A comparison of statistical models used to characterize species-habitat associations with movement data: Appendix 3

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# Overview

This document contains a coding tutorial that demonstrates how to perform the analyses associated with the case study in “*A comparison of statistical models used to characterize species-habitat associations with movement data*”. All analyses link the movement data of a ringed seal in eastern Hudson Bay, Canada, to modeled prey diversity.

# Set-up

## Load packages

# data wrangling  
library(here)  
library(tidyverse)  
library(lubridate)  
  
# mapping  
library(rnaturalearth)  
library(rgdal)  
library(terra)  
library(tidyterra)  
library(sf)  
library(viridis)  
  
# fitting models  
library(amt) # for selection functions  
library(momentuHMM) # for hidden Markov model  
  
# plotting  
library(ggplot2)

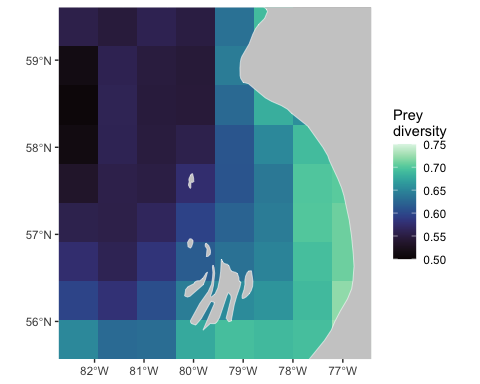
## Prey diversity data

Next we load in the fish data, which contains the spatial distribution of prey diversity in 2012. The data is in a .csv, and we will rasterize this using it’s specific coordinate reference system. This is a subset of the data from Florko et al. (2021a, 2021b).

# load prey diversity data  
fish <- read.csv(here("data/fish.csv"))  
  
# rasterize prey diversity data  
fish\_raster <- terra::rast(fish, crs = "+proj=laea +lat\_0=60 +lon\_0=-85 +x\_0=0 +y\_0=0 +datum=WGS84 +units=m +no\_defs +ellps=WGS84 +towgs84=0,0,0")

Visualize the fish data.

# prepare land data for mapping  
natearth <- ne\_countries(scale = "medium",returnclass = "sf")  
natearth <- natearth[which(natearth$continent!="Antarctica"),]  
  
# projection: project land to match fish raster   
nat\_trans <- st\_transform(natearth, crs(fish\_raster))  
  
# plot fish map  
fishmap <- ggplot() +   
 tidyterra::geom\_spatraster(data = fish\_raster) +  
 scale\_fill\_viridis(option = "mako", limits = c(0.5, 0.75), name = "Prey\ndiversity") +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F)  
fishmap



## Seal data

Next we load in one movement track from a ringed seal equipped with an ARGOS satellite telemetry transmitter over the course of over four months in the winter of 2012-2013. This is a subset of the data from Florko et al. (2023a).

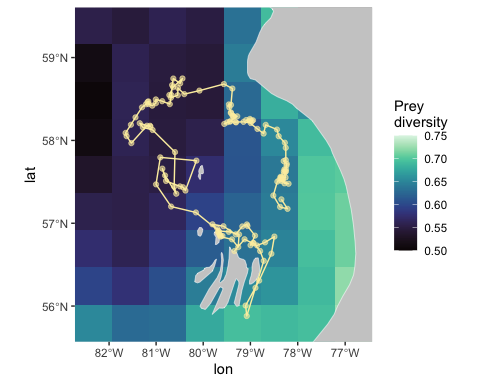
# load seal data  
seal <- read.csv(here("data/seal\_track\_m.csv"))   
head(seal)

## lon lat date id  
## 1 357940.9 -368949.6 2012-10-29 14:00 116484\_1  
## 2 371594.3 -353092.9 2012-10-30 14:00 116484\_1  
## 3 388429.2 -361478.4 2012-10-31 14:00 116484\_1  
## 4 399326.2 -357288.1 2012-11-01 14:00 116484\_1  
## 5 411788.2 -349500.7 2012-11-02 14:00 116484\_1  
## 6 407708.1 -372564.6 2012-11-03 14:00 116484\_1

# ensure the data is in the correct format  
seal <- seal %>%  
 mutate(id = as.character(id),  
 date = as.Date(date))

Visualize the seal data on top of the fish data.

# plot seal and fish data together  
sealfishmap <- fishmap +   
 geom\_point(data=seal, aes(x=lon, y=lat), alpha = 0.6, color = "#FCEEAE") +   
 geom\_path(data=seal, aes(x=lon, y=lat), color = "#FCEEAE")   
  
sealfishmap



# Fit models

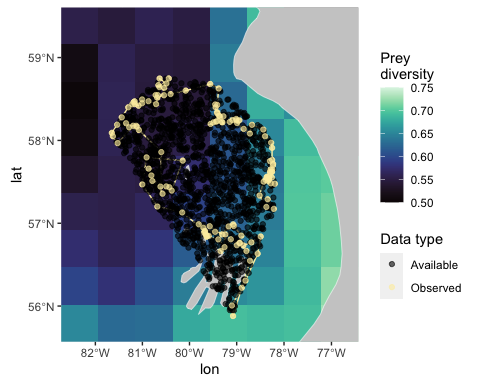
We will fit four models: 1) a resource selection function (RSF), 2) a step selection function (SSF) without habitat covariates in the movement kernel, 3) a SSF with a habitat covariate modifying the movement kernel, and 4) a hidden Markov model (HMM). All four of these models will include prey diversity as a covariate.

All of the step selection functions (both the RSF and two SSFs) will be fit using the amt package (Signer et al. 2019), while the HMM will use the functions from the momentuHMM package (McClintok and Michelot 2018).

## RSF

The RSF is the simplest of the four models. Fitting an RSF to movement data first requires us to generate a sample of availability points and extract covariates for the used and available locations.

# prep data and generate availability sample  
set.seed(2023)  
data\_rsf <- seal %>%  
 make\_track(lon, lat, date) %>% # convert data to track format  
 random\_points() # generate availability sample; default is ten times as many available points as observed points  
  
# plot used vs available locations on-top of prey diversity  
data\_rsf\_map <- sealfishmap +  
 geom\_point(data=data\_rsf, aes(x=x\_, y=y\_, color = case\_), alpha = 0.6) +  
 scale\_color\_manual(values = c("black", "#FCEEAE"),   
 label = c("Available", "Observed"), name = "Data type")   
data\_rsf\_map



We can see that the availability sample is generated within the minimum convex polygon of the used samples.

We now extract covariate (prey diversity) values for the used and available locations.

data\_rsf <- data\_rsf %>%  
 extract\_covariates(fish\_raster)

Next, we will fit the model. The response, case\_, is the used or available location, and preydiv is the covariate for prey diversity.

# fit rsf (a binomial logistic regression)  
rsf1 <- data\_rsf %>%  
 amt::fit\_rsf(case\_ ~ preydiv, model = TRUE)

View the summary.

# see model summary  
summary(rsf1)

##   
## Call:  
## stats::glm(formula = formula, family = stats::binomial(link = "logit"),   
## data = data, model = TRUE)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -0.5753 -0.4729 -0.4294 -0.3754 2.3363   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -6.118 1.400 -4.369 1.25e-05 \*\*\*  
## preydiv 6.353 2.312 2.748 0.006 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 938.28 on 1539 degrees of freedom  
## Residual deviance: 930.60 on 1538 degrees of freedom  
## AIC: 934.6  
##   
## Number of Fisher Scoring iterations: 5

We see that prey diversity is a significant positive covariate. We do not interpret the intercept, since it is not ecologically meaningful in a RSF. See Fieberg et al. (2021) for a detailed discussion on how to interpret parameters.

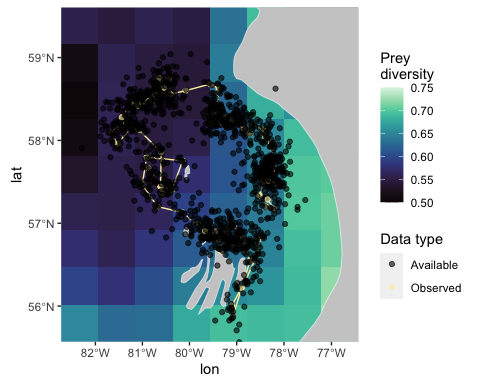
## SSF

Next we will fit our two SSFs. The workflow is similar to that of the RSF, however, the availability sample is generated differently. We transform the seal locations into a track format, then convert the track data into step format (i.e., with a start and an end), and then generate the availability sample.

# prep data and generate availability sample  
set.seed(2023)  
data\_ssf <- seal %>%  
 make\_track(lon, lat, date) %>% # convert data to track format  
 steps() %>% # convert track data to step format (i.e., with a start and an end)  
 random\_steps() # generate availability sample

Visualize the sample created.

# plot used vs available locations on-top of prey diversity  
data\_ssf\_map <- sealfishmap +  
 geom\_point(data=data\_ssf, aes(x=x2\_, y=y2\_, color = case\_), alpha = 0.6) +  
 scale\_color\_manual(values = c("black", "#FCEEAE"),   
 label = c("Available", "Observed"), name = "Data type")   
data\_ssf\_map



We can see that the availability sample is generated at each step and is not restricted to the minimum convex polygon.

We now extract prey diversity values for the used and available locations.

# extract prey diversity covariate  
data\_ssf <- data\_ssf %>%  
 extract\_covariates(fish\_raster, where = "end") #sample at end of step

We will transform both the step length and turning angle using log and cosine transformations, respectively.

# transform movement covariates  
data\_ssf <- data\_ssf %>%  
 mutate(cos\_ta = cos(ta\_),  
 log\_sl = log(sl\_))

Next, we will fit the models. The response, case\_, is used or available location, and preydiv is the covariate for prey diversity. log\_sl is the log transformation of step length, and cos\_ta is the cosine transformation of turning angle. strata(step\_id\_) specifies that the this is a *conditional* logistic regression that groups data by step identification number.

We are fitting two SSFs: one without a movement-related covariate (called ssf1), and one with a movement-related covariate (called ssf2).

# fit ssfs  
## ssf1: ssf without covariate affecting movement kernel  
ssf1 <- data\_ssf %>%  
 fit\_clogit(case\_ ~ preydiv + log\_sl + cos\_ta + strata(step\_id\_), model = TRUE)  
  
## ssf2: ssf with covariate affecting movement kernel  
ssf2 <- data\_ssf %>%  
 fit\_clogit(case\_ ~ preydiv\*log\_sl + cos\_ta + strata(step\_id\_), model = TRUE)

First we will interpret ssf1.

# see model summary  
summary(ssf1)

## Call:  
## coxph(formula = Surv(rep(1, 1518L), case\_) ~ preydiv + log\_sl +   
## cos\_ta + strata(step\_id\_), data = data, model = TRUE, method = "exact")  
##   
## n= 1516, number of events= 138   
## (2 observations deleted due to missingness)  
##   
## coef exp(coef) se(coef) z Pr(>|z|)  
## preydiv 0.957799 2.605953 6.772711 0.141 0.888  
## log\_sl -0.008404 0.991631 0.083328 -0.101 0.920  
## cos\_ta 0.031707 1.032215 0.130643 0.243 0.808  
##   
## exp(coef) exp(-coef) lower .95 upper .95  
## preydiv 2.6060 0.3837 4.477e-06 1.517e+06  
## log\_sl 0.9916 1.0084 8.422e-01 1.168e+00  
## cos\_ta 1.0322 0.9688 7.990e-01 1.333e+00  
##   
## Concordance= 0.494 (se = 0.029 )  
## Likelihood ratio test= 0.09 on 3 df, p=1  
## Wald test = 0.09 on 3 df, p=1  
## Score (logrank) test = 0.09 on 3 df, p=1

This model estimates the coefficients (coef) as well as the exponent of the coefficient (exp(coef)). The coefficients are as in our regular logistic regression (the RSF), and the exp(coef) quantifies the relative intensity of use of two locations that differ by 1 unit of prey diversity but are otherwise the same. The model suggests our seal would be 2.6 times more likely to choose a location with 1 unit higher prey diversity (see Fieberg et al. 2021). However, this is not significant (p = 0.888), and we see that the scale of prey diversity is much smaller (range = 0.5-0.75), and thus an increase in of 2.6 times per 1 unit prey diversity is not a meaningful increase.

