched their foraging 548 behavior as a function of conspecific densities generally achieved very poor resource-matching 549 success. The effect was especially pronounced when home ranging behavior was strong, which 550 limited the consumers' spatial exploration. These results suggest that pure 'local enhancement' 551 552 type mechanisms (Buckley 1997) wherein consumers aggregate in areas where others of their kind are already foraging cannot succeed in isolation. Instead, a modest level of directly tracking 553 the resources themselves, together with cueing in on conspecific activity, would likely improve 554 555 this strategy. This modification would also connect to the producer – scrounger dichotomy in studies of social group foraging behavior (Beauchamp 2000), wherein 'producers' behave 556 directly according to resources but 'scroungers' base their decisions on producers. 557 Increasing evidence suggests that memory is important for consumers that must acquire 558 resources in highly dynamic landscapes (Bracis and Mueller 2017, Abrahms et al. 2020). 559 560 Consequently, we were surprised to see that memory-based movement also provided some of the worst tracking of available resources. This deviation from expectations may stem from the 561 particular (rather crude) form of memory that we implemented in Scenario 6. Indeed, other 562 563 modeling work that considered memory at the individual (rather than collective) level, found that a rather sophisticated form of memory, including separate long- and short-term memory records, 564 565 was necessary to track resources in dynamic landscapes (Lin et al. 2021). 566 Collectively, these results suggest that tracking gradients (Scenarios 3, 4, and 5) may, in general, be more effective than tracking resource density directly (Scenario 2) or indirectly 567 568 (Scenario 1). One plausible reason for this is that gradients should be detectable over a broader

range of conditions than density per se. This would accord with the underlying biology.

Consider that, in practice, it would often be easier to assess the gradient of something than its 570 magnitude. For example, discerning whether movement was up or down a hill would likely be 571 easier than identifying the elevation. Such differential identifiability of gradients versus 572 magnitudes would likely hinge on the rate of movement relative to the scale of the gradient. 573 Intriguingly, the different scenarios for switching between home ranging and diffusive 574 575 movement did not rank consistently with regard to the level of resource matching that they afforded. Even something as simple as switching from a model with a single periodic resource 576 peak to one with two periodic resource peaks changed the relative performance of the different 577 578 scenarios for switching between home ranging and random movement (compare Figures 4 and 6). These differences appear to arise, primarily, because changing the number of resource peaks 579 changes the average location of resources relative to consumers with specific levels of mobility. 580 The degree to which consumers incorporate range-resident behavior in their movement 581 also played an important role in determining how well they overlap the distribution of their 582 583 resources in space and time. In particular, the strength of home ranging (relative to random dispersal) interacted with the behavioral cues for switching to shape resource overlap in a strong 584 way. Switching based on spatial resource gradients (whether immediately local or perceived over 585 586 a longer distance) provided particularly good matches to resource distributions when coupled with strong range-resident behavior. This result is intriguing given that a recent statistical 587 588 analysis of home range behavior found that many animals' movement patterns were well 589 described by models that included elements of both diffusive and range-resident behavior (Noonan et al. 2019). 590

591 The conditional similarities between Scenarios 3 and 4 (Supp. Fig. F), and separately,
592 between Scenarios 2 and 6 (Supp. Fig. G), are due to their underlying mathematics. Specifically,

the switching functions in Scenarios 2 and 3 were based on a derivative, whereas in Scenarios 4 593 and 6 the switching functions were based on a slope which approximated the respective 594 derivative for low enough R or Q. In contrast, for large values of R or Q, Scenarios 4 and 6 595 departed strongly from Scenarios 3 and 2, respectively, demonstrating how the introduction of 596 additional information caused different behavior by the home ranging component of the 597 598 population (Supp. Figs. F and G). This additional information may be either spatial (in the form of an increased perceptual range, Scenario 5) or temporal (in the form of a lingering memory, 599 Scenario 6), but in either case the additional information altered the basis for the behavioral 600 decision-making. 601

### 602 *Opportunities for optimal resource matching*

The existence of parameter regions featuring higher levels of resource matching success 603 amidst a sea of lower-performing parameters (Figs. 4 and 6, Supp. Figs. D and E) suggests that, 604 within a given movement strategy, resource matching could potentially be optimized. However, 605 the rate of switching (between home ranging and diffusive movement modes) and the switching 606 thresholds that are necessary to provide optimal resource matching differ quite strongly among 607 scenarios. For example, in Figure 4, low rates of switching provide marginally better resource 608 609 matching in Scenarios 1 and 6, but switching needs to occur at a faster rate when it occurs in conjunction with temporal resource gradients if consumers are to achieve the highest levels of 610 611 resource matching (Scenario 5).

