Modeling individual variability in habitat selection and movement using integrated step-selection analyses

31 July, 2023

Nilanjan Chatterjee[1,3], David Wolfson[1], Dongmin Kim[1], Juliana Velez[1], Smith Freeman[1], Nathan M. Bacheler[2], Kyle Shertzer[2], and John Fieberg[1,4]

[1] Department of Fisheries, Wildlife, and Conservation Biology, University of Minnesota

[2] Southeast Fisheries Science Center, National Marine Fisheries Service, Beaufort, NC 28516, USA.

[4] Corresponding author: nchatter@umn.edu

[5] Co-corresponding author: jfieberg@umn.edu

- Running headline: Individual variability in habitat selection

Word count: 6740

Abstract

1. *Integrated step-selection analyses* (ISSAs) are frequently used to study animal movement and habitat selection. Methods for incorporating random effects in ISSAs have been developed, making it possible to quantify variability among animals in their space-use patterns. Although it is possible to model variability in both habitat selection and movement parameters, applications to date have focused on the former despite the widely acknowledged and important role that movement plays in determining ecological processes from the individual to ecosystem level. One potential explanation for this omission is the absence of readily-available software or examples demonstrating methods for estimating movement parameters in ISSAs with random effects.

2. To demonstrate methods for characterizing among-individual variability in both movement and habitat-selection parameters, we fit two models to an acoustic telemetry data set involving locations of 35 red snapper (*Lutjanus campechanus*). In the first model, the distribution of snapper step lengths and turn angles were assumed to depend on a categorical habitat variable indicating the type of benthic habitat the fish was located in at the start of the movement step. In the second model, step lengths and turn angles were assumed to depend on a continuous variable measuring the distance between the fishes' current location and nearest edge habitat. In both models, we also quantified habitat selection for different benthic habitat classes and distance to edge habitat at the end of the movement step.

3. There was substantial among-individual variability in both habitat selection and movement parameters. Nonetheless, most red snapper selected for high-relief hardbottom habitat and for locations nearer to edge habitat. They also moved less when in high-relief hardbottom habitat or when they were close to reef edges. Turn angles were frequently near $\pm\pi$, but were more dispersed when fish were far away from edge habitat.

4. We provide code templates and functions for quantifying variability in movement and habitat-selection parameters when implementing ISSAs with random effects. In doing so, we hope to encourage ecologists conducting ISSAs to take full advantage of their ability to model among-individual variability in both habitat-selection and movement patterns.

- Key-words: Individual variability, Integrated step-selection analysis, *Lutjanus campechanus*, Mixed-effect, Random effect, Red snapper, Step-selection function

1 Introduction

Technological advances, including smaller and better tracking devices (Kays et al. 2015), widespread availability of remote sensing data products (Dodge et al. 2013; Neumann et al. 2015), and new statistical methods and software (Hooten et al. 2017; Joo et al. 2020) have provided exciting opportunities for studying how individuals move and select for different habitat features. By tracking individuals in the context of dynamic environmental conditions, we can identify drivers of movement and predict how climate and land-use change might influence both individual- and population-level fitness (Cagnacci et al. 2010).

Integrated step-selection analyses (ISSAs) have emerged as one of the most popular frameworks for analyzing animal telemetry data (Avgar et al. 2016; Fieberg et al. 2021; Northrup et al. 2022). Similar to species distribution models and resource-selection functions, ISSAs infer the importance of environmental covariates by comparing their distribution at used versus available locations. Integrated step-selection analyses offer several advantages over these other approaches, however, by: 1) allowing for temporally dynamic covariates driving species distribution patterns to be included in the model; 2) using an individual's movements to determine available habitat; and 3) relaxing the assumption of independence among locations to an assumption of independent "steps" or movements between sequential locations. Another advantage of ISSAs is the ability to model both habitat selection, using covariates at the end of the movement step, and habitat-dependent movement, by allowing an animal's step lengths (distances between sequential locations) and turn angles (changes in direction) to depend on habitat at the start of the movement step (Avgar et al. 2016; Fieberg et al. 2021). This strength has been widely recognized, and ISSAs have been used to explore how individuals alter their step lengths and turn angles in response to linear features such as roads and seismic lines (Prokopenko, Boyce, and Avgar 2017; Scrafford et al. 2018; Dickie et al. 2020).

Individuals from the same species often show substantial variation in their space-use patterns, and thus, it is appealing to model this variation using individual-specific parameters specified using random effects (Duchesne, Fortin, and Courbin 2010). However, random effects can be computationally challenging to include within the conditional logistic regression framework typically used to estimate parameters in ISSAs (Duchesne, Fortin, and Courbin 2010; Craiu et al. 2011). This led Craiu et al. (2011) to develop a two-step approach for fitting mixed conditional logistic regression models in this context. More recently, Muff, Signer, and Fieberg (2020) developed an approach for incorporating random effects in ISSAs by exploiting the equivalence between Poisson regression with stratum-specific intercepts and conditional logistic regression. This approach has quickly become commonplace when modeling habitat selection using data sets that include many individuals, and allows for both individual- and population-level inference. For example, one can estimate coefficients for a typical individual by setting all random effects to 0 (Fieberg et al. 2009, 2010), estimate variance parameters that capture among-individual variability in their habitat-selection coefficients (Muff, Signer, and Fieberg 2020), and explore functional responses in habitat selection by considering how individual-specific coefficients vary with habitat availability or other landscape metrics (Matthiopoulos et al. 2011; Aarts et al. 2013). A nice exemplification is given by Jones et al. (2020), who used random effects to explore whether variation among individual spotted owls (*Strix occidentalis*) in their habitat-selection parameters was related to patch size and configuration in a post-fire landscape.

Individuals also frequently exhibit variation in the extent of their movements, which can have implications for survival and fitness. For example, Fraser et al. (2001) found that Trinidad killifish (*Rivulus hartii*) identified in the lab as being more bold also moved more when released into their native streams; killifish movements were also positively correlated with individual growth in areas of the stream where predators were present. Although many studies have explored individual variation in habitat-selection parameters, little to no attention has been given to studying variation in movement parameters when using ISSAs with random effects (hereafter "mixed ISSAs"). One likely reason for this lack of attention is that the estimation of movement parameters in ISSAs is typically done using a complicated two-step process (Avgar et al. 2016; Fieberg et al. 2021). Tentative movement parameters are first estimated using observed step lengths and turn angles, ignoring the effect of habitat selection on observed movements, and then movement parameters are updated using additional coefficients from the fitted conditional logistic regression model (see Section 2.3.5). The `amt` package (Signer, Fieberg, and Avgar 2019) provides functions for implementing this two-step approach, but they only work when fitting models to individual animals. Furthermore, it is not immediately

clear how this process should be implemented when the goal is to estimate individual-specific movement parameters.

Here, we demonstrate how mixed ISSAs can be used to study among-individual variation in both movement and habitat-selection parameters using an acoustic telemetry data set of 35 red snapper (*Lutjanus campechanus*), an economically and ecologically important species distributed in the Gulf of Mexico and along the eastern coasts of North America, Central America, and northern South America. We analyze red snapper movements using two different mixed ISSAs, one in which step lengths and turn angles depend on a categorical benthic habitat class variable and a second in which they depend on a continuous variable quantifying distance between the current location and the nearest edge habitat. We show how to visualize individual variation in movement and habitat-selection patterns, and provide functions within an associated R package (`mixedSSF`) to facilitate the application of these methods to other data sets.

1.1 Red Snapper Biology

Red snapper is a reef-associated, demersal, gonochoristic fish species that can live 50+ years and matures around two years old (Wilson and Nieland 2001; White and Palmer 2004). The size of individuals can exceed 1000 mm and 12 kg. They are generalist predators, with adults feeding primarily on benthic invertebrates and other reef-associated fishes (Szedlmayer and Lee 2004; Wells, Cowan Jr, and Fry 2008). In the United States, red snapper are targeted by both recreational and commercial sectors, and these fisheries are managed in the Gulf of Mexico by the Gulf of Mexico Fishery Management Council and in the Atlantic Ocean by the South Atlantic Fishery Management Council. Previous studies of red snapper have found strong seasonal and diel patterns in their movements and an affinity for areas of high to moderate relief near edges of hardbottom habitat (Williams-Grove and Szedlmayer 2016, 2017; Bacheler et al. 2021; Bohaboy, Cass-Calay, and Patterson III 2022). We use acoustic telemetry and mixed ISSAs to quantify individual variability in snapper movements and to evaluate the following hypotheses: red snapper will 1) prefer hard bottom near the edge of reef-sand habitat transition; and 2) move in a more directed manner (larger distances with turn angles near 0) when they are in sandy habitats or far from the edge of reef-sand habitat.

2 Materials and Methods

2.1 Study Area

Our study site is approximately 37 m deep in waters off the coast of North Carolina, USA, between Cape Hatteras and Cape Lookout, Raleigh Bay (Fig. 1). The seafloor of the study site is composed of a patchy mix of rocky pavement and ledges in a matrix of sand (Fig. 1). We used a high-resolution bathymetric map (C. Taylor, National Centers for Coastal Ocean Science) for classification of benthic habitat into either sand or hardbottom.