We don’t interpret the values of log\_sl or cos\_ta, since we don’t expect those to affect occurrence since the availability sample is generated using the step length and turning angle from the observed track.

We also see that we get a warning “2 observations deleted due to missingness”, due to two of our available locations being found on land, where we do not have fish values. This could be mitigated by generating more than 10 (i.e., 15) available locations per used location, omitting the samples without prey diversity values, and then randomly selecting 10 available locations per used location of those that have values for prey diversity.

Next we will interpret ssf2.

# see model summary  
summary(ssf2)

## Call:  
## coxph(formula = Surv(rep(1, 1518L), case\_) ~ preydiv \* log\_sl +   
## cos\_ta + strata(step\_id\_), data = data, model = TRUE, method = "exact")  
##   
## n= 1516, number of events= 138   
## (2 observations deleted due to missingness)  
##   
## coef exp(coef) se(coef) z Pr(>|z|)  
## preydiv 2.791e+01 1.318e+12 2.177e+01 1.282 0.200  
## log\_sl 1.663e+00 5.273e+00 1.286e+00 1.293 0.196  
## cos\_ta 2.338e-02 1.024e+00 1.311e-01 0.178 0.858  
## preydiv:log\_sl -2.744e+00 6.433e-02 2.101e+00 -1.306 0.192  
##   
## exp(coef) exp(-coef) lower .95 upper .95  
## preydiv 1.318e+12 7.589e-13 3.919e-07 4.430e+30  
## log\_sl 5.273e+00 1.897e-01 4.241e-01 6.556e+01  
## cos\_ta 1.024e+00 9.769e-01 7.917e-01 1.324e+00  
## preydiv:log\_sl 6.433e-02 1.555e+01 1.046e-03 3.955e+00  
##   
## Concordance= 0.555 (se = 0.029 )  
## Likelihood ratio test= 1.81 on 4 df, p=0.8  
## Wald test = 1.81 on 4 df, p=0.8  
## Score (logrank) test = 1.81 on 4 df, p=0.8

Similar to ssf1, we don’t see any significant relationships. Note that we also included a term for preydiv\*log\_sl. Since we have this interaction, preydiv and log\_sl can not be interpreted indepently, thus we interpret the interaction. The interaction is not signficant, so this model does not suggest that prey diversity affects the movement speed of our ringed seal.

## HMM

### 2-state HMMs

Finally, we will fit the HMM using momentuHMM (McClintock and Michelot, 2018). In preparation, we define initial parameters, and then update the parameters using our fit model, to ultimately fit a more refined model. We will first fit a two-state model.

This HMM example is parameterized to allow the covariate, prey diversity, influence the state transition probability. We can also allow covariates to influence the observation probabilities. These covariates are typically abiotic, but we show a brief example of how one would fit such a model below our main HMM.

## prepare the data  
data\_hmm <- seal %>%  
 make\_track(lon, lat, date) %>%  
 extract\_covariates(fish\_raster) %>%  
 mutate(ID = 1,  
 x = x\_,  
 y = y\_,  
 date = t\_) %>%  
 dplyr::select(ID, x, y, date, preydiv) %>%  
 as.data.frame() %>%  
 st\_as\_sf(coords = c("x", "y")) %>%  
 st\_set\_crs("+proj=laea +lat\_0=60 +lon\_0=-85 +x\_0=0 +y\_0=0 +datum=WGS84 +units=m +no\_defs +ellps=WGS84 +towgs84=0,0,0") %>%  
 st\_transform("+proj=longlat +datum=WGS84") %>%  
 mutate(long = unlist(map(geometry,1)),  
 lat = unlist(map(geometry,2))) %>%  
 st\_drop\_geometry()  
  
# calculate step length  
data\_hmm <- momentuHMM::prepData(data\_hmm, coordNames = c("long", "lat"), type = "LL", covNames = c("preydiv"))

#### Basic 2-state HMM

Define the starting parameters.

# define parameters  
nbStates <- 2 # number of states  
stepDist <- "gamma" # step distribution  
angleDist <- "vm" # turning angle distribution  
dist <- list(step=stepDist,angle=angleDist)  
  
mu0 <- c(8, 38) # mean step length for each state  
sigma0 <- c(8, 8) # sd step length for each state  
stepPar0 <- c(mu0, sigma0)  
kappa0 <- c(0.35, 0.35) # turning angle for each state

Fit the two-state HMM.

set.seed(2023)  
hmm\_trans\_2 <- momentuHMM::fitHMM(data=data\_hmm, nbStates=nbStates,  
 stateNames = c("Slow movement", "Moderate movement"),  
 dist=dist,  
 Par0=list(step=stepPar0,angle=kappa0),  
 retryFits = 2, retrySD = 3)

## Attempting to improve fit using random perturbation. Press 'esc' to force exit from 'fitHMM'  
## Attempt 1 of 2 -- current log-likelihood value: -702.4317 Attempt 2 of 2 -- current log-likelihood value: -702.4317

#### 2-states with covariate effects on transition probabilities

Here, we will explore adding effect of covariates on transition probabilities. Define transition probability model.

formula = ~ preydiv # identify covariates

Retrieve parameters to refine the model.

Par0\_hmm\_trans\_2 <- momentuHMM::getPar0(hmm\_trans\_2, formula=formula)

Note: when new covariates are added to using getPar0(), the intercept coefficients are taken from the previous model, while initial value for slope coefficients are set to 0. We can see this by comparing the estimated transition probability parameters from the previous model to the initial parameters prepared for the next model with covariates.

# transition probability matrix (TPM) parameters from hmm1\_km  
hmm\_trans\_2$mle$beta

## 1 -> 2 2 -> 1  
## (Intercept) -3.312105 -0.5739618

# initial parameters for hmm2\_km with effect of preydiv on TPM  
Par0\_hmm\_trans\_2$beta

## 1 -> 2 2 -> 1  
## (Intercept) -3.312105 -0.5739618  
## preydiv 0.000000 0.0000000

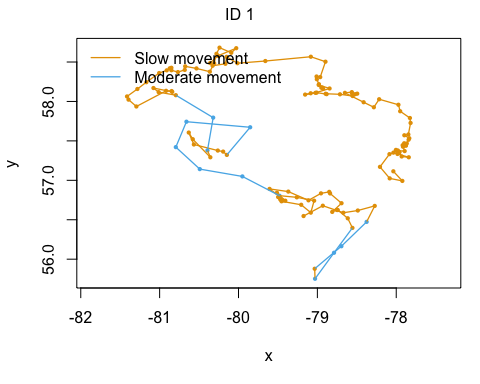
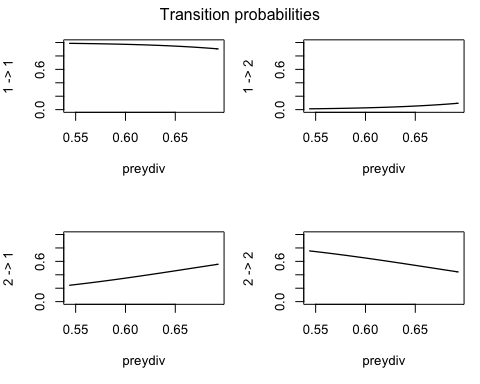
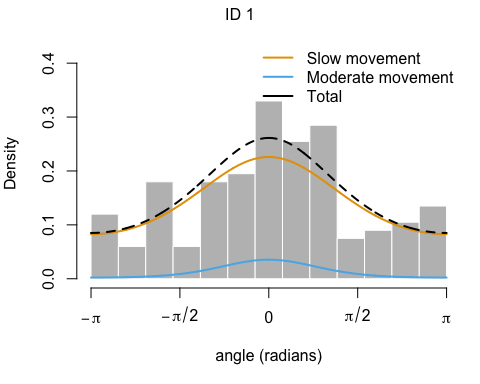
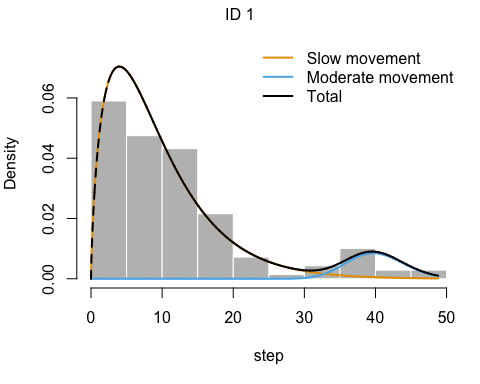
Fit a refined HMM with effect of prey diversity on transition probability using estimated parameters from the initial two-state HMM.

set.seed(2023)  
hmm\_trans\_2\_refined <- momentuHMM::fitHMM(data=data\_hmm, nbStates=2,  
 stateNames = c("Slow movement", "Moderate movement"),  
 dist=list(step=stepDist,angle=angleDist),  
 Par0=Par0\_hmm\_trans\_2$Par,  
 delta0 = Par0\_hmm\_trans\_2$delta,   
 beta0 = Par0\_hmm\_trans\_2$beta,  
 formula=formula)

Visualize the results.

plot(hmm\_trans\_2\_refined)

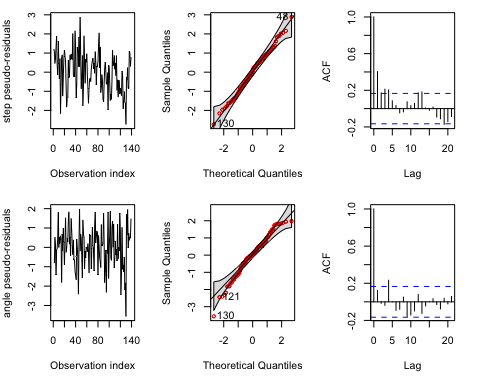
## Decoding state sequence... DONE



We can see from the step-length histogram and the map that it doesn’t look like this HMM is capturing the long step length movements as their own state. We can look at the pseudo-residuals of the model to confirm weather this is the case.

plotPR(hmm\_trans\_2\_refined)

## Computing pseudo-residuals...



We can see in the Q-Q plot for step length (top row, middle plot), that the observed step lengths (red points) are have a higher sample quantile than predicted by the model (shaded grey area) around the theoretical quantile around 1.5. This can be interpreted as the model predicting more steps around the 1.5th theoretical quantile than there are, or in other words, that the speed of steps around the 1.5th quantile are faster than the model predicts. This supports our previous conclusion that the model is not adequately capturing faster step lengths, which may be indicative of a missing state. There is also some autocorrelation in the step length (top row, right plot) above the dotted blue line, suggesting that the latent states do not explain all the variation in observed step length.

The residuals may be due to a missing state or missing effect of covariates on observation process. We will explore both of these.