Although our study considered models with continuous space, the high levels of resource
matching success observed in some scenarios brings to mind concepts like the marginal value
theorem for optimal resource tracking (Charnov 1976, McNair 1982) and the ideal free
distribution for optimal distribution of resources among consumers (Farnsworth and Beecham

1999, Křivan et al. 2008) that had their origins in patch-based models of consumers tracking 616 resources. To our knowledge, there is nothing like the marginal value theorem in partial 617 differential equation (PDE) models or other ecological models involving continuous space. 618 However, there is a strong foundation for the ideal-free distribution in continuous space models 619 (Arditi and Dacorogna 1988, Grunbaum 1988), and more recent PDE work demonstrates how 620 621 certain kinds of resource tracking strategies can lead to an ideal free distribution of consumers (Cantrell et al. 2008, 2010). Real world complications, such as perceptual constraints, can cause 622 departures from an ideal free distribution (Abrahams 1986), but 'approximately optimal' 623 solutions are possible even when underlying assumptions are violated (Griffen 2009, Street et al. 624 2018). 625

In general, optimal movement in heterogeneous landscapes requires that consumers 626 consider both space and time (Arditi and Dacorogna 1988, Cantrell et al. 2021). In this paper, 627 Scenarios 2,3, and 4 consider space, 5 considers time, and 6 considers both space and time (but 628 considers time, via memory, in a rather crude way). However, all of these scenarios involve 629 behaviors that are relatively simple, in that movement decisions are being made with respect to 630 metrics observable by many animals. Of the switching cues we examined, that of Scenario 2 is 631 632 closest to classical considerations of optimal foraging in patchy landscapes. From the marginal value theorem, we know that, for omniscient consumers, the best time to leave a patch is when 633 634 the rate of resource uptake on that patch drops below the system-wide average (Charnov 1976). 635 This criterion reflects elements present in both Scenarios 2 and 5. Scenario 2 is relevant because resource uptake should be proportional to the density of resources available. However, Scenario 636 637 5, where the focus is the temporal rate of change of resource density, is also relevant in that the 638 rate of change of available resources shapes the rate of resource uptake. For example, knowing

the rate of change in resource availability would offer consumers information on how much 639 longer they have to gather resources. This information could be far more valuable than just 640 knowing what resources are available at an exact spatiotemporal location. These conceptual links 641 to the marginal value theorem are particularly strong for cases where behavioral changes are 642 framed in terms of optimal 'giving up times' (McNair 1982) or residence times (Turchin 1991). 643 644 Overall, Scenario 5 afforded much better opportunities for resource overlap than did Scenario 2 (Figures 4, 6, Supp. Figs. D, E). This result raises intriguing questions about optimal foraging in 645 646 dynamic landscapes, including the possibility that consumers tracking both the rate of change in 647 local conditions and their own rate of change of resource uptake may be especially adept at maximizing resource gain. This will be explored in future work. Additional future directions 648 could include models that combine memory and perception together, or that combine local 649 650 enhancement type strategies (Scenario 1) with gradient-following behavior. In summary, we compared the performance of alternative methods by which consumers 651 652 can be reasonably said to be tracking gradients related to their resources. Optimal resource matching is achievable via all six scenarios, at least to some degree. Within most scenarios, a 653 broad range of parameter values yields similarly high levels of resource matching success. Thus, 654 655 even if consumers were channelized to possess particular resource tracking abilities and were unable to switch among scenarios, wide parametric regions of 'nearly optimal' resource 656

657 matching success would provide a broad evolutionary target wherein good foraging success is

obtainable even when the parameters cannot be fine-tuned. Such broad targets would be

advantageous given the high degree of temporal resource variability that exists in natural systems

660 (e.g., Abrahms et al. 2020).