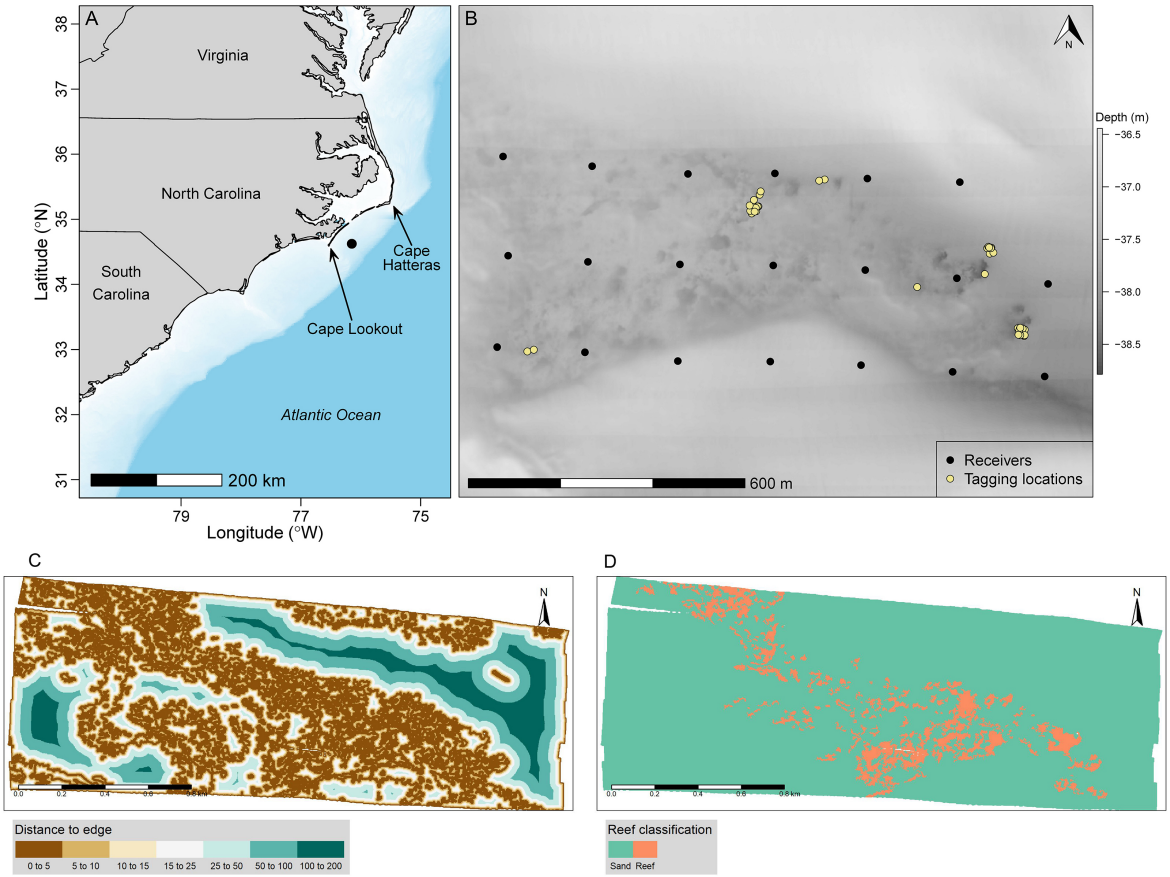

Figure 1: (A) Broad-scale location of study (filled black circle) on the continental shelf between Cape Lookout and Cape Hatteras, North Carolina, USA, in 2019. Water depth is shown in blue: the lightest blue indicates water less than 5 m deep, while the darkest blue is greater than 100 m deep. (B) Close-up view of the study area where a Vemco positioning system was used to estimate fine-scale positions of red snapper (*Lutjanus campechanus*). Background shows a multibeam sonar map that is scaled to depth (right y-axis), submersible receivers are represented by filled black circles, and tagging and release locations are represented by light yellow points. Environmental variables used in the habitat-selection modelling (C) distance-to-edge habitat; and (D) benthic habitat class (sand or hardbottom).

2.2 Data Collection

We caught red snapper from May—September, 2019 using hook-and-line methods or baited fish traps and tagged them with 13g externally-attached Vemco V13P-1x transmitters that had an average battery life of 613 days and a pulse interval of 130-230 seconds. Locations were collected from May 2019 to December 2019 using a 400 x 1200 m regularly spaced grid array of 20 VR2AR acoustic receivers placed on the sea floor (Fig. 1, Bacheler et al. 2021). We used an additional V13P-1x reference transmitter to quantify the accuracy of data collection between transmitters and acoustic receivers by deploying it at a known location and quantifying the horizontal error of all estimated positions over the duration of the study.

2.2.1 Data pre-processing

We thinned the telemetry data to equally spaced intervals of 6 $\pm$ 1 minutes using the `track_resample` function in the `amt` R package (Signer, Fieberg, and Avgar 2019). We then converted the location data to a

set of steps representing movements between sequential observations and dropped any steps that had a step length > 100 meters and a turn angle > 170 degrees, assuming these steps likely resulted from erroneous locations with large measurement error (Bjørneraas et al. 2010). Lastly, we created a *distance-to-edge* habitat covariate measuring the nearest distance to habitat separating sand and hardbottom habitat classes (Fig. 1).

2.3 Integrated Step-Selection Analysis (ISSA)

We quantified movements and habitat selection via an integrated step-selection analysis (iSSA) (Avgar et al. 2016; Fieberg et al. 2021). Integrated step-selection analyses assume that animal space use is captured by the product of two kernels, a movement-free selection kernel, $w(.)$, representing habitat preferences and a selection-free movement kernel, $\phi(.)$, that quantifies how the animal would move in the absence of habitat selection (Fieberg et al. 2021).

In our iSSA, we considered the following integrated step-selection model:

$$u(s, t+\Delta t)|u(s', t), \psi = \frac{w(x(s, t+\Delta t); \beta)\phi(s, s', x(s', t); \gamma)}{\int_{\tilde{s} \in\ G} w(x(\tilde{s}, t+\Delta t); \beta)\phi(\tilde{s}, s', x(s', t); \gamma) d\tilde{s}}, \tag{1}$$

where $u(s, t+\Delta t)|u(s', t), \psi$ represents the conditional probability of an animal being present at location s at time $t+\Delta t$, given that it was at location s' at time t and arrived there via the bearing ψ, $x(s', t)$ and $x(s, t+\Delta t)$ are habitat covariates measured at the start and end of the movement step, respectively, and β and γ are sets of parameters that quantify habitat selection and movement tendencies, respectively. Lastly, note that the denominator in equation (1) integrates over the geographic area, G, that represents the area in which an animal could have potentially moved based on its prior observed movements and ensures that the right-hand side is a proper probability distribution; $\tilde{s}$ is a dummy variable for integration.

2.3.1 Movement-Free Selection Kernel

We modeled $w(.)$ as a log-linear function of benthic habitat class and distance-to-edge measured at the end of the movement step:

$$w(x(s, t+\Delta t); \beta) = \exp(\mathrm{I}(\mathrm{Hardbottom}(t+\Delta t))_{ij}\beta_{1i} + d_{ij}(t+\Delta t)\beta_{2i}), \tag{2}$$

where i indexes the different individuals and j indexes the movement steps, $d_{ij}(t+\Delta t)$ is the distance to edge habitat at the end of the movement step, and $\mathrm{I}(\mathrm{Hardbottom}(t+\Delta t))_{ij}$ is equal to 1 if the end of the movement step falls in the Hardbottom habitat class, and 0 otherwise. We used random effects to allow each individual to have its own set of habitat-selection parameters:

$$\beta_{1i} = \bar{\beta}_1 + b_{1i} \tag{3}$$

$$\beta_{2i} = \bar{\beta}_2 + b_{2i} \tag{4}$$

where $\bar{\beta}_h$ $(h = 1, 2)$ represents the mean coefficient across the population of individuals, and the b_{hi} are Normally-distributed random effects associated with each explanatory variable in the model. We assumed the coefficients for Hardbottom habitat varied independently from the distance-to-edge coefficients:

$$\left[b_{1i}, b_{2i}\right]^T \sim N(0, \Sigma_\beta), \text{ with } \Sigma_\beta = \begin{bmatrix} \sigma^2_{b_1} & 0 \\ 0 & \sigma^2_{b_2} \end{bmatrix} \tag{5}$$

2.3.2 Selection-Free Movement Kernels

We considered two different habitat-dependent movement kernels. In the first model, we assumed step-lengths and turn angles depended on the habitat class the fish was located in at the start of the movement step. In the second model, we assumed step-lengths and turn angles depended on the distance between the fish and the nearest edge habitat at the start of the movement step, $d_{ij}(t)$.

2.3.3 Model 1: Movement Dependent on Habitat Class

We assumed the step lengths associated with individual i's movements starting in habitat class k, sl_{ik}, followed a Gamma distribution with individual-specific shape and scale parameters:

$$sl_{ik} \sim \text{Gamma}(\alpha_{ik}, \nu_{ik}) \tag{6}$$

where $(k = 1, 2)$ for sand and hardbottom, respectively. We assumed turn angles associated with individual i's movements starting in habitat class k, θ_{ik}, followed a von Mises distribution with individual-specific concentration parameters, κ_{ik}, and with means, μ_k that were either 0 (assuming individuals had a tendency to move in a consistent direction) or $\pm\pi$ (assuming individuals were largely stationary or moving back and forth along linear features). We set μ_k to $\pm\pi$ and κ to $|\kappa|$ when estimates of κ were negative and set μ_k to 0 otherwise:

$$\theta_{ik} \sim \text{von Mises}(\mu_k, \kappa_{ik}) \tag{7}$$

There are multiple ways that one might specify a model for the random effects, and these specifications are complicated due to how the movement parameters are estimated (Section 2.3.5). In our approach, we included a single fish-specific random effect for each type of parameter (α, ν, κ), which allowed the shape, scale, and concentration parameters to vary by individual, while forcing *differences* between habitat classes to be consistent across individuals. We describe the model in more detail (Section 2.4 after describing the workflow used to estimate parameters in Section 2.3.5).