#### 2-states with covariate effects on observation probabilities

First we define the functions for covariates on observation probabilities of step length mean and turn angle concentration.

distFormula <- ~ preydiv  
stepDM <- list(mean = distFormula, sd = distFormula)  
angleDM <- list(concentration = distFormula)  
DM <- list(step = stepDM, angle = angleDM)

Next we will define initial parameters for this model. Note, when including parameters on observation probabilities, initial parameters must be on the working scale (i.e., from negative to positive infinity). The following parameters were obtained from refitting the model with different starting parameters and using retryFits argument in fitHMM.

Par0\_hmm\_obs\_2 <- list(step = c(7, -9,   
 8, -8,  
 5, -6,   
 0.1, 3),  
 angle = c(7, -14,  
 3, -6))

Fit HMM.

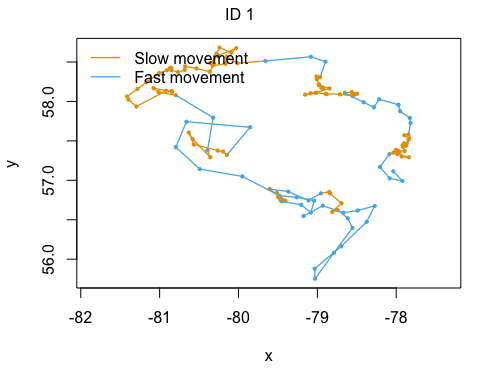
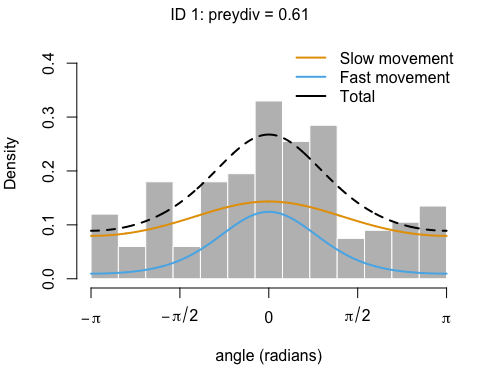
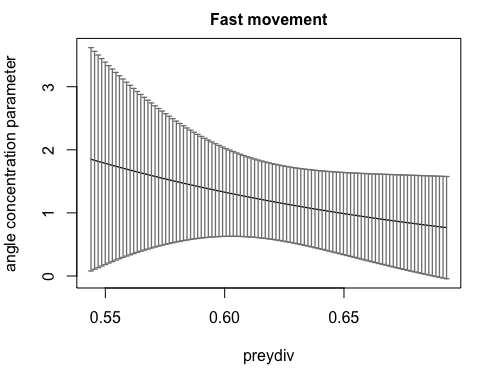
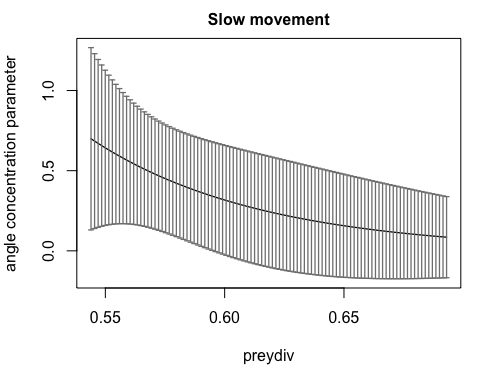
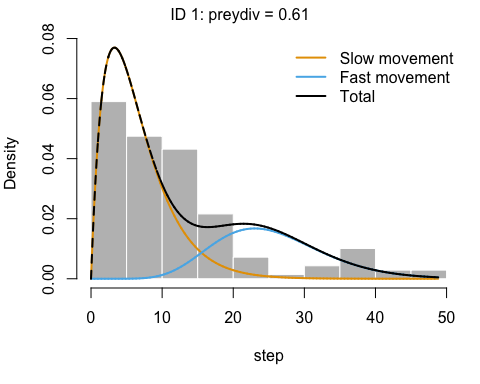
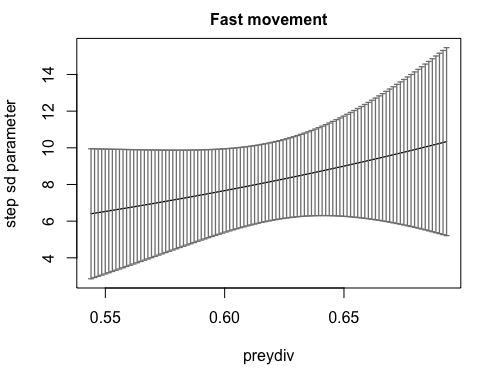
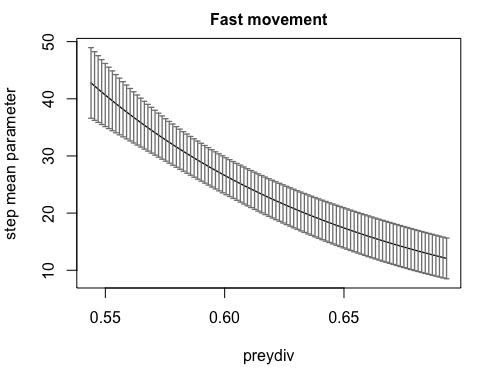
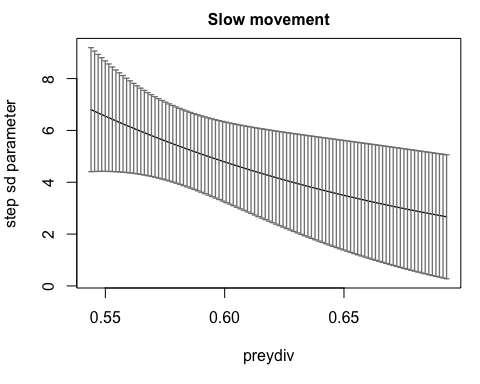
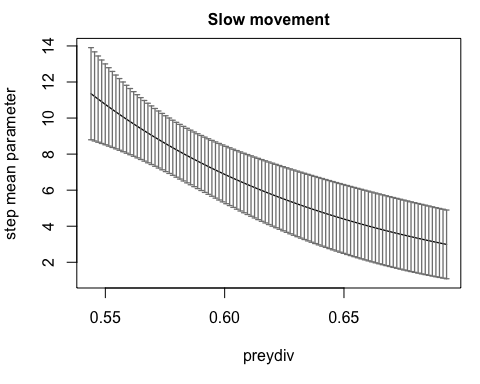
set.seed(2023)  
hmm\_obs\_2 <- momentuHMM::fitHMM(data=data\_hmm, nbStates=2,  
 stateNames = c("Slow movement", "Fast movement"),  
 dist=list(step=stepDist,angle=angleDist),  
 Par0 = Par0\_hmm\_obs\_2,  
 DM = DM,   
 retryFits = 2, retrySD = 3)

## Attempting to improve fit using random perturbation. Press 'esc' to force exit from 'fitHMM'  
## Attempt 1 of 2 -- current log-likelihood value: -692.1698 Attempt 2 of 2 -- current log-likelihood value: -692.1698

Visualize the results.

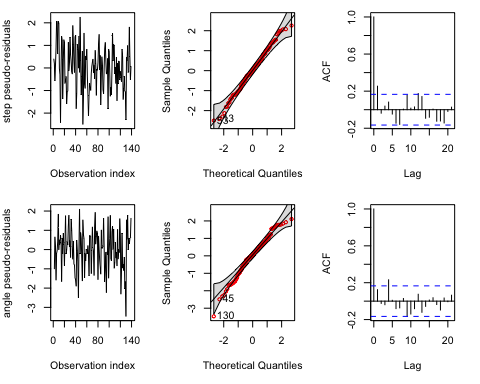
plot(hmm\_obs\_2, ask = F, plotCI = T)

## Decoding state sequence... DONE



plotPR(hmm\_obs\_2)

## Computing pseudo-residuals...



We see that when including covariates on a 2-state model, step length of both states decreases as preydiv increases. The mean step length of slow state varies from 12 to 4 with preydiv, while for the fast state, mean step length varies from 42 to 12. For both states, the turn angle concentration also decreases with prey div. In other words, as prey diversity increases, behaviors become slower and more tortuous. The decoded state map also looks like it’s adequately distinguishing faster travelling and slower resident states. Very importantly, we see that the Q-Q plots are significantly improved, with most of the data falling within the quantile bands. However, the ACF plots are not noticeably better than previous models, suggesting there is still latent autocorrelation we are not capturing.

### 3-state HMMs

Next, we will explore adding a third state to the HMM. We start with a basic HMM without any covariates, then explore adding covariates to transition and observation probabilities.

#### Basic 3-state HMM

First, we define starting parameters for a three-state HMM.

# define parameters  
nbStates <- 3 # number of states  
stepDist <- "gamma" # step distribution  
angleDist <- "vm" # turning angle distribution  
  
mu0 <- c(5, 12, 38) # mean step length for each state  
sigma0 <- c(3, 5, 8) # sd step length for each state  
stepPar0 <- c(mu0, sigma0)  
kappa0 <- c(0.35, 0.55, 0.5) # turning angle for each state

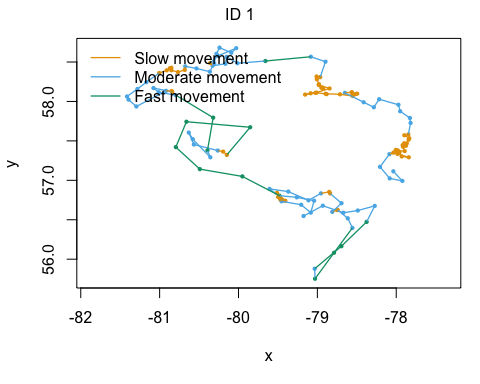
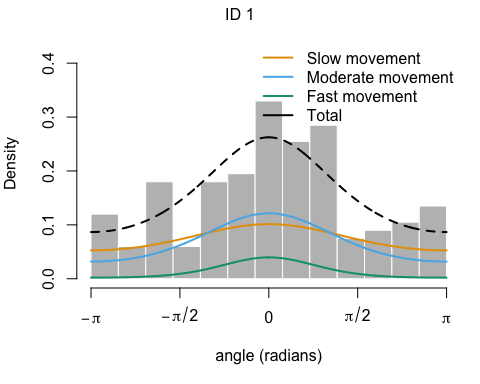
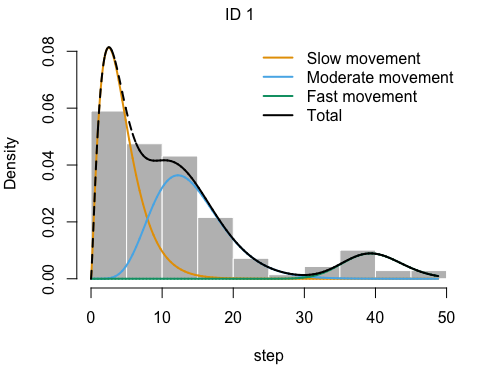
Fit the three-state HMM.

set.seed(2023)  
hmm\_3 <- momentuHMM::fitHMM(data=data\_hmm, nbStates=nbStates,  
 stateNames = c("Slow movement", "Moderate movement", "Fast movement"),  
 dist=list(step=stepDist,angle=angleDist),  
 Par0=list(step=stepPar0,angle=kappa0))

Explore model

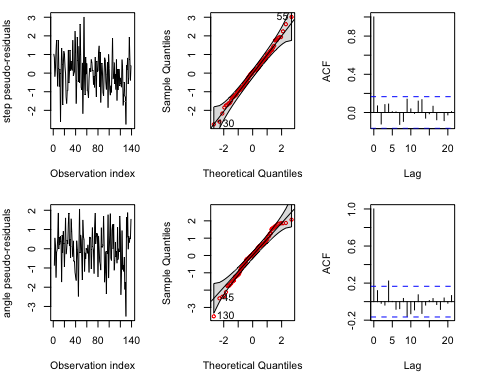
plot(hmm\_3, ask = F)

## Decoding state sequence... DONE



plotPR(hmm\_3)

## Computing pseudo-residuals...



The predicted state map seems to adequately capture slow, moderate, and fast movement. Importantly, both the Q-Q and ACF plots are significantly improved from previous 2-state models. Therefore, the remainder of our analysis will be built on the 3-state model.