661

662

663	DECLARATIONS
664	i. Funding
665	This work was supported by NSF awards DMS1853465 and DMS1853478
666 667	ii. Conflicts of interest/Competing interests
668 669	The authors have no conflicts of interest nor competing interests. The authors have no relevant financial or non-financial interests to disclose.
670 671	iii. Ethics approval
672	Not applicable.
673 674	iv. Consent to participate
675	Not applicable.
676 677 678 679	v. Consent for publication Not applicable.
680	vi. Availability of data and material
681	Not applicable.
682	
683	vii. Code availability
684 685	Code is available on request from WFF.
686	viii. Authors' contributions
687 688 689	WFF, RSC and GCC conceived of the original problem. CS and EG helped refine the project. CS developed the code with assistance from TH and EG. WFF wrote the initial draft and all authors have edited and revised the text.
690	
691	REFERENCES
692 693 694 695	<ul> <li>Abrahams, M. V. Patch choice under perceptual constraints: a cause for departures from an ideal free distribution. <i>Behavioral Ecology and Sociobiology</i> 19.6 (1986): 409-415.</li> <li>Abrahms, B., Hazen, E.L., Aikens, E.O., Savoca, M.S., Goldbogen, J.A., Bograd, S.J., Jacox, M.G., Irvine, L.M., Palacios, D.M. and Mate, B.R., 2019. Memory and resource tracking</li> </ul>

- drive blue whale migrations. *Proceedings of the National Academy of Sciences*, *116*(12),
  pp.5582-5587.
- Arditi, R., and B. Dacorogna. Optimal foraging on arbitrary food distributions and the definition
  of habitat patches. *The American Naturalist* 131.6 (1988): 837-846.

- Beauchamp, G. U. Y. "Learning rules for social foragers: implications for the producer–
   scrounger game and ideal free distribution theory." *Journal of Theoretical Biology* 207.1 (2000): 21-35.
- Bhattacharyya, A. (1943). "On a measure of divergence between two statistical populations
  defined by their probability distributions". *Bulletin of the Calcutta Mathematical Society*. 35: 99–109.
- Bracis, C., Gurarie, E., Van Moorter, B. and Goodwin, R.A., 2015. Memory effects on
  movement behavior in animal foraging. *PloS One*, *10*(8), p.e0136057.
- Bracis, C. and Mueller, T., 2017. Memory, not just perception, plays an important role in terrestrial mammalian migration. *Proceedings of the Royal Society B: Biological Sciences*, 284(1855), p.20170449.
- Buckley, N.J., 1997. Spatial-concentration effects and the importance of local enhancement in
   the evolution of colonial breeding in seabirds. *The American Naturalist*, *149*(6), pp.1091 1112.
- Cantrell, R.S., Cosner, C. and Lou, Y., 2010. Evolution of dispersal and the ideal free
   distribution. *Mathematical Biosciences & Engineering*, 7(1), p.17.
- Cantrell, R.S., Cosner, C. and Lou, Y., 2008. Approximating the ideal free distribution via
   reaction-diffusion-advection equations. *Journal of Differential Equations*, 245(12),
   pp.3687-3703.
- Cantrell, R.S., Cosner, C. and Yu, X., 2018. Dynamics of populations with individual variation
   in dispersal on bounded domains. *Journal of Biological Dynamics*, 12(1), pp.288-317.
- Cantrell, R.S., Cosner, C. and Yu, X., 2020. Populations with individual variation in dispersal in
   heterogeneous environments: Dynamics and competition with simply diffusing
   populations. *Science China Mathematics*, 63(3), pp.441-464.
- Cantrell, R.S., Cosner, C. and Lam, K.Y., 2021. Ideal free dispersal under general spatial
  heterogeneity and time periodicity. *SIAM Journal on Applied Mathematics*, *81*(3), pp.789813.
- Catania, K.C., 2013. Stereo and serial sniffing guide navigation to an odor source in a
   mammal. *Nature Communications*, 4(1), pp.1-8.
- Charnov, E.L., 1976. Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, 9(2), pp.129-136.
- Cvikel, N., Berg, K.E., Levin, E., Hurme, E., Borissov, I., Boonman, A., Amichai, E. and Yovel,
   Y., 2015. Bats aggregate to improve prey search but might be impaired when their density
   becomes too high. *Current Biology*, 25(2), pp.206-211.
- Dusenbery, D.B., 1998. Spatial sensing of stimulus gradients can be superior to temporal sensing
   for free-swimming bacteria. *Biophysical Journal*, 74(5), pp.2272-2277.
- Figert-Berg, K., Hurme, E.R., Greif, S., Goldstein, A., Harten, L., Flores-Martínez, J.J., Valdés,
   A.T., Johnston, D.S., Eitan, O., Borissov, I. and Shipley, J.R., 2018. Resource ephemerality
- drives social foraging in bats. *Current Biology*, 28(22), pp.3667-3673.
- Fagan, W.F., Gurarie, E., Bewick, S., Howard, A., Cantrell, R.S. and Cosner, C., 2017.
   Perceptual ranges, information gathering, and foraging success in dynamic landscapes. *The American Naturalist*, 189(5), pp.474-489.
- Fagan, W.F. 2019. Migrating whales depend on memory to exploit reliable resources.
- 743 *Proceedings of the National Academy of Sciences USA*, 116: 5217-5219.