2.3.4 Model 2: Movement Dependent on Distance to Reef Edge

We assumed the jth step length for individual i, sl_{ij}, followed a gamma distribution with individual-specific shape and scale parameters that depended on the distance from edge habitat, $d_{ij}(t)$, at the start of the movement step. We assumed turn angles, θ_{ij}, followed a von Mises distribution with individual-specific concentration parameters, κ_{ij}, that also depended on $d_{ij}(t)$. We used the same strategy for modeling μ_{ij} as with model 1 (setting μ_{ij} to 0 whenever κ_{ij} was positive and to $\pm\pi$ when κ_{ij} was negative).

$$sl_{ij} \sim \text{Gamma}(\alpha_{ij}, \nu_{ij}) \tag{8}$$

$$\theta_{ij} \sim \text{von Mises}(\mu_{ij}, \kappa_{ij}) \tag{9}$$

We again used Normally-distributed random effects to model among-individual variability in the selection-free movement kernels, which we detail in Section 2.4.

2.3.5 Parameter Estimation

We used the following workflow to estimate the parameters in the movement model:

1. We fit a single tentative selection-free movement kernel, $\phi(s, s'; \hat{\gamma})$, to the observed step-lengths and turn angles pooled across all individuals. Here, $\hat{\gamma}$ consisted of a single shape (α_0), scale (ν_0), and concentration parameter (κ_0). We set the mean of the von Mises distribution to 0.

2. We generated time-dependent available locations by simulating 10 potential movements from each previously observed location using the tentative selection-free movement kernel, $\phi(s, s'; \hat{\gamma})$ from step 1.

3. We formed strata by matching each observed step with its set of random steps. We then fit the equivalent of a mixed-effects conditional logistic regression model using these strata and the "Poisson trick" from Muff, Signer, and Fieberg (2020). We quantified selection for different habitat classes and distance-to-edge habitat by including these covariates measured at the end of the movement step. We also included the step length, log(step length), and cos(turn angle) for each step as well as their interactions with habitat class (model 1) or distance to edge habitat (model 2) at the start of the movement step. These latter covariates allowed us to estimate updated movement kernels associated with each habitat class (model 1) or as a function of distance to edge habitat (model 2), taking into account habitat selection (see step 4).

4. We updated the movement parameters in $\phi(s, s'; \gamma)$ using the regression coefficients associated with movement characteristics (e.g., step length, log(step length), and cosine(turn angle) and their interactions with habitat class or distance to edge at the start of the movement step) as described in Section 2.4 (Avgar et al. 2016; Fieberg et al. 2021). When adjusted κ parameters were negative, we took their absolute value and set the mean of the von-Mises distribution to $\pm\pi$; otherwise, we assumed the mean of the von-Mises distribution was equal to 0.

5. We estimated the mean step length for a typical individual (i.e., one with all random effects set equal to 0) in sand and hardbottom habitat classes (model 1) and for quantiles of $d_{ij}(t)$ (model 2). We used the delta method to quantify uncertainty in these estimates.

2.4 Understanding the Random-Effects Specification for Movement Parameters

Step 4 of the implementation process is key to understanding the random effects specification for the movement parameters. As described in Avgar et al. (2016) and Appendix C of Fieberg et al. (2021), we can obtain updated estimates of movement parameters that account for habitat selection if we include specific movement characteristics in our conditional logistic regression model; these characteristics depend on the assumed distributions used to model step lengths and turn angles. For our model specification using the Gamma and von Mises distributions, we need to include step length, log(step length) and cos(turn angle). Further, to allow our movement parameters to vary by habitat class, we need to include interactions between these movement characteristics and habitat class (model 1) or distance to edge (model 2) at the start of the movement step. In our models, we included random effects for step length, log(step length) and cos(turn angle) but not their interactions with habitat class or distance to nearest edge habitat. Although in principle, interactions could also be modeled using random effects; this would lead to a substantially larger number of variance/covariance parameters that would need to be estimated with relatively few individuals.

Let $\beta_{sl}, \beta_{\log(sl)},$ and $\beta_{cos(\theta)}$ represent the fixed-effects coefficients associated step length, log(step length) and cos(turn angle), respectively. Further, let $b_{sl_i}, b_{\log(sl)_i}, b_{cos(\theta)_i}$ represent fish-specific random effects associated with these variables. In the first model, we estimate updated movement parameters for our reference class (sandy habitat) using:

$$\alpha_{1i} = \alpha_0 + \beta_{sl} + b_{sl_i} \tag{10}$$

$$\nu_{1i} = \frac{1}{\frac{1}{\nu_0} - (\beta_{\log(sl)} + b_{\log(sl)_i})} \tag{11}$$

$$\kappa_{1i} = \kappa_0 + \beta_{cos(\theta)} + b_{cos(\theta)_i} \tag{12}$$

We can estimate updated parameters for the hardbottom habitat class by also including the coefficients for the interaction terms. For example, let $\beta_{sl:I(Hardbottom(t))}$, $\beta_{log(sl):I(Hardbottom(t))}$, and $\beta_{cos(\theta):I(Hardbottom(t))}$ be the interaction terms associated with the hardbottom habitat class at the start of the movement step. We can obtain updated estimates for α_{2i}, ν_{2i}, and κ_{2i} using:

$$\alpha_{2i} = \alpha_0 + \beta_{sl} + \beta_{sl:I(Hardbottom(t))} + b_{sl_i} \tag{13}$$

$$\nu_{2i} = \frac{1}{\frac{1}{\nu_0} - (\beta_{\log(sl)} + \beta_{log(sl):I(Hardbottom(t))} + b_{\log(sl)_i})} \tag{14}$$

$$\kappa_{2i} = \kappa_0 + \beta_{cos(\theta)} + \beta_{cos(\theta):I(Hardbottom(t))} + b_{cos(\theta)_i} \tag{15}$$

In our second model, our movement parameters were allowed to vary as a function of $d_{ij}(t)$. In that case, equations (10), (11), and (12) are used to estimate updated movement parameters when $d_{ij}(t) = 0$. Let $\beta_{sl:d}$, $\beta_{log(sl):d}$, and $\beta_{cos(\theta):d}$ represent the interaction terms between step length, log(step length), cos(turn angle) and distance to the nearest edge habitat at the start of the movement step. We can obtain updated estimates of movement parameters for any other distance, δ, using:

$$\alpha_\delta = \alpha_0 + \beta_{sl} + \delta\beta_{sl:d} + b_{sl_i} \tag{16}$$

$$\nu_{2i} = \frac{1}{\frac{1}{\nu_0} - (\beta_{\log(sl)} + \delta\beta_{log(sl):d} + b_{\log(sl)_i})} \tag{17}$$

$$\kappa_{2i} = \kappa_0 + \beta_{cos(\theta)} + \delta\beta_{cos(\theta):d} + b_{cos(\theta)_i} \tag{18}$$

In both models, we assumed the random effects were Normally-distributed and allowed $b_{sl_i}, b_{\log(sl)_i}, b_{cos(\theta)_i}$ to co-vary independently from the habitat-selection coefficients.

$$\left[b_{sl_i}, b_{\log(sl)_i}, b_{cos(\theta)_i}\right]^T \sim N(0, \Sigma_b), \text{ with } \Sigma_b = \begin{bmatrix} \sigma^2_{b_{sl}} & \sigma^2_{b_{sl},b_{\log(sl)}} & \sigma^2_{b_{sl},b_{cos(\theta)}} \\ \sigma^2_{b_{sl},b_{\log(sl)}} & \sigma^2_{b_{\log(sl)}} & \sigma^2_{b_{\log(sl)},b_{cos(\theta)}} \\ \sigma^2_{b_{sl},b_{cos(\theta)}} & \sigma^2_{b_{\log(sl)},b_{cos(\theta)}} & \sigma^2_{b_{cos(\theta)}} \end{bmatrix} \tag{19}$$

3 Software and Data Availability

We used the *amt* package (Signer, Fieberg, and Avgar 2019) to facilitate the calculation of step lengths and turn angles and the *glmmTMB* package (Magnusson et al. 2017) to fit the mixed-effects model. We developed an R package, `mixedssf` (available at https://github.com/smthfrmn/movement-utilities) to facilitate estimation and visualization of updated movement parameters. All analyses were carried out in R 4.0 (R Core Team 2020). Data and code for reproducing all of the analyses will be archived in the Data Repository of the University of Minnesota upon acceptance.

4 Results

A total of 35 individuals were acoustically-tagged in this study. The number of relocations (range 265-52,189) as well as the number of tracking days (range 3-223) were substantially different across individuals (Supplementary Table 1). Median horizontal error from 18,026 detections of the reference transmitter was 0.8m with a range of approximately 0.6-2.0m (Bacheler et al. 2021). We dropped a total of 13,802 observations (4% of the total) that did not satisfy the filtering criteria.