#### 3-states with covariate effects on transition probabilities

Here, we will explore adding effects of covariates on the transition probabilities. Note that this is the most typical application of covariates to HMM, and this model is the main model we focus on in the main paper.

First, define transition probability model, and retrieve parameters to refine the model.

formula = ~ preydiv # identify covariates  
  
Par0\_hmm3 <- momentuHMM::getPar0(hmm\_3, formula=formula)

Fit a refined HMM with the parameters from the initial three-state HMM.

set.seed(2023)  
hmm\_trans\_3 <- momentuHMM::fitHMM(data=data\_hmm, nbStates=3,  
 stateNames = c("Slow movement", "Moderate movement", "Fast movement"),  
 dist=list(step=stepDist,angle=angleDist),  
 Par0=Par0\_hmm3$Par,  
 delta0 = Par0\_hmm3$delta,   
 beta0 = Par0\_hmm3$beta,  
 formula=formula)

We can view the parameters and regression coefficients for the transition probabilities.

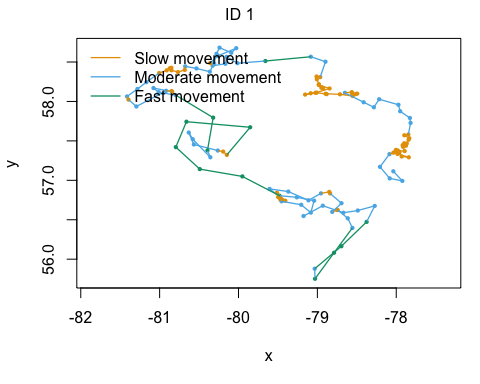
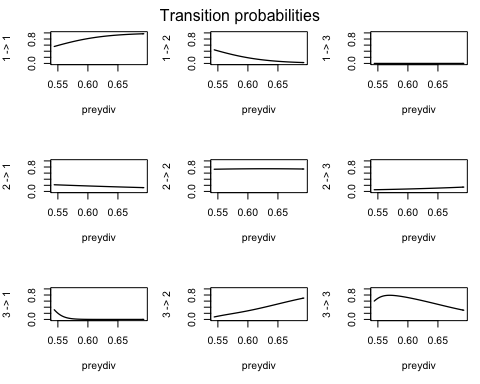
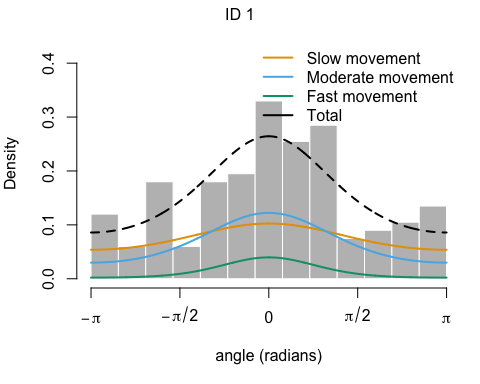
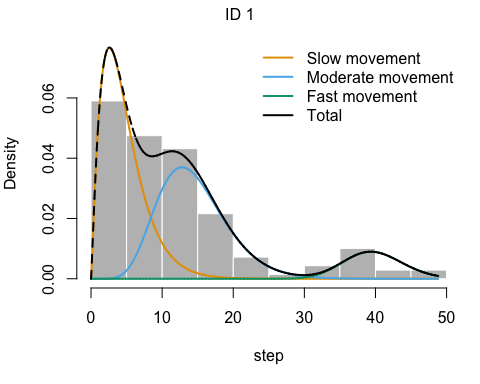
hmm\_trans\_3$CIbeta

## $step  
## $step$est  
## mean\_1:(Intercept) mean\_2:(Intercept) mean\_3:(Intercept) sd\_1:(Intercept)  
## [1,] 1.544323 2.669887 3.68362 1.144003  
## sd\_2:(Intercept) sd\_3:(Intercept)  
## [1,] 1.580641 1.424134  
##   
## $step$se  
## mean\_1:(Intercept) mean\_2:(Intercept) mean\_3:(Intercept) sd\_1:(Intercept)  
## [1,] 0.141362 0.05561547 0.02967768 0.2033532  
## sd\_2:(Intercept) sd\_3:(Intercept)  
## [1,] 0.132132 0.2030604  
##   
## $step$lower  
## mean\_1:(Intercept) mean\_2:(Intercept) mean\_3:(Intercept) sd\_1:(Intercept)  
## [1,] 1.267259 2.560883 3.625453 0.7454379  
## sd\_2:(Intercept) sd\_3:(Intercept)  
## [1,] 1.321667 1.026143  
##   
## $step$upper  
## mean\_1:(Intercept) mean\_2:(Intercept) mean\_3:(Intercept) sd\_1:(Intercept)  
## [1,] 1.821388 2.778892 3.741787 1.542568  
## sd\_2:(Intercept) sd\_3:(Intercept)  
## [1,] 1.839615 1.822125  
##   
##   
## $angle  
## $angle$est  
## concentration\_1:(Intercept) concentration\_2:(Intercept)  
## [1,] -1.132571 -0.3513391  
## concentration\_3:(Intercept)  
## [1,] 0.3820636  
##   
## $angle$se  
## concentration\_1:(Intercept) concentration\_2:(Intercept)  
## [1,] 0.5790591 0.3212703  
## concentration\_3:(Intercept)  
## [1,] 0.37962  
##   
## $angle$lower  
## concentration\_1:(Intercept) concentration\_2:(Intercept)  
## [1,] -2.267506 -0.9810172  
## concentration\_3:(Intercept)  
## [1,] -0.3619779  
##   
## $angle$upper  
## concentration\_1:(Intercept) concentration\_2:(Intercept)  
## [1,] 0.002364172 0.2783391  
## concentration\_3:(Intercept)  
## [1,] 1.126105  
##   
##   
## $beta  
## $beta$est  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) 11.95759 -28.98618 0.8889846 -6.008464 52.18805 -12.38337  
## preydiv -22.38610 0.00000 -3.8455964 6.298986 -97.11339 19.08809  
##   
## $beta$se  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) 6.490798 1.901943e-05 6.070081 7.694364 0.8924444 9.787294  
## preydiv 10.919036 NaN 9.973558 12.461283 0.5617634 15.703774  
##   
## $beta$lower  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) -0.7641397 -28.98622 -11.00815 -21.08914 50.43889 -31.56611  
## preydiv -43.7870196 NaN -23.39341 -18.12468 -98.21442 -11.69075  
##   
## $beta$upper  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) 24.679321 -28.98614 12.78612 9.072212 53.93721 6.799378  
## preydiv -0.985184 NaN 15.70222 30.722652 -96.01235 49.866916  
##   
##   
## $delta  
## $delta$est  
## Moderate movement Fast movement  
## (Intercept) 13.03817 -3.673484  
##   
## $delta$se  
## Moderate movement Fast movement  
## (Intercept) 0.002596365 0.01153526  
##   
## $delta$lower  
## Moderate movement Fast movement  
## (Intercept) 13.03308 -3.696092  
##   
## $delta$upper  
## Moderate movement Fast movement  
## (Intercept) 13.04326 -3.650875

It’s helpful to visualize the results for easier interpretation of the parameters and regression coefficients.

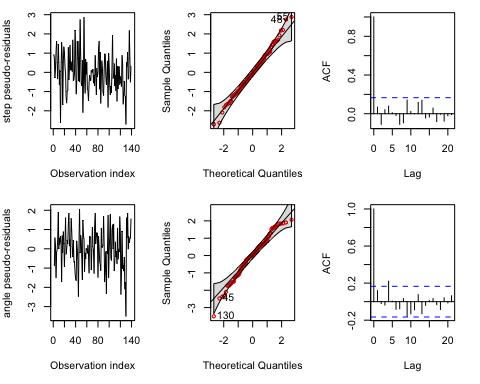
plot(hmm\_trans\_3)

## Decoding state sequence... DONE



plotPR(hmm\_trans\_3)

## Computing pseudo-residuals...



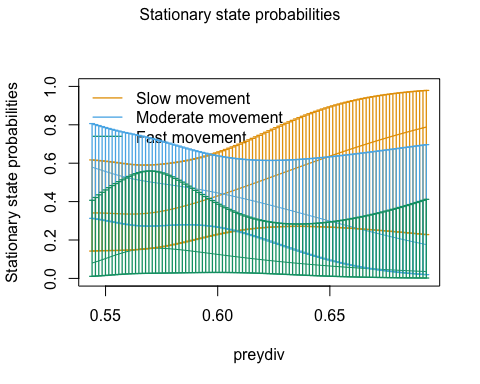
We can see that this three-state HMM does much better than the two-state HMM. We can see that those long step-lengths are captured in state 3, and the map of the decoded states appears to group different looking movement patterns as different states. Further, the pseudo-residual plot for step length looks much better, with the observed points in the Q-Q plot falling within the predicted Q-Q bands. As well, all the step length autocorrelation is below the blue line.

The plots show that as prey diversity increases, the step length mean appears to decrease during slow movement. Mean step length does not appear to change significantly during moderate movement. Due to low frequency of travelling state, the confidence intervals of effect of prey diversity on step length mean are unreliable.

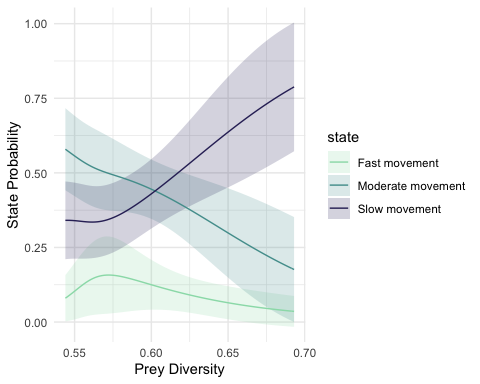
There is no significant effect of prey diversity in turn angle concentration on any state. While not significant in our data set, turn angle concentration may decrease as prey diversity increases during slow movement (i.e., becomes more tortuous), and may be worth exploring with larger sample sizes.

Last, there is no apparent effect of prey diversity on transitions from slow movement or moderate movement. However, as prey diversity increases, there appears to be a decrease in the transition probability from travel to slow movement, an increase in transition probability from fast to moderate movement, and a peak in remaining within the travelling state when prey diversity is around 0.57. However, the overall stationary state probability distribution does not appear to vary significantly when considering all state transitions:

statianary\_est <- plotStationary(hmm\_trans\_3, plotCI = TRUE, return = T) # returns a list of data frames with estimated stationary state distribution and confidence intervals (useful for plotting with ggplot)



# combine into long data.frame as required by ggplot  
statianary\_est <- dplyr::bind\_rows(statianary\_est[[1]]) %>%   
 mutate(state = rep(hmm\_trans\_3$stateNames, each = 101))  
  
# set colors  
colours.states <- c("#99DDB6", "#539D9C", "#312C66")  
  
# generate plot  
ggplot(statianary\_est, aes(x = cov, y = est, fill = state)) +   
 geom\_ribbon(aes(ymin = est-se, ymax = est+se), alpha = 0.2) +   
 geom\_line(aes(col = state)) +  
 scale\_colour\_manual(values = colours.states) +  
 scale\_fill\_manual(values = colours.states) +  
 ylab("State Probability") +   
 xlab("Prey Diversity") +  
 theme\_minimal()



This plot shows that the probability of being in the slow behavior, which is often of importance for conservation because it is thought to be associated with foraging, had a positive relationship with prey diversity, the probability of being in the moderate speed behavior decreases with prey diversity, and the probability of being in fast behavior remained relatively constant with prey diversity, with a potential peak in low-medium prey diversity.