- Fagan, W. F., T. Hoffman, D. Dahiya, E. Gurarie, S. Cantrell, and C. Cosner. 2020. Improved
  foraging by switching between diffusion and advection: Benefits from movement that
  depends on spatial context. *Theoretical Ecology*, 13; 127-136.
- Farnsworth, K.D. and Beecham, J.A., 1999. How do grazers achieve their distribution? A
  continuum of models from random diffusion to the ideal free distribution using biased
  random walks. *The American Naturalist*, 153(5), pp.509-526.
- 750 Gleiss, A.C., Jorgensen, S.J., Liebsch, N., Sala, J.E., Norman, B., Hays, G.C., Quintana, F.,
- Grundy, E., Campagna, C., Trites, A.W. and Block, B.A., 2011. Convergent evolution in
  locomotory patterns of flying and swimming animals. *Nature Communications*, 2, p.352.
- Griffen, B. D. Consumers that are not 'ideal' or 'free' can still approach the ideal free
  distribution using simple patch-leaving rules. *Journal of Animal Ecology*, 78.5 (2009): 919927.
- Grünbaum, D., 1998. Using spatially explicit models to characterize foraging performance in
   heterogeneous landscapes. *The American Naturalist*, 151(2), pp.97-113.
- Gurarie, E., Andrews, R.D. and Laidre, K.L., 2009. A novel method for identifying behavioural
   changes in animal movement data. *Ecology Letters*, 12(5), pp.395-408.
- Gurarie, E., Bracis, C., Delgado, M., Meckley, T.D., Kojola, I. and Wagner, C.M., 2016. What is
   the animal doing? Tools for exploring behavioural structure in animal movements. *Journal* of Animal Ecology, 85(1), pp.69-84.
- Gurarie, E., C. Fleming, W. F. Fagan, K. Laidre, J. Hernandez-Pliego, and O. Ovaskainen. 2017.
   Correlated velocity models as a fundamental unit of animal movement: synthesis and
   applications. *Movement Ecology*. 5: 1
- Gurarie, E., S. Potluri<sup>1</sup>, C. Cosner, R. Cantrell, W.F. Fagan. In press. Memories of migrations
   past: Sociality and cognition in dynamic, seasonal environments. *Frontiers in Ecology and Evolution*, In press.
- Holdo, R.M., Holt, R.D. and Fryxell, J.M., 2009. Opposing rainfall and plant nutritional
  gradients best explain the wildebeest migration in the Serengeti. *The American Naturalist*, 173(4), pp.431-445.
- Johnsen, P.B. and Teeter, J.H., 1980. Spatial gradient detection of chemical cues by
  catfish. *Journal of Comparative Physiology*, *140*(2), pp.95-99.
- Kareiva, P. and Odell, G., 1987. Swarms of predators exhibit "preytaxis" if individual predators
  use area-restricted search. *The American Naturalist*, *130*(2), pp.233-270.
- Kramer, D.L. and McLaughlin, R.L., 2001. The behavioral ecology of intermittent
  locomotion. *American Zoologist*, *41*(2), pp.137-153.
- Křivan, V., Cressman, R. and Schneider, C., 2008. The ideal free distribution: a review and
  synthesis of the game-theoretic perspective. *Theoretical Population Biology*, 73(3), pp.403425.
- Lam, K.Y. and Lou, Y., 2014. Evolution of conditional dispersal: evolutionarily stable strategies
   in spatial models. *Journal of Mathematical Biology*, 68(4), pp.851-877.
- Lin, H.Y., Fagan, W.F. and Jabin, P.E., 2021. Memory-driven movement model for periodic
   migrations. *Journal of Theoretical Biology*, *508*, p.110486.
- Loiselle, B.A. and Blake, J.G., 1991. Temporal variation in birds and fruits along an elevational
  gradient in Costa Rica. *Ecology*, 72(1), pp.180-193.
- McLaughlin, R.L. and Grant, J.W.A., 2001. Field examination of perceptual and energetic bases
   for intermittent locomotion by recently-emerged brook charr in still-water pools.
   Behaviour, 138(5), pp 550, 574
- 789 Behaviour, 138(5), pp.559-574.