There was substantial variability in the estimated individual-specific habitat-selection parameters, with both positive and negative coefficients for each explanatory variable (Fig. 2, 6). Comparing mean coefficients and their SEs, we see that the "typical individual" prefers hardbottom to sand habitat (Fig. 2), though the coefficient for I(hardbottom) was negative for 3 individuals. Evaluating movement kernels for an individual with random effects = 0 (Fig. 3, Supplementary Table 3), we see that the typical snapper also tends to move less when in hardbottom habitat and as they get closer to edge habitat. The distribution of turn angles also becomes more dispersed when fish are farther from habitat edges ($\hat{\beta}_{cos(\theta):d} = 0.006$; $p < 0.001$; Fig. 3). Similar to habitat selection, there was substantial among-individual variability in both the distributions of step-lengths and turn angles (Fig. 4, Supplementary Fig. 7) in both models.

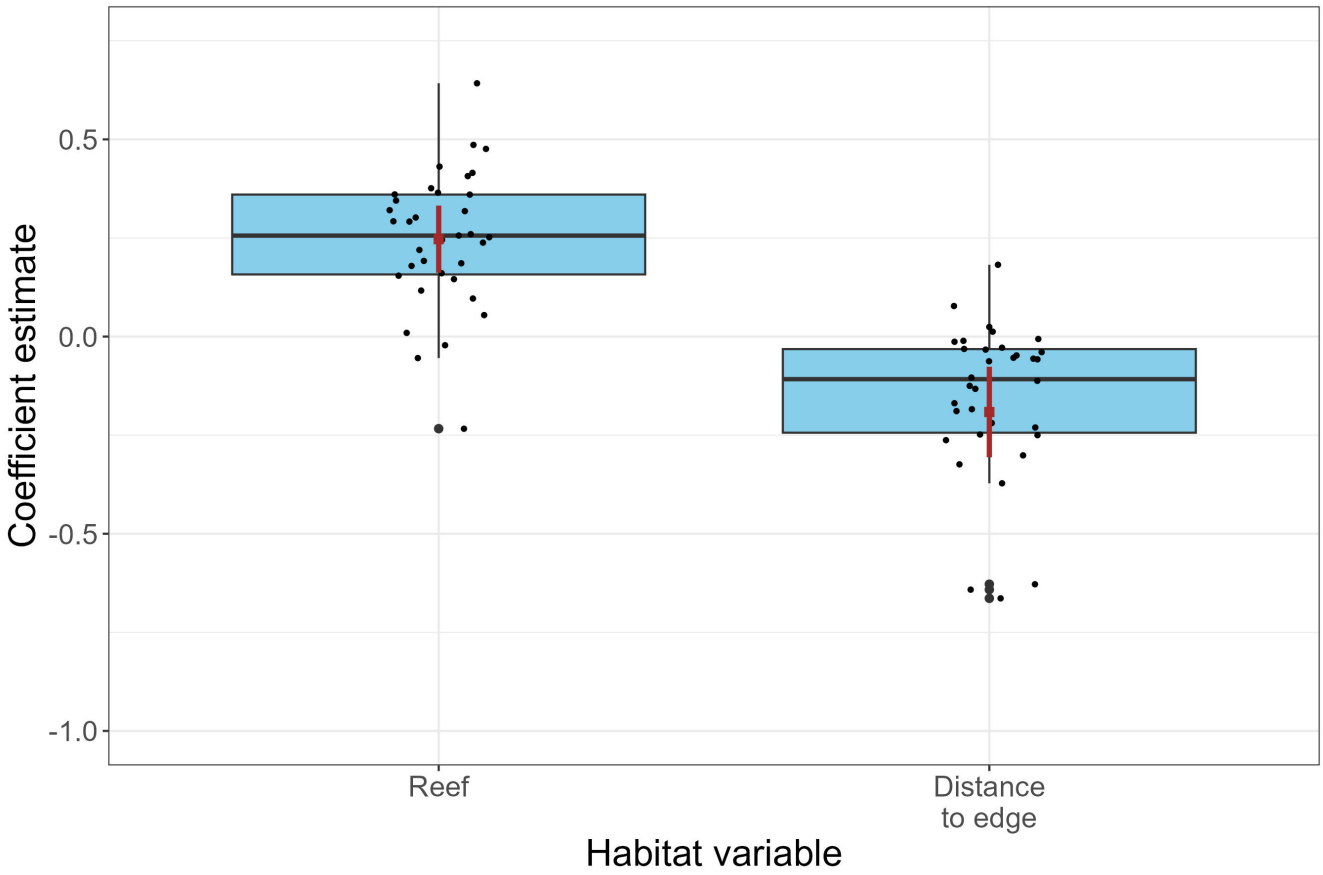

Figure 2: Box plot summarizing the individual habitat-selection coefficients (black dots) associated with hardbottom habitat and the distance-to-edge covariate from Model 1. Boxes bound the 25th and 75th percentiles, solid line within the box indicates the median, and the whiskers extend to 1.5 times the interquartile range of the observations. The mean coefficient, along with a 95% confidence interval for the mean, is depicted in brown.

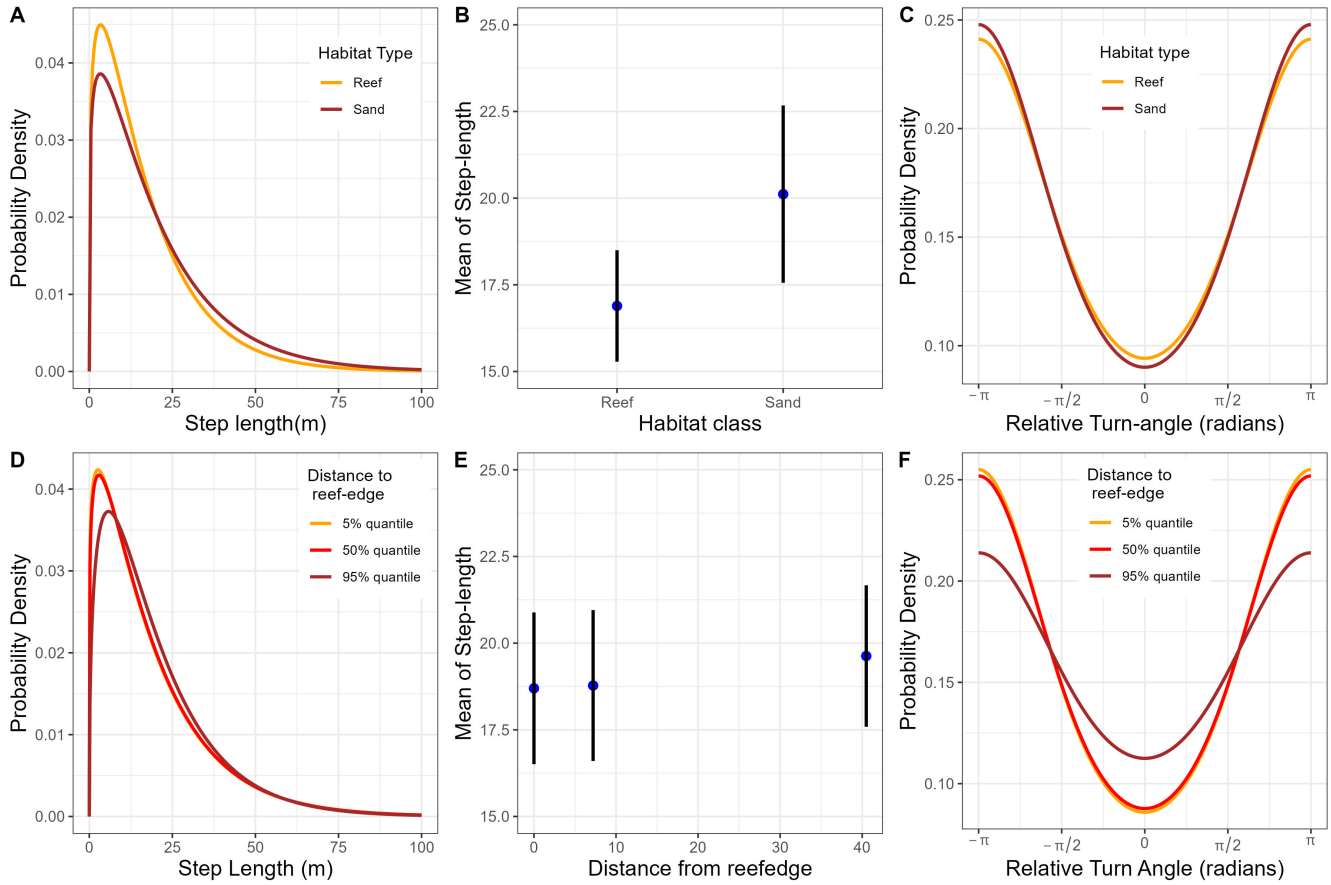

Figure 3: Estimated step-length and turn-angle distributions for a typical red snapper, i.e., one with all random effects equal to 0, for sand and hardbottom habitat classes (A, C) and different quantiles of distance to edge habitat (D, F) with estimates of mean speed for sand and hardbottom habitat class (B) or for different quantiles of distance to edge habitat (E).