#### 3-states with covariate effects on transition and observation probabilities

Here we allow prey diversity to influence the step length and turning angle in the observation probabilities. The covariates allowed to influence the observation probabilities are typically abiotic (e.g., snow depth), but for the sake of this tutorial, we will fit this model using prey diversity. Note that our downstream analyses focus on the main HMM, where we allow prey diversity to influence the state transition probability.

First we define the formulas. Here, we will focus on the effects of prey diversity on step length mean and turning angle concentration.

distFormula <- ~ preydiv  
stepDM <- list(mean = distFormula, sd = ~ 1)   
angleDM <- list(concentration = distFormula)   
DM <- list(step = stepDM, angle = angleDM)

Next we grab the parameters from our refined three-state HMM and update the model to include a design matrix (DM) for effects of covariates on distributions.

Par0\_hmm\_obstrans\_3 <- momentuHMM::getPar0(hmm\_trans\_3, DM = DM)

Just as when we added covariates to the transition probability, when adding new covariates to observation probabilities using getPar0(), the intercept coefficients are taken from the previous model and initial slope coefficients are set to 0. We can see this by comparing the previously estimated parameters to the initial parameters for the next model with covariates. Note that when DM is not included in the model, momentuHMM assumes initial parameters are on the natural scale (i.e., on the scale of how observations are measured). However, when DM is included, then initial parameters must be provided on the working scale (i.e., the scale in which the optimization occurs, between negative and positive infinity). To convert working-scale parameters to the natural scale, we must apply the inverse of the link function associated with that parameter (Table 2 in the vignette for momentuHMM). In the case of mean and standard deviation associated with the gamma distribution used for step length, the link function is log(), therefore we must apply exp() to convert the working scale parameters returned by getPar0() to the natural scale.

# transition probability matrix (TPM) parameters from hmm1\_km   
# 'natural scale'  
hmm\_trans\_3$mle$step

## Slow movement Moderate movement Fast movement  
## mean 4.68480 14.438341 39.79019  
## sd 3.13931 4.858069 4.15426

# initial parameters for hmm2\_km with effect of preydiv on TPM  
# working scale converted to natural scale using inverse of link function  
exp(Par0\_hmm\_obstrans\_3$Par$step)

## mean\_1:(Intercept) mean\_1:preydiv mean\_2:(Intercept) mean\_2:preydiv   
## 4.684800 1.000000 14.438341 1.000000   
## mean\_3:(Intercept) mean\_3:preydiv sd\_1:(Intercept) sd\_2:(Intercept)   
## 39.790186 1.000000 3.139310 4.858069   
## sd\_3:(Intercept)   
## 4.154260

Fit the model.

# fit HMM with parameters from hmm2\_km and initial slope parameters set to 0  
set.seed(2023)  
hmm\_obstrans\_3 <- momentuHMM::fitHMM(data=data\_hmm, nbStates=3,  
 stateNames = c("Slow movement", "Moderate movement", "Fast movement"),  
 dist=list(step=stepDist,angle=angleDist),  
 Par0=Par0\_hmm\_obstrans\_3$Par,  
 delta0 = Par0\_hmm\_obstrans\_3$delta,   
 beta0 = Par0\_hmm\_obstrans\_3$beta,  
 formula=formula,  
 DM = DM)

## =======================================================================

## Fitting HMM with 3 states and 2 data streams

## -----------------------------------------------------------------------

## step ~ gamma(mean=~preydiv, sd=~1)

## angle ~ vm(concentration=~preydiv)

##   
## Transition probability matrix formula: ~preydiv

##   
## Initial distribution formula: ~1

## =======================================================================

## DONE

#### 3-states with covariate effects on observation probabilities

First we define the formulas.

stepDM <- list(mean = distFormula, sd = ~ 1)   
angleDM <- list(concentration = distFormula)   
DM <- list(step = stepDM, angle = angleDM)

Get initial parameter estimates based on hmm\_trans\_3

Par0\_hmm\_obs\_3 <- getPar0(hmm\_trans\_3, DM = DM)

Fit the model.

hmm\_obs\_3 <- momentuHMM::fitHMM(data=data\_hmm, nbStates=3,  
 stateNames = c("Slow movement", "Moderate movement", "Fast movement"),  
 dist=list(step=stepDist,angle=angleDist),  
 Par0=Par0\_hmm\_obs\_3$Par,  
 DM = DM)

## =======================================================================

## Fitting HMM with 3 states and 2 data streams

## -----------------------------------------------------------------------

## step ~ gamma(mean=~preydiv, sd=~1)

## angle ~ vm(concentration=~preydiv)

##   
## Transition probability matrix formula: ~1

##   
## Initial distribution formula: ~1

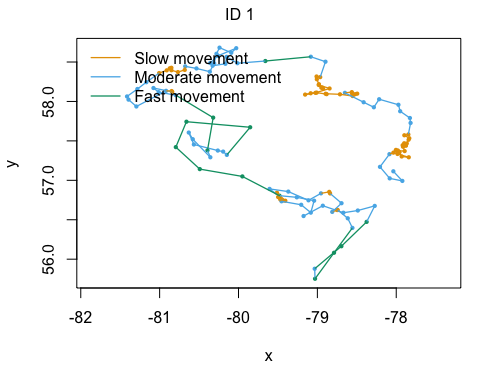
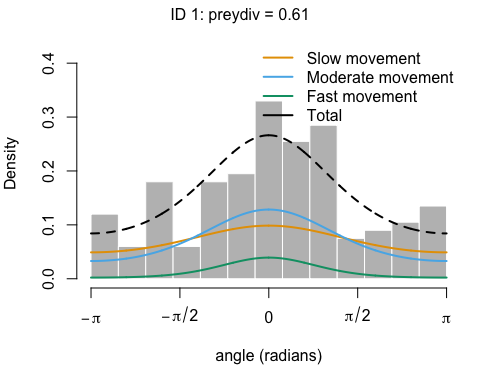
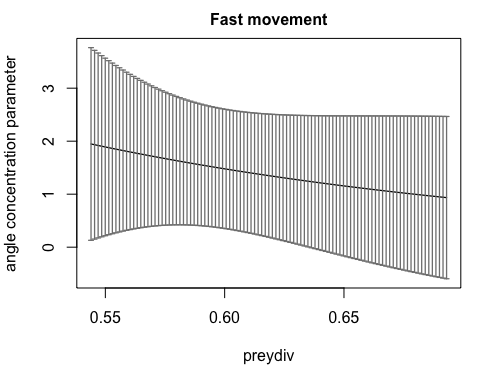
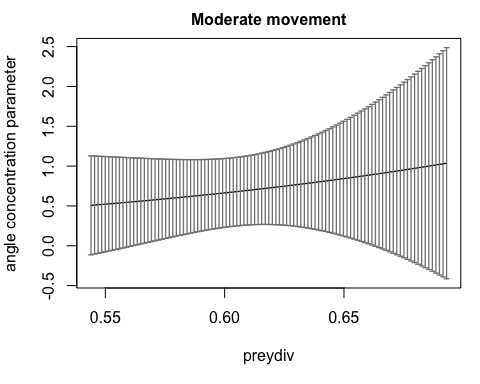
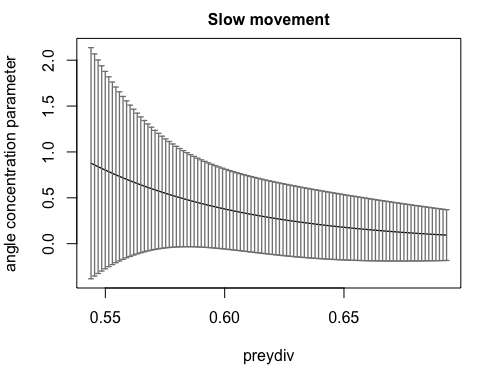
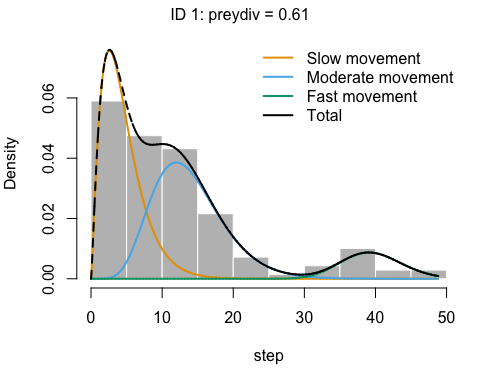
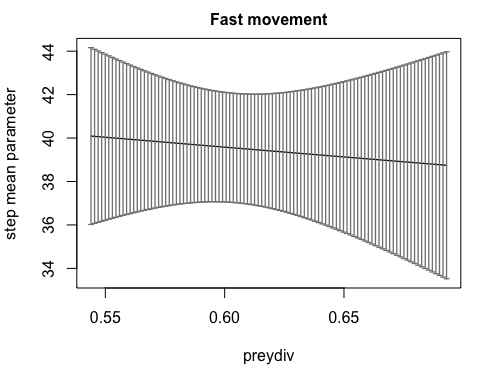
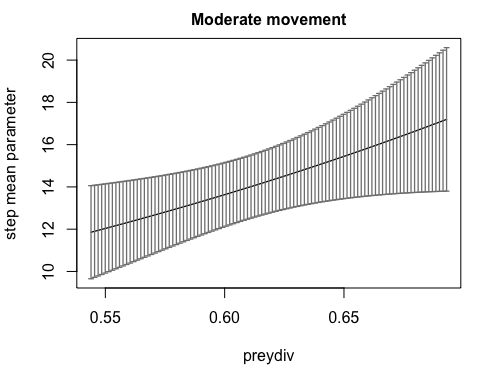
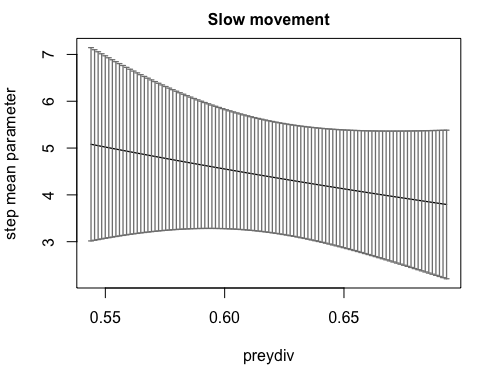
## =======================================================================

## DONE

Visualize the results.

plot(hmm\_obs\_3, ask = F, plotCI = T)