- McNair, J.N., 1982. Optimal giving-up times and the marginal value theorem. *The American Naturalist*, *119*(4), pp.511-529.
- Mech, S. G., and P. A. Zollner. 2002. Using body size to predict perceptual range. *Oikos* 98: 47–
   52. doi:10.1034/j.1600-0706.2002.980105.x.
- Morales, J.M., Haydon, D.T., Frair, J., Holsinger, K.E. and Fryxell, J.M., 2004. Extracting more
  out of relocation data: building movement models as mixtures of random
  walks. *Ecology*, 85(9), pp.2436-2445.
- Newlands, N.K., M. E. Lutcavage, and T. J. Pitcher, Analysis of foraging movements of Atlantic
  Bluefin tuna (*Thunnus thynnus*): Individuals switch between two modes of search
  behaviour, *Population Ecology*, 46 (2004), 39-53.
- Noonan, M.J., et al. 2019. A comprehensive analysis of autocorrelation and bias in home range
   estimation. *Ecological Monographs*, 89(2), p.e01344.
- Prevedello, J. A., G. Forero-Medina, and M. V. Vieira, Does land use affect perceptual range?
  Evidence from two marsupials of the Atlantic Forest, *Journal of Zoology*, 284 (2011), 5359. doi:10.1111/j.1469 -7998.2010.00783.x.
- Rajan, R., Clement, J.P. and Bhalla, U.S., 2006. Rats smell in stereo. *Science*, *311*(5761),
   pp.666-670.
- Raji, J.I. and M. DeGennaro, Genetic analysis of mosquito detection in humans, *Current Opinion in Insect Science*, 20 (2017), 34-38.
- Schlägel, U.E. and Lewis, M.A., 2014. Detecting effects of spatial memory and dynamic
   information on animal movement decisions. *Methods in Ecology and Evolution*, 5(11),
   pp.1236-1246.
- Turchin, P., 1991. Translating foraging movements in heterogeneous environments into the
   spatial distribution of foragers. *Ecology*, 72(4), pp.1253-1266.
- Tyson, R. C., J. B. Wilson, and W. D. Lane. 2011. Beyond diffusion: Modelling local and long distance dispersal for organisms exhibiting intensive and extensive search modes,
   *Theoretical Population Biology* 79:70-81.
- Vergara, P.M., Soto, G.E., Rodewald, A.D. and Quiroz, M., Behavioral switching in Magellanic
   woodpeckers reveals perception of habitat quality at different spatial scales. *Landscape Ecology*, pp.1-14.
- Ward, D. and D. Saltz, Foraging at different spatial scales: Dorcas gazelles foraging for lilies
  in the Negev desert, *Ecology* 75 (1994), 48-58.
- Uhlenbeck, G. E., and L. S. Ornstein. 1930. On the theory of the Brownian motion. *Physical Review*, 36:823–841.
- Zollner, P. A., and S. L. Lima. 1997. Landscape-level perceptual abilities in white-footed mice:
  perceptual range and the detection of forested habitat. *Oikos*, 80: 51–60.
- doi:10.2307/3546515.
- 827

- 828
- 829 830

×10<sup>-3</sup> Scenario 1 Scenario 2 Scenario 3 20 20 20 8 0.03 0.04 Time (years) Time (years) Time (years) 6 19 19 19 0.025 0.03 4 18 18 0.02 18 0.02 2 0.015 17 17 17 0 0 L 0 μ L μ μ L Spatial coordinate (x) Spatial coordinate (x) Spatial coordinate (x) Scenario 4 Scenario 5 Scenario 6 20 20 20 0.05 0.04 Time (years) Time (years) Time (years) 0.015 0.04 19 19 19 0.03 0.01 0.03 18 18 18 0.02 0.02 0.005 17 17 17 0 0 0 L L μ μ μ L Spatial coordinate (x) Spatial coordinate (x) Spatial coordinate (x)