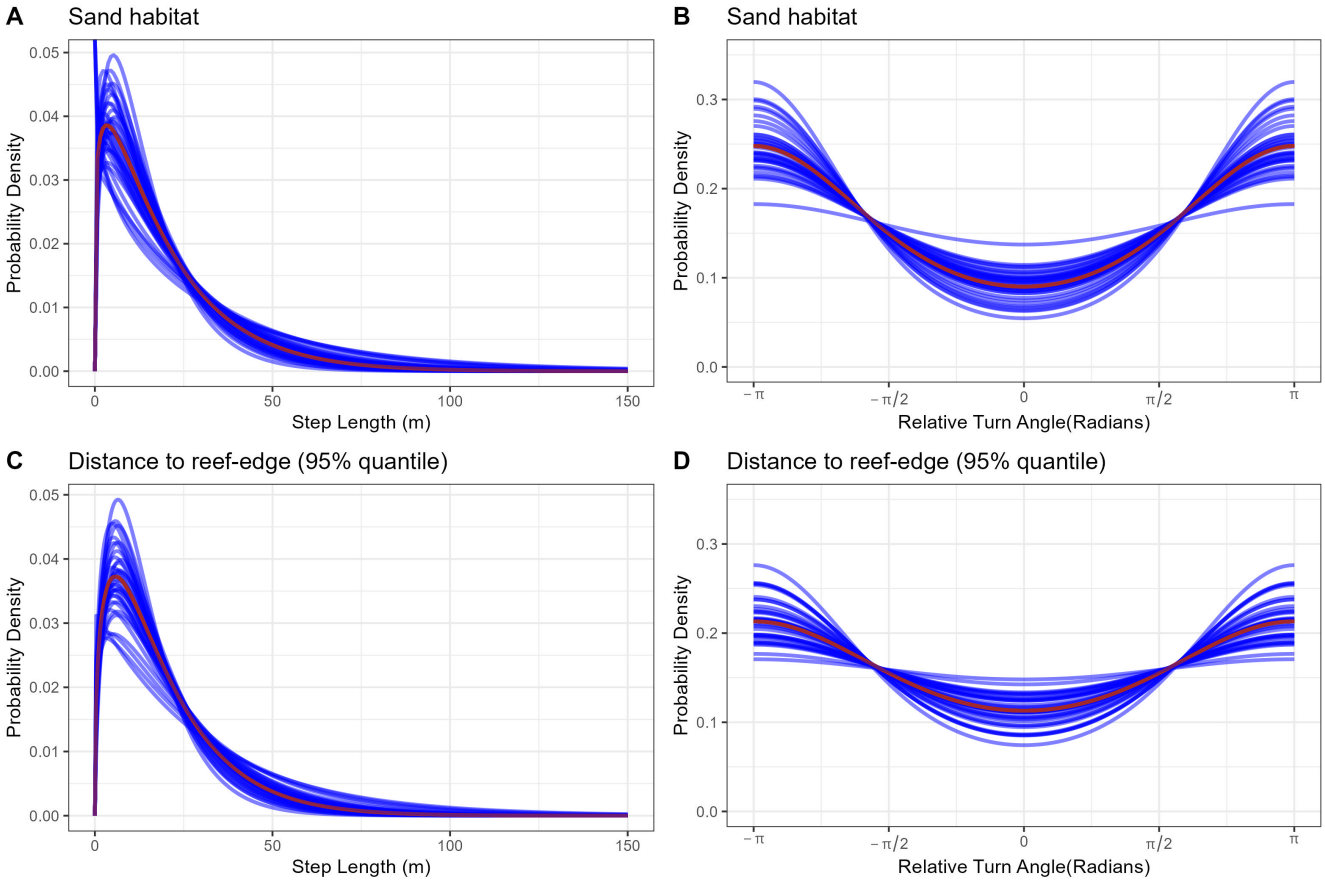

Figure 4: Estimated step-length and turn-angle distributions for different individuals (blue) and for a typical individual (i.e., an individual with all random effects set to 0) (red) in sandy habitat (A-B) and at 95% distance quantile from edge habitat (C-D).

5 Discussion

An understanding of the causes and consequences of variability in animal movement and habitat selection is important for addressing many questions in applied and theoretical ecology (Shaw 2020). For example, behavioral ecologists are increasingly interested in studying personalities and behavioral syndromes using mixed-effect models applied to metrics of animal movement and habitat selection (Hertel et al. 2019, 2020). Consistent and quantifiable intra- and inter-individual variability in movement also drives many important ecological processes, including individual foraging rates, social interactions, disease dynamics, and spread of invasive species (Spiegel et al. 2017; Webber et al. 2020, 2023).

Using empirical data from tracked red snappers, we demonstrate how mixed ISSAs can be used to study both intra- and inter-specific variation in animal movements. By including interactions between movement attributes and environmental covariates (benthic habitat class or distance to edge of hardbottom habitat), we were able to quantify how individuals altered their movements depending on local habitat features. Interestingly, we found that individuals tended to move less in habitat most strongly selected for (i.e., hardbottom habitat). Turn angles also tended to be more dispersed when fish were close to edges of reef habitat, suggesting that these locations may serve as important foraging areas. Similar interactions with temporal covariates could be used to study how individuals alter their movements through time (e.g., Forester, Im, and Rathouz 2009; Giroux et al. 2023).

Random effects associated with each individual allowed us to quantify among-individual variability in both

habitat-selection parameters and movement kernels. As is often the case, we found substantial among-individual variability in habitat-selection parameters; we also found substantial variability in individual movement kernels. These results suggest that random effects may be important for properly accounting for statistical dependencies arising from having repeated measures on the same individuals. They also help to demonstrate the power of mixed ISSAs for quantifying inter- and intra-individual variability in animal movements.

Individual variability in red snapper movement and habitat use has important management implications. For instance, red snapper vulnerability to capture by fishers is likely related to their movement and habitat use, which could create the potential for evolutionary effects of fishing (Claireaux, Jørgensen, and Enberg 2018). Similarly, individual variability in behavior likely affects detection probabilities of red snapper sampled by surveys, and this heterogeneity may bias abundance estimates. Indeed, abundance estimates from surveys are the most important data source on population dynamics for stock assessments, which are used by resource managers to inform regulatory decisions.

The application of mixed ISSAs can be challenging, especially when analyzing data sets containing small numbers of individuals. In our applications, we did not include random effects for interactions between environmental predictors and movement characteristics (step length, log(step length), cos(turn angle)). This decision reduced the number of variance parameters that needed to be estimated but also constrained the degree of inter-individual variability that was included in our models. Complex models with many random effects can sometimes lead to computational issues, so these types of choices are commonplace when fitting generalized linear mixed effects models (Bolker et al. 2009). Additional guidance related to model-building strategies (e.g., methods for determining an appropriate level of model complexity) would be helpful. The two-step approach to parameter estimation (Avgar et al. 2016; Fieberg et al. 2021) and Poisson trick for implementing mixed ISSAs (Muff, Signer, and Fieberg 2020) also complicates parameter interpretation and model inference. Software implementations that directly fit models for mixed ISSAs in a single step would also be a welcome advance.

Individual variability has long been recognized as fundamental to understanding broad patterns in ecology, including those that emerge from the aggregation or interactions of smaller-scale individual units (Levin 1992). Recent attention has been given to methods that scale individual movement models to broader levels of animal space use or ecological dynamics. These studies include the use of step-selection analyses to derive utilization distributions and infer broad-scale patterns in space use (Potts and Börger 2023), and the integration of intra-specific variation from movement data in larger contexts such as community ecology (Costa-Pereira et al. 2022) and biodiversity studies (Jeltsch et al. 2013). Mixed ISSAs can be used to parameterize movement models for a population of individuals, which can then be simulated to explore population-level space-use patterns (Signer, Fieberg, and Avgar 2017). By providing annotated code with functions to easily fit and visualize models of animal movement using mixed ISSAs, we hope ecologists will take full advantage of their ability to quantify within- and among-individual variability in both movement and habitat-selection parameters to better understand ecological phenomena and species responses to changing environments.

Declarations

All tagging protocols were approved by the Institutional Animal Care and Use Committee (# NCA19-002) of the North Carolina Aquariums. Research activities were carried out under a Scientific Research Permit issued to Nathan Bacheler by the Southeast Regional Office of the U.S. National Marine Fisheries Service, in accordance with the relevant guidelines and regulations on the ethical use of animals as experimental subjects. Mention of trade names or commercial companies is for identification purposes only and does not imply endorsement by the National Marine Fisheries Service, NOAA. The scientific results and conclusions, as well as any views and opinions expressed herein, are those of the authors and do not necessarily reflect those of any government agency.

Funding

JF and NC were supported by National Aeronautics and Space Administration award 80NSSC21K1182 and JF received partial salary support from the Minnesota Agricultural Experimental Station.

Authors' contributions

NC led the analysis with contributions from DW, DK, JV, SF, and JF, KS and NB collected the data, SF validated, documented, and created functions for implementing the analyses, JF, NC, and NB led the writing of the manuscript. All authors discussed, edited, read, and approved the final manuscript.

Acknowledgements

JF and NC were supported by National Aeronautics and Space Administration award 80NSSC21K1182 and JF received partial salary support from the Minnesota Agricultural Experimental Station.

References

Aarts, Geert, John Fieberg, Sophie Brasseur, and Jason Matthiopoulos. 2013. "Quantifying the Effect of Habitat Availability on Species Distributions." *Journal of Animal Ecology* 82 (6): 1135–45.

Avgar, Tal, Jonathan R Potts, Mark A Lewis, and Mark S Boyce. 2016. "Integrated Step Selection Analysis: Bridging the Gap Between Resource Selection and Animal Movement." *Methods in Ecology and Evolution* 7 (5): 619–30.

Bacheler, Nathan M, Kyle W Shertzer, Brendan J Runde, Paul J Rudershausen, and Jeffrey A Buckel. 2021. "Environmental Conditions, Diel Period, and Fish Size Influence the Horizontal and Vertical Movements of Red Snapper." *Scientific Reports* 11 (1): 1–16.