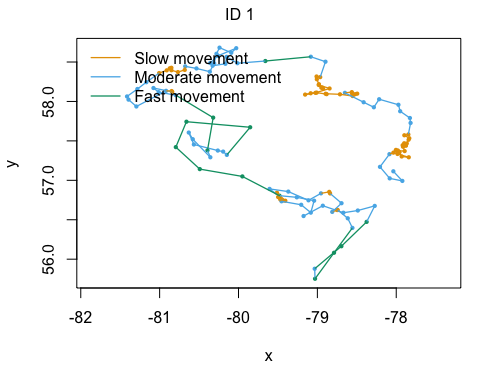
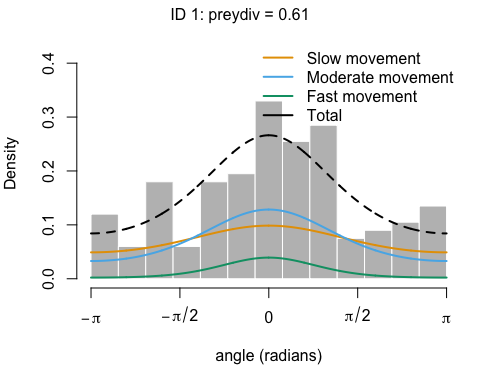
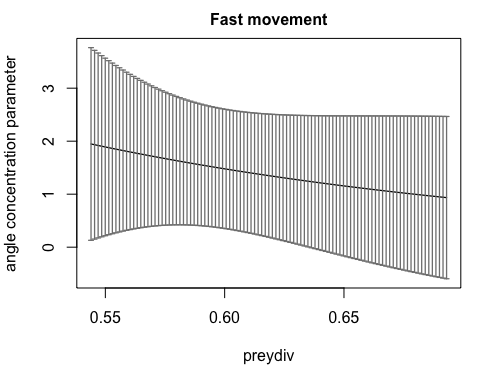
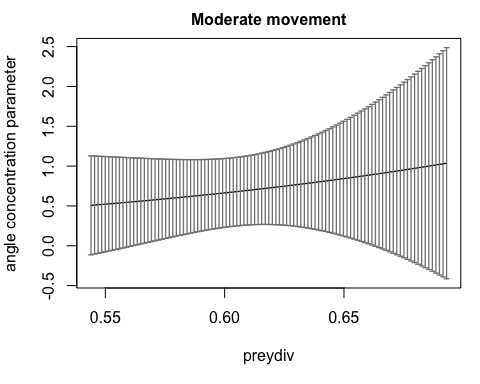
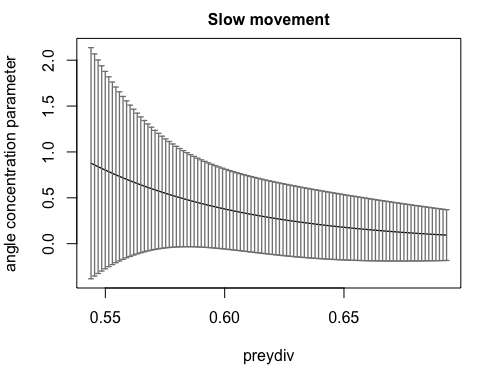
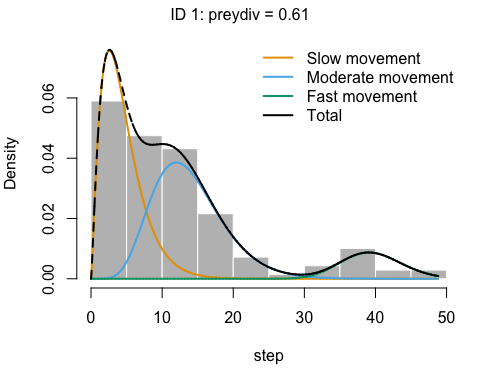
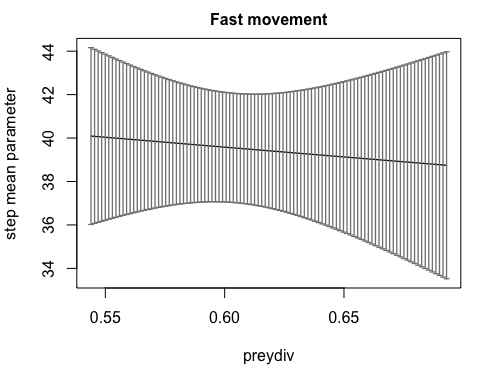
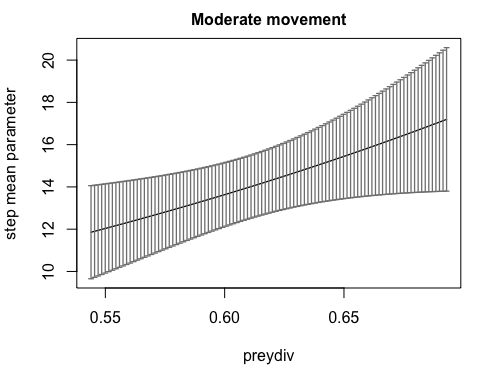
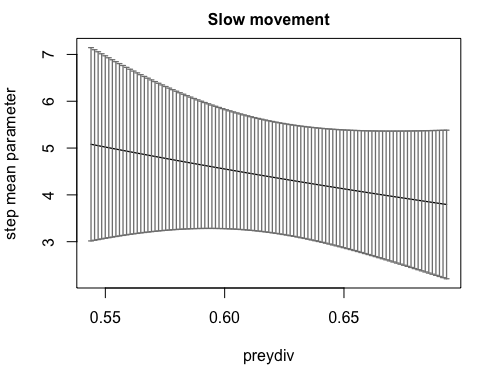
## Decoding state sequence... DONE



Visualize the results.

plot(hmm\_obs\_3, ask = F, plotCI = TRUE)

## Decoding state sequence... DONE



View parameters

hmm\_obs\_3$CIbeta

## $step  
## $step$est  
## mean\_1:(Intercept) mean\_1:preydiv mean\_2:(Intercept) mean\_2:preydiv  
## [1,] 2.690414 -1.957697 1.115528 2.495038  
## mean\_3:(Intercept) mean\_3:preydiv sd\_1:(Intercept) sd\_2:(Intercept)  
## [1,] 3.815786 -0.2290479 1.082236 1.610697  
## sd\_3:(Intercept)  
## [1,] 1.454613  
##   
## $step$se  
## mean\_1:(Intercept) mean\_1:preydiv mean\_2:(Intercept) mean\_2:preydiv  
## [1,] 1.317648 2.125084 0.6738791 1.09184  
## mean\_3:(Intercept) mean\_3:preydiv sd\_1:(Intercept) sd\_2:(Intercept)  
## [1,] 0.4106169 0.6782186 0.2022278 0.1188858  
## sd\_3:(Intercept)  
## [1,] 0.2406382  
##   
## $step$lower  
## mean\_1:(Intercept) mean\_1:preydiv mean\_2:(Intercept) mean\_2:preydiv  
## [1,] 0.1078717 -6.122784 -0.2052512 0.3550701  
## mean\_3:(Intercept) mean\_3:preydiv sd\_1:(Intercept) sd\_2:(Intercept)  
## [1,] 3.010991 -1.558332 0.6858769 1.377685  
## sd\_3:(Intercept)  
## [1,] 0.9829711  
##   
## $step$upper  
## mean\_1:(Intercept) mean\_1:preydiv mean\_2:(Intercept) mean\_2:preydiv  
## [1,] 5.272957 2.207391 2.436306 4.635005  
## mean\_3:(Intercept) mean\_3:preydiv sd\_1:(Intercept) sd\_2:(Intercept)  
## [1,] 4.62058 1.100236 1.478595 1.843709  
## sd\_3:(Intercept)  
## [1,] 1.926256  
##   
##   
## $angle  
## $angle$est  
## concentration\_1:(Intercept) concentration\_1:preydiv  
## [1,] 8.037653 -15.01587  
## concentration\_2:(Intercept) concentration\_2:preydiv  
## [1,] -3.28635 4.793973  
## concentration\_3:(Intercept) concentration\_3:preydiv  
## [1,] 3.344218 -4.922257  
##   
## $angle$se  
## concentration\_1:(Intercept) concentration\_1:preydiv  
## [1,] 7.428896 12.71922  
## concentration\_2:(Intercept) concentration\_2:preydiv  
## [1,] 4.843114 7.895969  
## concentration\_3:(Intercept) concentration\_3:preydiv  
## [1,] 4.099148 6.96634  
##   
## $angle$lower  
## concentration\_1:(Intercept) concentration\_1:preydiv  
## [1,] -6.522717 -39.94508  
## concentration\_2:(Intercept) concentration\_2:preydiv  
## [1,] -12.77868 -10.68184  
## concentration\_3:(Intercept) concentration\_3:preydiv  
## [1,] -4.689965 -18.57603  
##   
## $angle$upper  
## concentration\_1:(Intercept) concentration\_1:preydiv  
## [1,] 22.59802 9.913337  
## concentration\_2:(Intercept) concentration\_2:preydiv  
## [1,] 6.205979 20.26979  
## concentration\_3:(Intercept) concentration\_3:preydiv  
## [1,] 11.3784 8.731517  
##   
##   
## $beta  
## $beta$est  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) -1.709311 -18.73859 -1.691819 -2.287285 -16.34934 -0.4409921  
##   
## $beta$se  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) 0.4740712 NaN 0.4488078 0.5062071 NaN 0.5859873  
##   
## $beta$lower  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) -2.638473 NaN -2.571467 -3.279433 NaN -1.589506  
##   
## $beta$upper  
## 1 -> 2 1 -> 3 2 -> 1 2 -> 3 3 -> 1 3 -> 2  
## (Intercept) -0.7801483 NaN -0.8121724 -1.295137 NaN 0.7075218  
##   
##   
## $delta  
## $delta$est  
## Moderate movement Fast movement  
## (Intercept) 16.82743 -4.223506  
##   
## $delta$se  
## Moderate movement Fast movement  
## (Intercept) NaN NaN  
##   
## $delta$lower  
## Moderate movement Fast movement  
## (Intercept) NaN NaN  
##   
## $delta$upper  
## Moderate movement Fast movement  
## (Intercept) NaN NaN

# Plots of predicted relationships with the covariate

Here we are plotting a model’s estimated relationship between the resource covariate and probability of selection can be useful for general ecological inference. We will calculate the log of the relative selection strength (log-RSS) for each selection function model. The log-RSS is a measure of how likely a location (for the RSF) or step (for SSFs) is to end in a proposed location (x1) to a single reference location (x2, the mean prey diversity), where zero indicates no preference, >1 indicates selection, and <1 indicates avoidance (Avgar et al. 2017, Fieberg et al. 2021).

First, we prepare a dataframe to predict on.

# prep the fish data  
newfish <- fish\_raster %>%  
 terra::as.data.frame(xy = TRUE) %>%  
 filter(x > 100000 & x < 600000 & y > -550000 & y < 0)

## RSF

Since the RSF does not incorporate movement, we will calculate the log-RSS of the movement-free habitat selection kernel. This is easily done using log\_rss() from amt.

First, we make a base dataframe to create x1 and x2 from. The values of log\_sl and cos\_ta do not matter, but we need populated columns in order for the log\_rss function to work.

base <- newfish %>%   
 mutate(log\_sl = mean(data\_ssf$log\_sl),  
 cos\_ta = cos(1))  
  
# x1 is our base dataframe  
x1 <- base

Next, we modify the base data frame, where prey diversity is held at its mean.

x2 <- base %>%   
 mutate(preydiv = mean(base$preydiv))

Now we will apply log\_rss() to each row. Since log\_rss() only assessed one location relative to a reference point, we will use lapply to iterate through all locations.

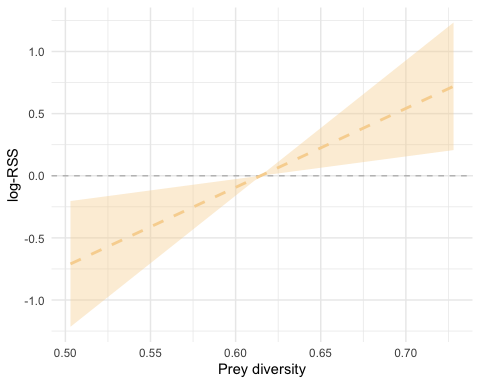
log\_rss\_list <- lapply(1:nrow(x1), function(i) {  
 # Calculate log-RSS for that row  
 xx <- log\_rss(rsf1, x1[i,], x2[i,], ci = "se")  
 # Return the element $df  
 return(xx$df)  
})  
  
# combine rows  
res1 <- dplyr::bind\_rows(log\_rss\_list)

Visualize results.