831 Supplemental Figures.

### 833

834 Supplementary Figure A. Density plot of the diffusive component of the forager population in a

landscape with a single, periodic resource peak. Diffusion is utilized in very different ways

across the six movement scenarios. For example, large portions of the population are diffusing in

locations away from the resource peak in Scenarios 1 and 6. Diffusion occurs concentrated near
the resource peak in Scenarios 2 through 5, but in a strongly periodic fashion in Scenarios 2 and

5. Fixed parameters:  $\theta = 0.01$ , D = 0.1; Scenario 1:  $w_0 = 0.01$ ; Scenario 2:  $m_0 = 0.035$ ; Scenario

840 3:  $\varphi_0 = 0.0037$ ; Scenario 4:  $\varphi_0 = 0.0018$ , R = 10; Scenario 5:  $\delta_0 = 0.0014$ ; Scenario 6  $M_0 = 0.02$ , 841 Q = 20.9.



Supplemental Figure B. Densities of the home ranging component of the population for a 844

- landscape with two in-phase resource patches. Compare with Figure 3 for the one resource patch 845
- case. Fixed parameters:  $\theta = 0.01$ , D = 0.1; Scenario 1:  $w_0 = 0.01$ ; Scenario 2:  $m_0 = 0.035$ ; 846
- Scenario 3:  $\varphi_0 = 0.0037$ ; Scenario 4:  $\varphi_0 = 0.0018$ , R = 10; Scenario 5:  $\delta_0 = 0.0014$ , in Scenario 6 847  $M_0 = 0.02, Q = 20.9.$
- 848



851 Supplemental Figure C. Locations and times when the home ranging component of the

consumer population is actively switching into the diffusive foraging model for cases with two

in-phase resource patches. Note that the blue and yellow portions of the plots are largely

complementary to those in Fig. 2. However, in scenario 5 (panel e), the switching to diffusion takes place as the resource peak is waning not increasing. Fixed parameters:  $\theta = 0.01$ , D = 0.1;

856 Scenario 1:  $w_0 = 0.01$ ; Scenario 2:  $m_0 = 0.035$ ; Scenario 3:  $\varphi_0 = 0.0037$ ; Scenario 4:  $\varphi_0 =$ 

857 0.0018, R = 10; Scenario 5:  $\delta_0 = 0.0014$ ; Scenario 6  $M_0 = 0.02$ , Q = 20.9.





863 Supplementary Figure D. Resource matching with a single resource peak. Fixed parameters: D = 0.1,  $\theta = 0.005$  (top array),  $\theta = 0.02$  (bottom array).

865

859

Top:





0.001

0.015 -

0.005

0

0

v 0.01 -

0.75

0.65

0.55

0.45

0.015 -

0.005

0

0

0.001

 $\phi_0$ 

0.002

0.003

v 0.01

0.003

 $\delta_0$ 

0.004

0.75

0.65

0.55

0.45

0.015 -

0.005

0 -

0

0.01

 $M_0$ 

**ഗ** 0.01

0.75

0.65

0.55

0.45

0.02

0.03



Supplemental Figure F. For the case of two in-phase resource patches, locations and times when the resource conditions in Scenario 4 favor the consumer population to actively switch from the diffusive foraging mode to the home ranging mode as a function of the perceptual range, *R*. To be clear, this plot is showing the locations where the switching is actually taking place, not the perceptual radii themselves. Thus, based on very large perceptual radii, it turns out that the switching should only happen in selected small areas. Yellow:  $\alpha = s$ , Blue:  $\alpha = 0$ . Parameters: *L* = 100,  $\mu_{\Box} = 33.3$ ,  $\mu_{\Box} = 66.6$ ,  $\varphi_0 = 0.001$ .

- 880
- 881



883 Supplemental Figure G. Portions of space-time when the consumer population in Scenario 6 is

actively switching from the diffusive foraging mode to the home ranging mode as a function of

885 memory length, *Q*, for the case of two in-phase resource patches. Yellow:  $\alpha = s$ , Blue:  $\alpha = 0$ .

886 Parameters: L = 100,  $\mu_1 = 33.3$ ,  $\mu_2 = 66.6$ ,  $M_0 = 0.01$ .