Bjørneraas, Kari, Bram Van Moorter, Christer Moe Rolandsen, and Ivar Herfindal. 2010. "Screening Global Positioning System Location Data for Errors Using Animal Movement Characteristics." *The Journal of Wildlife Management* 74 (6): 1361–66.

Bohaboy, Erin C, Shannon L Cass-Calay, and William F Patterson III. 2022. "Fine-Scale Movement of Northern Gulf of Mexico Red Snapper and Gray Triggerfish Estimated with Three-Dimensional Acoustic Telemetry." *Scientific Reports* 12 (1): 14274.

Bolker, Benjamin M, Mollie E Brooks, Connie J Clark, Shane W Geange, John R Poulsen, M Henry H Stevens, and Jada-Simone S White. 2009. "Generalized Linear Mixed Models: A Practical Guide for Ecology and Evolution." *Trends in Ecology & Evolution* 24 (3): 127–35.

Cagnacci, Francesca, Luigi Biotani, Roger Powell, and Mark Boyce. 2010. "Animal Ecology Meets GPS-Based Radiotelemetry: A Perfect Strom of Opportunities and Challenges." *Philosophical Transactions of the Royal Society B* 365 (1550): 2157–62.

Claireaux, Marion, Christian Jørgensen, and Katja Enberg. 2018. "Evolutionary Effects of Fishing Gear on Foraging Behavior and Life-History Traits." *Ecology and Evolution* 8 (22): 10711–21.

Costa-Pereira, Raul, Remington J. Moll, Brett R. Jesmer, and Walter Jetz. 2022. "Animal Tracking Moves Community Ecology: Opportunities and Challenges." *Journal of Animal Ecology* 91 (7): 1334–44. https://doi.org/https://doi.org/10.1111/1365-2656.13698.

Craiu, Radu V, Thierry Duchesne, Daniel Fortin, and Sophie Baillargeon. 2011. "Conditional Logistic Regression with Longitudinal Follow-up and Individual-Level Random Coefficients: A Stable and Efficient Two-Step Estimation Method." *Journal of Computational and Graphical Statistics* 20 (3): 767–84.

Dickie, Melanie, Scott R McNay, Glenn D Sutherland, Michael Cody, and Tal Avgar. 2020. "Corridors or Risk? Movement Along, and Use of, Linear Features Varies Predictably Among Large Mammal Predator and Prey Species." *Journal of Animal Ecology* 89 (2): 623–34.

Dodge, Somayeh, Gil Bohrer, Rolf Weinzierl, Sarah C Davidson, Roland Kays, David Douglas, Sebastian Cruz, Jiawei Han, David Brandes, and Martin Wikelski. 2013. "The Environmental-Data Automated Track Annotation (Env-DATA) System: Linking Animal Tracks with Environmental Data." *Movement Ecology* 1 (1): 1–14.

Duchesne, Thierry, Daniel Fortin, and Nicolas Courbin. 2010. "Mixed Conditional Logistic Regression for Habitat Selection Studies." *Journal of Animal Ecology* 79 (3): 548–55.

Fieberg, John, Jason Matthiopoulos, Mark Hebblewhite, Mark S Boyce, and Jacqueline L Frair. 2010. "Correlation and Studies of Habitat Selection: Problem, Red Herring or Opportunity?" *Philosophical Transactions of the Royal Society B: Biological Sciences* 365 (1550): 2233–44.

Fieberg, John, Randall H Rieger, Michael C Zicus, and Jonathan S Schildcrout. 2009. "Regression Modelling of Correlated Data in Ecology: Subject-Specific and Population Averaged Response Patterns." *Journal of Applied Ecology* 46 (5): 1018–25.

Fieberg, John, Johannes Signer, Brian Smith, and Tal Avgar. 2021. "A 'How to'guide for Interpreting Parameters in Habitat-Selection Analyses." *Journal of Animal Ecology* 90 (5): 1027–43.

Forester, James D, Hae Kyung Im, and Paul J Rathouz. 2009. "Accounting for Animal Movement in Estimation of Resource Selection Functions: Sampling and Data Analysis." *Ecology* 90 (12): 3554–65.

Fraser, Douglas F, James F Gilliam, Michael J Daley, An N Le, and Garrick T Skalski. 2001. "Explaining Leptokurtic Movement Distributions: Intrapopulation Variation in Boldness and Exploration." *The American Naturalist* 158 (2): 124–35.

Giroux, Aline, Zaida Ortega, Nina Attias, Arnaud Léonard Jean Desbiez, Denis Valle, Luca Börger, and Luiz Gustavo Rodrigues Oliveira-Santos. 2023. "Activity Modulation and Selection for Forests Help Giant Anteaters to Cope with Temperature Changes." *Animal Behaviour*.

Hertel, Anne G, Martin Leclerc, Dan Warren, Fanie Pelletier, Andreas Zedrosser, and Thomas Mueller. 2019. "Don't Poke the Bear: Using Tracking Data to Quantify Behavioural Syndromes in Elusive Wildlife." *Animal Behaviour* 147: 91–104.

Hertel, Anne G, Petri T Niemelä, Niels J Dingemanse, and Thomas Mueller. 2020. "A Guide for Studying Among-Individual Behavioral Variation from Movement Data in the Wild." *Movement Ecology* 8 (1): 1–18.

Hooten, Mevin B, Devin S Johnson, Brett T McClintock, and Juan M Morales. 2017. *Animal Movement: Statistical Models for Telemetry Data*. CRC press.

Jeltsch, Florian, Dries Bonte, Guy Pe'er, Björn Reineking, Peter Leimgruber, Niko Balkenhol, Boris Schröder, et al. 2013. "Integrating Movement Ecology with Biodiversity Research-Exploring New Avenues to Address Spatiotemporal Biodiversity Dynamics." *Movement Ecology* 1 (1): 1–13.

Jones, Gavin M, H Anu Kramer, Sheila A Whitmore, William J Berigan, Douglas J Tempel, Connor M Wood, Brendan K Hobart, et al. 2020. "Habitat Selection by Spotted Owls After a Megafire Reflects Their Adaptation to Historical Frequent-Fire Regimes." *Landscape Ecology* 35: 1199–1213.

Joo, Rocio, Matthew E Boone, Thomas A Clay, Samantha C Patrick, Susana Clusella-Trullas, and Mathieu Basille. 2020. "Navigating Through the r Packages for Movement." *Journal of Animal Ecology* 89 (1): 248–67.

Kays, Roland, Margaret C Crofoot, Walter Jetz, and Martin Wikelski. 2015. "Terrestrial Animal Tracking as an Eye on Life and Planet." *Science* 348 (6240): aaa2478.

Levin, Simon A. 1992. "The Problem of Pattern and Scale in Ecology: The Robert h. MacArthur Award Lecture." *Ecology* 73 (6): 1943–67.

Magnusson, Arni, Hans Skaug, Anders Nielsen, Casper Berg, Kasper Kristensen, Martin Maechler, Koen van Bentham, Ben Bolker, Mollie Brooks, and Maintainer Mollie Brooks. 2017. "Package 'Glmmtmb'." *R Package Version 0.2. 0*.

Matthiopoulos, Jason, Mark Hebblewhite, Geert Aarts, and John Fieberg. 2011. "Generalized Functional Responses for Species Distributions." *Ecology* 92 (3): 583–89.

Muff, Stefanie, Johannes Signer, and John Fieberg. 2020. "Accounting for Individual-Specific Variation in Habitat-Selection Studies: Efficient Estimation of Mixed-Effects Models Using Bayesian or Frequentist Computation." *Journal of Animal Ecology* 89 (1): 80–92.

Neumann, Wiebke, Sebastian Martinuzzi, Anna B Estes, Anna M Pidgeon, Holger Dettki, Göran Ericsson, and Volker C Radeloff. 2015. "Opportunities for the Application of Advanced Remotely-Sensed Data in Ecological Studies of Terrestrial Animal Movement." *Movement Ecology* 3: 1–13.

Northrup, Joseph M., Eric Vander Wal, Maegwin Bonar, John Fieberg, Michel P. Laforge, Martin Leclerc, Christina M. Prokopenko, and Brian D. Gerber. 2022. "Conceptual and Methodological Advances in Habitat-Selection Modeling: Guidelines for Ecology and Evolution." *Ecological Applications* 32 (1): e02470. https://doi.org/https://doi.org/10.1002/eap.2470.

Potts, Jonathan R., and Luca Börger. 2023. "How to Scale up from Animal Movement Decisions to Spatiotemporal Patterns: An Approach via Step Selection." *Journal of Animal Ecology* 92 (1): 16–29. https://doi.org/https://doi.org/10.1111/1365-2656.13832.

Prokopenko, Christina M, Mark S Boyce, and Tal Avgar. 2017. "Characterizing Wildlife Behavioural Responses to Roads Using Integrated Step Selection Analysis." *Journal of Applied Ecology* 54 (2): 470–79.

R Core Team. 2020. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org.

Scrafford, Matthew A, Tal Avgar, Rick Heeres, and Mark S Boyce. 2018. "Roads Elicit Negative Movement and Habitat-Selection Responses by Wolverines (Gulo Gulo Luscus)." *Behavioral Ecology* 29 (3): 534–42.

Shaw, Allison K. 2020. "Causes and Consequences of Individual Variation in Animal Movement." *Movement Ecology* 8 (1): 12.

Signer, Johannes, John Fieberg, and Tal Avgar. 2017. "Estimating Utilization Distributions from Fitted Step-Selection Functions." *Ecosphere* 8 (4): e01771.

———. 2019. "Animal Movement Tools (Amt): R Package for Managing Tracking Data and Conducting Habitat Selection Analyses." *Ecology and Evolution* 9 (2): 880–90.