# plot  
line\_rsf <- ggplot(res1, aes(x = preydiv\_x1, y = (log\_rss))) +  
 geom\_hline(yintercept = 0, linetype = "dashed", color = "gray") +  
 geom\_line(size = 1, color = "#F8D59F",linetype = 2) +  
 geom\_ribbon(aes(ymin=lwr, ymax=upr, x=preydiv\_x1), alpha = 0.4, fill = "#F8D59F") +  
 xlab("Prey diversity") +  
 ylab("log-RSS") +  
 theme\_minimal()

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
  
## Warning: Please use `linewidth` instead.

line\_rsf



We see a positive relationship between prey diversity and log-RSS, which suggests that our seal are more likely to be present in areas with higher prey diversity than areas with low prey diversity. Note the bowtie shape of the standard error is due to log-RSS calculating selection strength relative to a starting step, in this case, where prey diversity is set to its mean.

## SSF

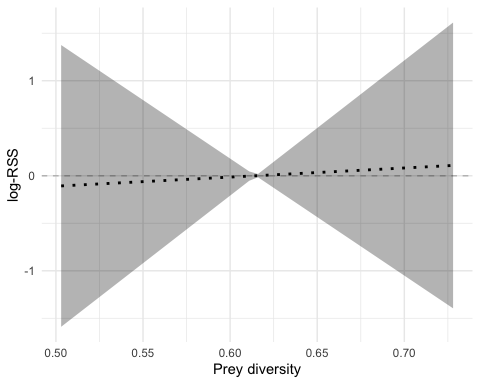
We can also calculate the log-RSS for our SSFs following the same workflow as for the RSF. Since log\_rss() passes to predict(), it is important that the fit SSF includes model = TRUE.

First, we will calculate log-RSS for ssf1. Again, since log\_rss() only assesses one location relative to a reference point, we will use lapply to iterate through all locations, and bind the rows together after so that we have a single data frame for plotting.

## log-RSS prediction for ssf1  
# apply log\_rss() to each row  
log\_rss\_list <- lapply(1:nrow(x1), function(i) {  
 # Calculate log-RSS for that row  
 xx <- log\_rss(ssf1, x1[i,], x2[i,], ci = "se")  
 # Return the element $df  
 return(xx$df)  
})  
  
# combine rows  
res2 <- dplyr::bind\_rows(log\_rss\_list) %>%  
 mutate(Speed = "without int.")

Visualize results.

line\_ssf1 <- ggplot() +  
 geom\_hline(yintercept = 0, linetype = "dashed", color = "grey") +  
 geom\_line(data = res2, aes(x = preydiv\_x1, y = log\_rss, color = Speed, group = Speed), size = 1, linetype = 3, color = "black") +   
 geom\_ribbon(data = res2, aes(ymin=lwr, ymax=upr, x=preydiv\_x1, fill = Speed, group = Speed), alpha = 0.3, fill = "black") +  
 xlab("Prey diversity") +  
 ylab("log-RSS") +  
 theme\_minimal()  
line\_ssf1



We see no relationship between prey diversity and log-RSS, which suggests that our seal is similarily likely to be present in areas with higher prey diversity and areas with low prey diversity.

Now we will calculate log-RSS for ssf2. We will estimate the log-RSS for three different step-lengths (slow, moderate, fast). We set these speeds as the 25th, 50th, and 75th percentiles of step-length, then loop the log-RSS for each speed. First, identify what the percentiles are.

# determine the 25th (slow), 50th (moderate), and 75th (fast) percentiles of step-length  
nums <- seal %>%  
 make\_track(lon, lat, date) %>%  
 steps %>%  
 mutate(log\_sl = log(sl\_)) %>%  
 dplyr::reframe(quants = quantile(log\_sl, c(0.25, 0.5, 0.75))) %>%  
 pull()

Now apply log-RSS to each row, for each speed (step length percentile).

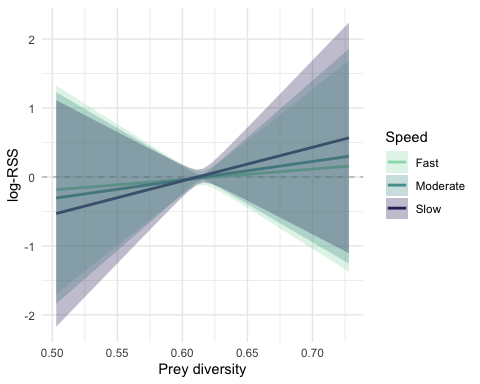
# set-up to run function for each speed  
results\_ssf2 <- lapply(nums, function(j) {  
x1$log\_sl <- j  
  
# calculate log-RSS  
 log\_rss\_list <- lapply(1:nrow(x1), function(i) {  
 # Calculate log-RSS for that row  
 xx <- log\_rss(ssf2, x1[i,], x2[i,], ci = "se")  
 # Return the element $df  
 return(xx$df)  
 })  
 # bind rows within each speed's prediction  
 res3 <- dplyr::bind\_rows(log\_rss\_list)  
} )

Bind the output together, and name the step lengths based on how long they are, so that we can interpret them in the subsequent plot as different speeds.

results\_ssf2 <- dplyr::bind\_rows(results\_ssf2) %>%  
 mutate(log\_sl\_x1 = as.factor(round(log\_sl\_x1,1)),  
 Speed = dplyr::case\_when(as.factor(log\_sl\_x1) == '8.4' ~ "Slow",  
 as.factor(log\_sl\_x1) == "9.2" ~ "Moderate",  
 as.factor(log\_sl\_x1) == "9.6" ~ "Fast"))

Visualize results.

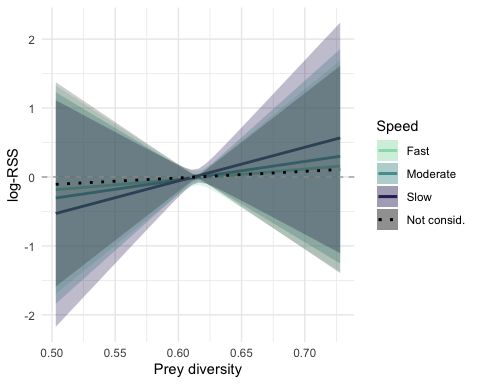
line\_ssf2 <- ggplot(results\_ssf2, aes(x = preydiv\_x1, y = (log\_rss))) +  
 geom\_hline(yintercept = 0, linetype = "dashed", color = "gray") +  
 geom\_line(size = 1, aes(color = Speed, group = Speed, linetype = Speed)) +  
 geom\_ribbon(aes(ymin=lwr, ymax=upr, x=preydiv\_x1, fill = Speed, group = Speed), alpha = 0.3) +  
 scale\_colour\_manual(values=c(colours.states,"#000000")) +  
 scale\_fill\_manual(values=c(colours.states,"#000000")) +  
 scale\_linetype\_manual(values = c("solid", "solid", "solid")) +  
 xlab("Prey diversity") +  
 ylab("log-RSS") +  
 theme\_minimal()  
line\_ssf2



We can see a weak positive relationship between prey diversity and log-RSS, however, with confidence intervals (shading) covering zero, suggesting no significant relationship between prey diversity and log-RSS. We also see that the confidence intervals cover each other, suggesting that different speeds do not have different relationships between prey diversity and log-RSS.

Typically these models would be interpreted independently. But it’s worth noting that while the effects are minimal and the confidence intervals overlap, when comparing ssf1 and ssf2, ssf2 provides more information about the animal’s relationship with prey diversity.

ggplot(results\_ssf2, aes(x = preydiv\_x1, y = (log\_rss))) +  
 geom\_hline(yintercept = 0, linetype = "dashed", color = "gray") +  
 geom\_line(size = 1, aes(color = Speed, group = Speed, linetype = Speed)) +  
 geom\_ribbon(aes(ymin=lwr, ymax=upr, x=preydiv\_x1, fill = Speed, group = Speed), alpha = 0.3) +  
 xlab("Prey diversity") +  
 ylab("log-RSS") +  
 theme\_minimal() +  
 geom\_hline(yintercept = 0, linetype = "dashed", color = "gray") +  
 geom\_line(data = res2, aes(x = preydiv\_x1, y = log\_rss, color = Speed, group = Speed, linetype = Speed), size = 1) +   
 geom\_ribbon(data = res2, aes(ymin=lwr, ymax=upr, x=preydiv\_x1, fill = Speed, group = Speed), alpha = 0.2) +  
 scale\_color\_manual(values = c("#99DDB6", "#539D9C", "#312C66", "black"),   
 labels = c("Fast", "Moderate", "Slow", "Not consid."),   
 name = "Speed") +  
 scale\_fill\_manual(values = c("#99DDB6", "#539D9C", "#312C66", "black"),   
 labels = c("Fast", "Moderate", "Slow", "Not consid."),   
 name = "Speed") +  
 scale\_linetype\_manual(values = c("solid", "solid", "solid", "dotted"),   
 labels = c("Fast", "Moderate", "Slow", "Not consid."),   
 name = "Speed")



Here, we see that adding the interaction between prey diversity and step length did not better explain our data or provide additional ecological insight about our seal.

## HMM

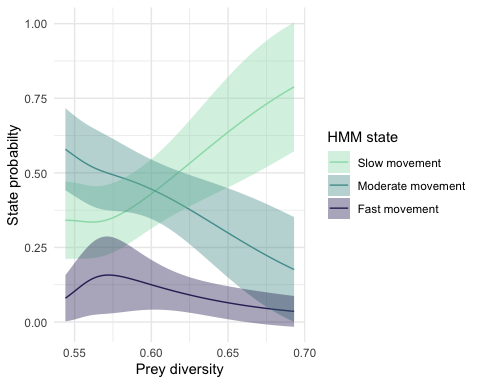
Exploring the insight on the relationship between our seal and prey diversity is fundamentally different for the HMM. Here, we will grab and plot the stationary state probabilities. This is easily done using plotStationary() from momentuHMM.

# grab stationary probabilities  
ps <- momentuHMM::plotStationary(hmm\_trans\_3, plotCI= TRUE, return = TRUE)

# grab values for data frame  
state1 <- ps$preydiv$'Slow movement' %>% mutate(state = 1)  
state2 <- ps$preydiv$'Moderate movement' %>% mutate(state = 2)  
state3 <- ps$preydiv$'Fast movement' %>% mutate(state = 3)  
  
# bind to one data frame  
pdat <- rbind(state1, state2, state3) %>%  
 mutate(state = as.character(state))

Visualize results.

line\_hmm <- ggplot() +   
 geom\_line(data = pdat, aes(x = cov, y = est, color = state)) +  
 geom\_ribbon(data = pdat, aes(x=cov, y=est, ymax=est+se, ymin=est-se, fill = state),   
 alpha = 0.4, show.legend = TRUE) +  
 ylab("State probabilty") +  
 xlab("Prey diversity") +  
 scale\_color\_manual(values = c("#99DDB6", "#539D9C", "#312C66"), name = "HMM state",  
 labels=c("Slow movement", "Moderate movement", "Fast movement")) +  
 scale\_fill\_manual(values = c("#99DDB6", "#539D9C", "#312C66"), name = "HMM state",  
 labels=c("Slow movement", "Moderate movement", "Fast movement")) +  
 theme\_minimal()  
  
line\_hmm



Here we can see that each state has a different relationship between the stationary state probability and prey diversity. The slow movement state has a positive relationship between stationary state probability and prey diversity, the moderate movement state has a negative relationship with prey diversity, and the fast movement state does not appear to have a directional relationship with prey diversity.