Spiegel, Orr, Stephan T. Leu, C. Michael Bull, and Andrew Sih. 2017. "What's Your Move? Movement as a Link Between Personality and Spatial Dynamics in Animal Populations." *Ecology Letters* 20 (1): 3–18. https://doi.org/https://doi.org/10.1111/ele.12708.

Szedlmayer, Stephen T, and Jason D Lee. 2004. "Diet Shifts of Juvenile Red Snapper (*Lutjanus Campechanus*) with Changes in Habitat and Fish Size." *Fishery Bulletin* 102 (2): 366–75.

Webber, Quinn M. R., Gregory F. Albery, Damien R. Farine, Noa Pinter-Wollman, Nitika Sharma, Orr Spiegel, Eric Vander Wal, and Kezia Manlove. 2023. "Behavioural Ecology at the Spatial–Social Interface." *Biological Reviews* 98 (3): 868–86. https://doi.org/https://doi.org/10.1111/brv.12934.

Webber, Quinn M. R., Michel P. Laforge, Maegwin Bonar, Alec L. Robitaille, Christopher Hart, Sana Zabihi-Seissan, and Eric Vander Wal. 2020. "The Ecology of Individual Differences Empirically Applied to Space-Use and Movement Tactics." *The American Naturalist* 196 (1): E1–15. https://doi.org/10.1086/708721.

Wells, RJ David, James H Cowan Jr, and Brian Fry. 2008. "Feeding Ecology of Red Snapper *Lutjanus Campechanus* in the Northern Gulf of Mexico." *Marine Ecology Progress Series* 361: 213–25.

White, D Byron, and Sandra M Palmer. 2004. "Age, Growth, and Reproduction of the Red Snapper, *Lutjanus Campechanus*, from the Atlantic Waters of the Southeastern US." *Bulletin of Marine Science* 75 (3): 335–60.

Williams-Grove, Laura Jay, and Stephen T Szedlmayer. 2016. "Acoustic Positioning and Movement Patterns of Red Snapper *Lutjanus Campechanus* Around Artificial Reefs in the Northern Gulf of Mexico." *Marine Ecology Progress Series* 553: 233–51.

———. 2017. "Depth Preferences and Three-Dimensional Movements of Red Snapper, *Lutjanus Campechanus*, on an Artificial Reef in the Northern Gulf of Mexico." *Fisheries Research* 190: 61–70.

Wilson, Charles A, and David L Nieland. 2001. "Age and Growth of Red Snapper, *Lutjanus Campechanus*, from the Northern Gulf of Mexico Off Louisiana." *Fishery Bulletin* 99 (4): 653–65.

Appendix

5.1 Supplemtary Table

Table 1: Number of locations, start and end dates, and number of days tracked for individual fish in the study.

id	Relocations	Start time	End time	No. of days tracked
2	18814	2019-05-07 08:32:37	2019-09-15 05:21:32	131
3	20785	2019-05-07 08:43:54	2019-08-28 10:42:55	113
4	604	2019-05-07 09:36:17	2019-05-10 18:58:42	3
5	15201	2019-05-07 08:53:12	2019-08-13 16:53:59	98
6	799	2019-05-07 08:57:33	2019-06-05 05:27:29	29
7	2755	2019-05-07 09:00:13	2019-06-26 17:22:27	50
8	16635	2019-05-07 09:19:17	2019-08-27 11:04:43	112
9	21297	2019-05-07 10:10:58	2019-12-16 07:51:58	223
10	4698	2019-05-07 10:33:04	2019-05-26 12:02:14	19
11	1290	2019-05-07 10:37:17	2019-06-19 09:57:00	43
12	22384	2019-05-07 10:56:51	2019-08-01 04:59:41	86
14	265	2019-05-07 11:06:47	2019-07-27 06:55:55	81
15	3005	2019-05-07 11:11:24	2019-05-20 17:51:28	13
16	52189	2019-05-07 11:19:54	2019-12-16 07:48:31	223
17	20316	2019-05-07 11:12:51	2019-07-29 07:58:04	83
18	5208	2019-05-07 11:30:55	2019-07-01 05:01:34	55
19	13505	2019-05-07 13:00:15	2019-07-14 05:40:40	68
20	12427	2019-05-07 12:53:10	2019-08-29 02:28:48	114
22	6755	2019-05-07 13:26:23	2019-06-20 03:29:39	44
23	1316	2019-05-07 14:14:46	2019-05-14 07:54:02	7
25	7979	2019-08-13 09:38:49	2019-11-11 12:04:01	90
26	1309	2019-08-13 10:16:40	2019-09-25 21:53:27	43
27	15277	2019-08-13 10:22:06	2019-12-15 16:15:58	124
29	4370	2019-08-13 10:30:32	2019-09-16 05:59:46	34
31	12774	2019-08-13 10:20:52	2019-11-09 09:57:45	88
32	7208	2019-08-13 11:00:50	2019-10-12 06:52:30	60
33	8586	2019-08-13 10:48:59	2019-09-30 06:55:07	48
37	22483	2019-08-13 12:30:40	2019-12-02 00:37:00	111
38	1766	2019-08-13 13:13:12	2019-12-15 16:14:22	124
39	3299	2019-08-13 12:49:03	2019-12-15 15:50:52	124
40	969	2019-08-13 12:54:02	2019-12-10 18:07:51	119
41	2324	2019-08-13 12:53:17	2019-12-15 16:18:55	124
42	450	2019-08-13 13:11:03	2019-11-27 06:28:52	106
46	10996	2019-08-30 11:39:53	2019-11-12 08:21:11	74
49	6253	2019-09-22 08:31:50	2019-11-06 04:51:00	45

Table 2: Coefficient estimates (95% CI) of the variables used in Model 1 and Model 2. Stars denote the significant p-value (+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001).

Variable	Model 1	Model 2
sl_	-0.005 [-0.012, 0.002]	-0.007 [-0.015, 0.000]+
log_sl_	0.108 [0.042, 0.173]**	0.072 [0.004, 0.140]*
cos(ta_)	-0.855 [-0.927, -0.782]***	-0.893 [-0.962, -0.823]***
reefEnd	0.247 [0.162, 0.332]***	0.235 [0.151, 0.318]***
distance to reefedge	-0.013 [-0.021, -0.005]**	-0.023 [-0.032, -0.014]***
sl_ × reefStart	-0.015 [-0.017, -0.012]***	NA
log_sl_ × reefStart	0.053 [0.029, 0.076]***	NA
cos(ta_) × reefStart	0.036 [-0.004, 0.076]+	NA
sl_ × distance to reefedge	NA	0.000 [0.000, 0.000]***
log_sl_ × distance to reefedge	NA	0.006 [0.005, 0.008]***
cos(ta_) × distance to reefedge	NA	0.006 [0.004, 0.007]***
SD (sl_ id)	0.02	0.021
SD (log_sl_ id)	0.175	0.181
SD (cos(ta_) id)	0.182	0.173
SD (distance to reefedge id)	0.021	0.023
SD (reefEnd id)	0.208	0.203
Cor (sl_~log_sl_ id)	-0.948	-0.942
Cor (sl_~cos(ta_) id)	0.254	0.321
Cor (log_sl_~cos(ta_) id)	-0.194	-0.257
Num.Obs.	465488	465586
R2 Marg.	1	1
R2 Cond.	NA	NA
AIC	182377.9	182695.3
BIC	182576.8	182894.3
RMSE	0.22	0.22

reefStart and *reefEnd* indicate the habitat class at the start or end of the step, respectively. *sl_* stands for step length, *log_sl_* stands for the log(step length) and *cos(ta_)* stands for the cosine of turn angle

Table 3: Estimated parameters in statistical distributions used to model step length and turn angles as a function of benthic habitat class (model 1) or distance to edge (model 2). The mean of the step-length distribution was calculated assuming a gamma distribution and the sd error was calculated using the delta method. The tentative distribution was observed from data and then movement parameters were updated using the coefficients of reef-class from model 1 and the distance to reef edge variable from model 2.

	shape	scale	mean	sd	kappa
Tentative	1.090	18.240	19.884	1.382	0.348
Sand	1.198	16.794	20.115	1.305	-0.506
Reef	1.251	13.505	16.890	0.820	-0.470
5%_quantile	1.162	16.088	18.697	0.906	-0.544
50%_quantile	1.181	15.895	18.777	0.904	-0.504
95%_quantile	1.417	13.851	19.628	0.879	-0.318

5.2 Supplementary figures

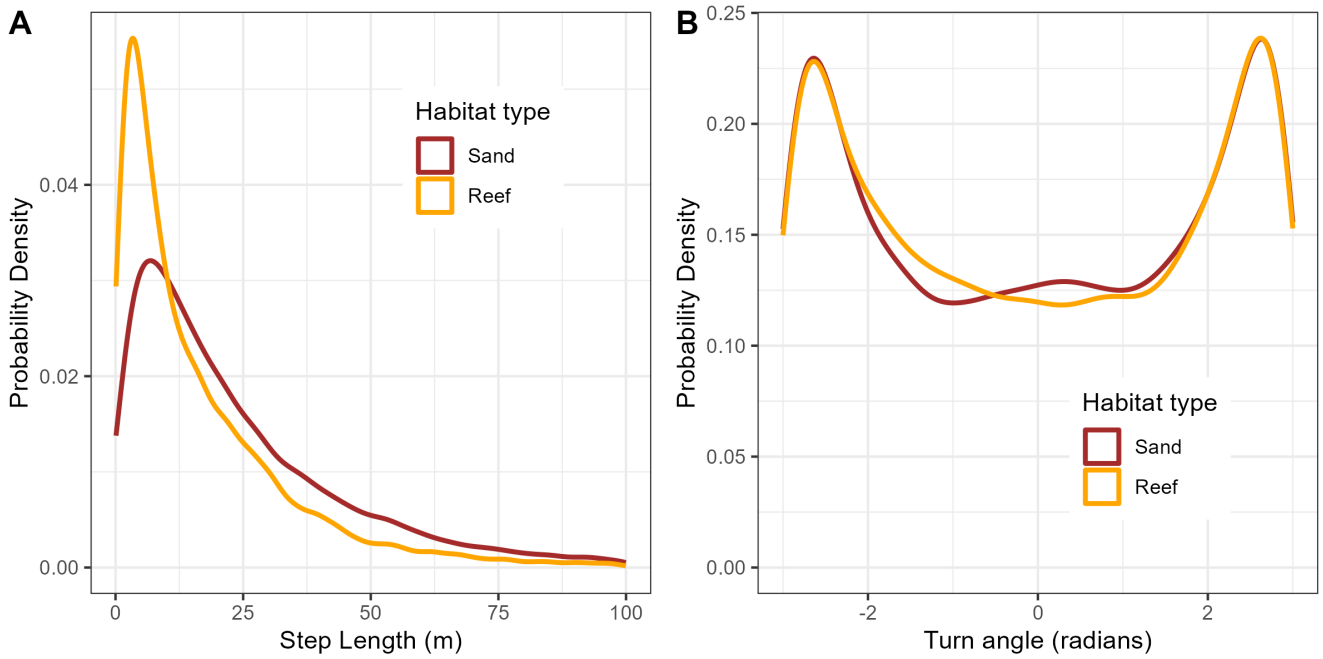

Figure 5: Empirical distribution of step lengths (m) and turn angles (radians) using data pooled across 35 red snappers and resampled with a fix-interval of six minutes

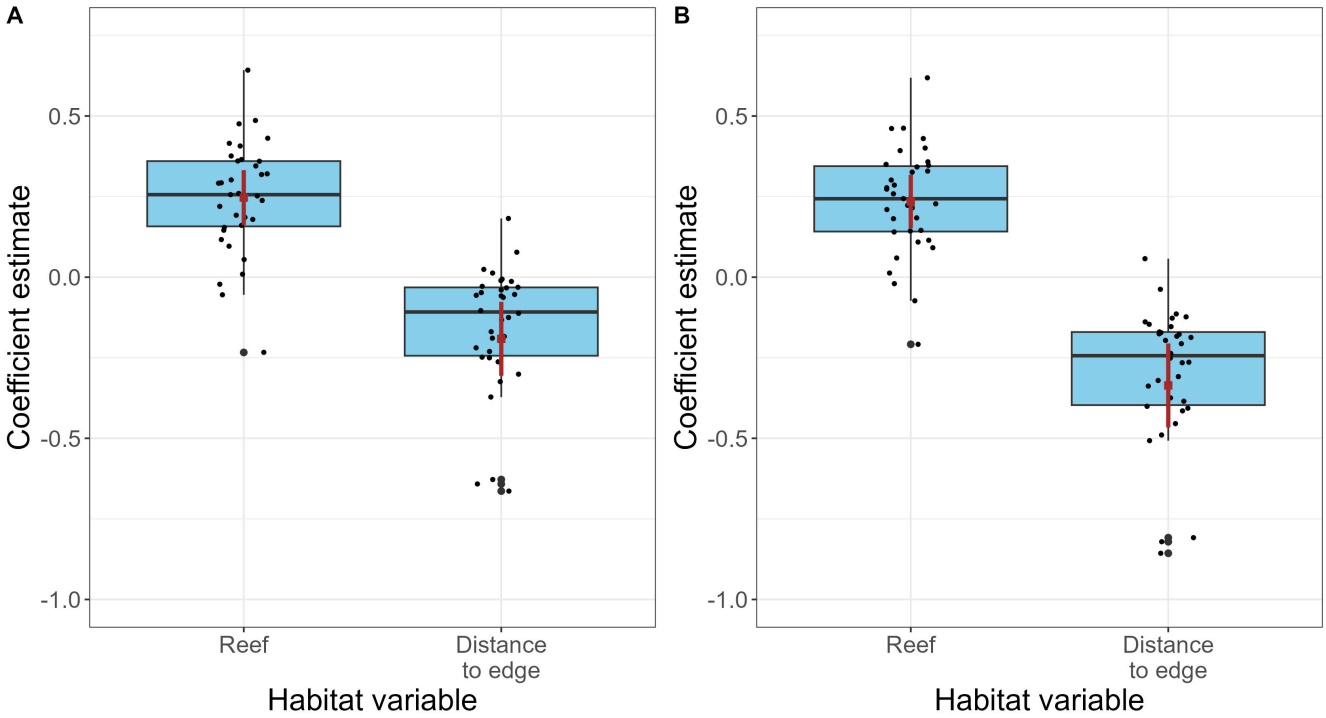

Figure 6: Box plot summarizing the individual habitat-selection coefficients (black dots) associated with hardbottom habitat and the distance-to-edge covariate from Model 1 (A) and Model 2(B). Boxes bound the 25th and 75th percentiles, solid line within the box indicates the median, and the whiskers extend to 1.5 times the interquartile range of the observations. The mean coefficient, along with a 95% confidence interval for the mean, is depicted in brown.

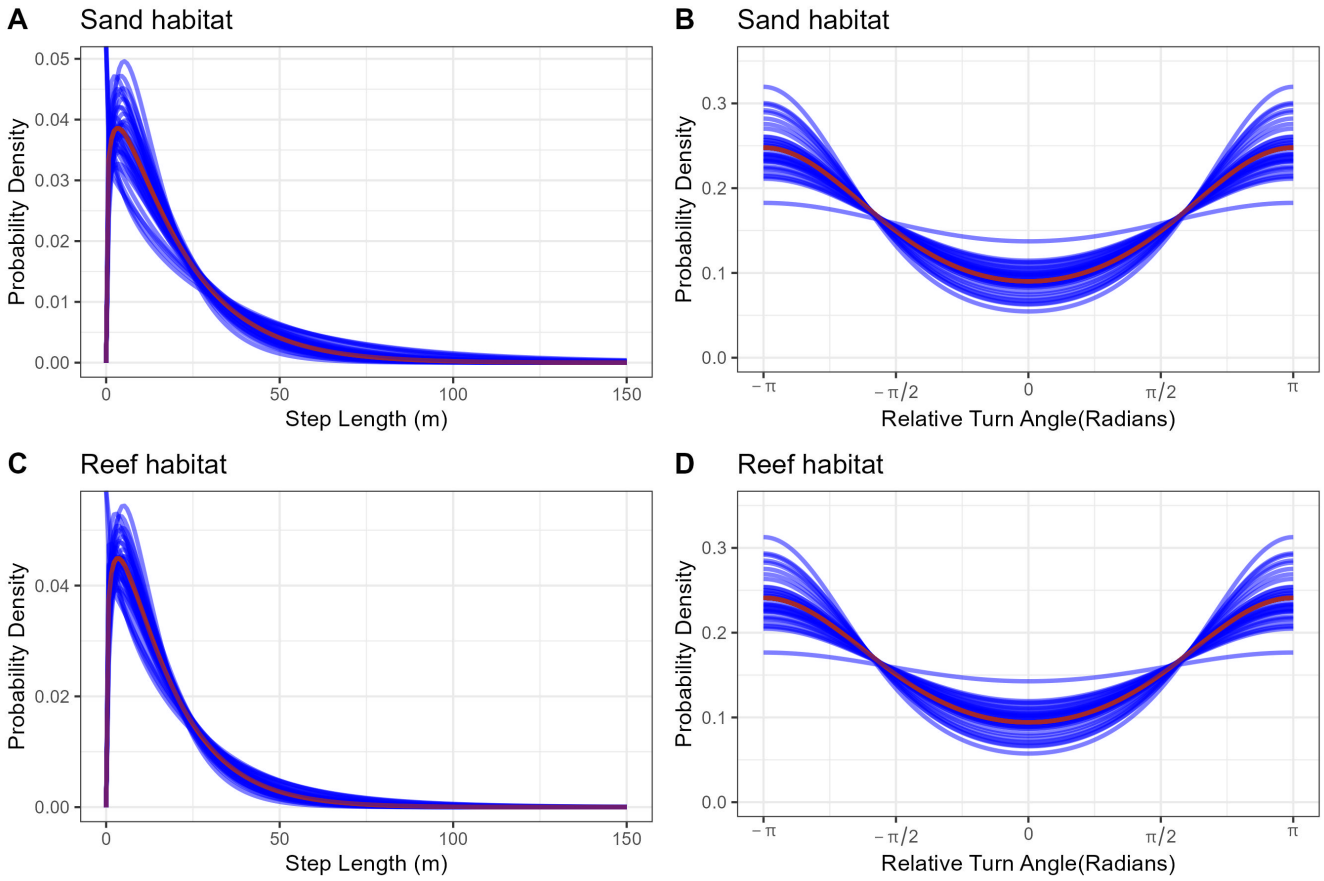

Figure 7: Estimated step length and turn angle distributions for different individuals (blue) and for a typical individual (i.e., an individual with all random effects set to 0)(red) in sand (A-B) and hardbottom habitats (C-D).