# Prediction maps

Now we will estimate the utilization distributions from each model to demonstrate how differences in the relationships with a covariate can results in vastly different spatial patterns. The utilization distribution is defined as the two-dimensional relative frequency distribution of space use of an animal (Van Winkle 1975). This is a simple calculation for the RSF, where we multiply the model coefficient with the resource (prey diversity), exponentiate (since it is a logistic regression), and normalize the estimate. The calculations are more complex for the SSFs since they are conditional models that integrate the movement process. Thus, for the SSFs we calculate the steady-state utilization distribution (SSUD), which is the long-term expectation of the space-use distribution across the landscape (Signer et al. 2017). amt has functions to estimate the SSUD.

## RSF

We can predict the estimated probability of use from the RSF by hand. First, grab the model coefficients and predict for each cell.

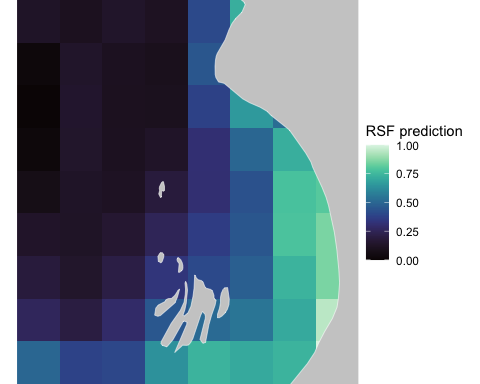
# grab model coefficients  
modcoef <- summary(rsf1)$coef  
  
# prediction for each cell  
x <- exp(modcoef[2] \* newfish$preydiv)

We will normalize the results next.

# range fn  
range01 <- function(x){(x-min(x))/(max(x)-min(x))}  
  
# set the range from zero to one  
newfish$rsf\_prediction <- range01(x)

Visualize results.

map\_rsf <- ggplot() +   
 geom\_tile(data = newfish, aes(x = x,y = y, fill = rsf\_prediction)) +  
 scale\_fill\_viridis(option = "mako", name = "RSF prediction",limits = c(0,1)) +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F) +  
 theme\_void()  
map\_rsf



## SSF

We can use the amt functions to estimate the SSUDs from the simple SSF that does not allow prey diversity to affect the movement kernel. When estimating the SSUDs, the functions require that covariates are specifically labelled as occuring at the end of the step (i.e., preydiv\_end). This is easily implemented by specificing where = "both" when using extract\_covariates, which will then produce a column for preydiv\_start and preydiv\_end. By default, as in our initial fitting, extract\_covariates extracts data for the end of the step, but does not record the \_start or \_end suffix. Thus, we are re-extracting covariates for ease throughout the generation of the SSUDs.

# generate availability sample  
set.seed(2023)  
data\_ssf <- seal %>%  
 mutate(date = as.POSIXct(date)) %>%  
 make\_track(lon, lat, date) %>%  
 steps() %>%  
 random\_steps() %>%   
 arrange(case\_) %>%  
 amt::extract\_covariates(fish\_raster, where = "both")  
  
# fit SSF1 model  
m1 <- data\_ssf |>   
 fit\_clogit(case\_ ~ preydiv\_end + log(sl\_) + cos(ta\_) +   
 strata(step\_id\_))

Now we will set the starting position for the simulation.

start <- make\_start((seal %>%  
 mutate(date = as.POSIXct(date)) %>%  
 make\_track(lon, lat, date))[1,])

We can also set constants for how many steps we want to simulate. Additionally, we set a burn-in number of steps, where we later remove this number of steps from the simulated path to reduce the influence of the starting point.

n\_steps = 1e4 # number of steps  
burnin <- n\_steps/50 # number of steps to remove for the burn-in

Generate the redistribution kernel.

k1 <- redistribution\_kernel(m1, map = fish\_raster, start = start,  
 stochastic = TRUE,  
 tolerance.outside = 1,  
 n.control = n\_steps)

Simulate the path. This function will likely take about five minutes on most laptops. As such, I have added the resulting simulated paths /data/p1\_1e4 Feel free to uncomment the read.csv line to load it in instead of running the simulate\_path if prefered. Additionally, I have also ran the simulation with 1e5 steps. This takes about 12 hours to run, so we will not use those data here, but this can be loaded as /data/p1\_1e4. Our plots in the main paper use 1e5 steps.

set.seed(2023)  
p1 <- amt::simulate\_path(x = k1, n = n\_steps, start = start, verbose = TRUE)  
  
#p1 <- read.csv(here("data/p1\_1e4.csv")) %>% as\_tibble()

Remove the burn-in.

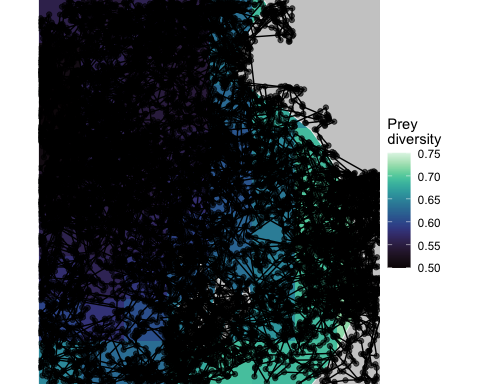
p1\_burnt <- p1 %>% dplyr::slice(-c(1:burnin))

Visualize the simulated path.

ssf\_track\_1 <- fishmap +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 geom\_point(data = p1\_burnt, aes(x = x\_,y = y\_), alpha = 0.61) +  
 geom\_path(data = p1\_burnt, aes(x = x\_,y = y\_)) +  
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F) +  
 theme\_void()

## Coordinate system already present. Adding new coordinate system, which will  
## replace the existing one.

ssf\_track\_1

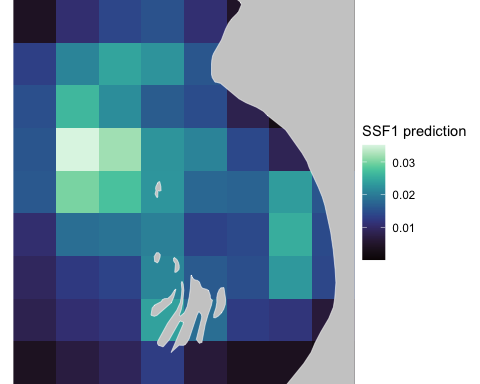


We will use this track to estimate the SSUD. We will convert the estimated SSUD to a data frame for easy plotting.

uds\_ssf1 <- tibble(rep = 1:nrow(p1\_burnt),   
 x\_ = p1\_burnt$x\_, y\_ = p1\_burnt$y\_,  
 t\_ = p1\_burnt$t\_, dt = p1\_burnt$dt) %>%  
 filter(!is.na(x\_)) %>%  
 make\_track(x\_, y\_) %>%   
 hr\_kde(trast = fish\_raster, which\_min = "global") %>%  
 hr\_ud() %>%   
 terra::as.data.frame(xy = TRUE)

Visualize the results.

map\_ssf1 <- ggplot() +   
 geom\_tile(data = uds\_ssf1, aes(x = x,y = y, fill = preydiv)) +  
 scale\_fill\_viridis(option = "mako", name = "SSF1 prediction") +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F) +  
 theme\_void()  
map\_ssf1



The map shows that probability of use is fairly generally distributed in space.

We will follow the same steps to generate a SSUD for the SSF that allows prey diversity to affect the movement kernel.

m2 <- data\_ssf %>%  
 fit\_clogit(case\_ ~ preydiv\_end \* log(sl\_) + cos(ta\_) +   
 strata(step\_id\_))

Generate the redistribution kernel.

set.seed(2023)  
k2 <- redistribution\_kernel(m2, map = fish\_raster, start = start,  
 stochastic = TRUE,  
 tolerance.outside = 1,  
 n.control = n\_steps)

Simulate the path. Similar to SSF1, this function may take some time to run. I have stored the simulated path with 1e5 locations in data/p2\_1e4, or for the full simulation, data/p2\_1e5, for loading in here if you prefer not to run it on your own computer.

set.seed(2023)  
p2 <- amt::simulate\_path(x = k2, n = n\_steps, start = start, verbose = TRUE)   
#p2 <- read.csv(here("data/p2\_1e4.csv")) %>% as\_tibble()

Remove burn-in.

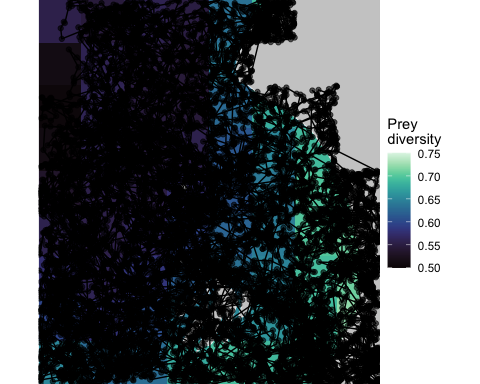
p2\_burnt <- p2 %>% dplyr::slice(-c(1:burnin))

Visualize simulated track.

ssf\_track\_2 <- fishmap +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 geom\_point(data = p2\_burnt, aes(x = x\_,y = y\_), alpha = 0.61) +  
 geom\_path(data = p2\_burnt, aes(x = x\_,y = y\_)) +  
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F) +  
 theme\_void()

## Coordinate system already present. Adding new coordinate system, which will  
## replace the existing one.

ssf\_track\_2

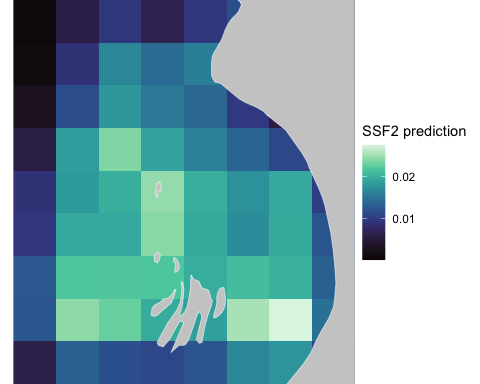


Estimate the SSUD.

uds\_ssf2 <- tibble(rep = 1:nrow(p2\_burnt),   
 x\_ = p2\_burnt$x\_, y\_ = p2\_burnt$y\_,  
 t\_ = p2\_burnt$t\_, dt = p2\_burnt$dt) |>   
 filter(!is.na(x\_)) |>   
 make\_track(x\_, y\_) |>   
 hr\_kde(trast = fish\_raster, which\_min = "global") %>%  
 hr\_ud() %>%   
 terra::as.data.frame(xy = TRUE)

Visualize the SSUD.

map\_ssf2 <- ggplot() +   
 geom\_tile(data = uds\_ssf2, aes(x = x,y = y, fill = preydiv)) +  
 scale\_fill\_viridis(option = "mako", name = "SSF2 prediction") +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F) +  
 theme\_void()  
map\_ssf2



## HMM

We will first estimate the stationary state probabilities of each state based on prey diversity. This is easily done using the momentuHMM function stationary(). This function predicts the probability of being in each state given a covariate (prey diversity).

x <- as.data.frame(momentuHMM::stationary(hmm\_trans\_3,   
 data.frame(preydiv = newfish$preydiv)))  
newfish$hmm\_state1 <- x$Slow.movement  
newfish$hmm\_state2 <- x$Moderate.movement  
newfish$hmm\_state3 <- x$Fast.movement

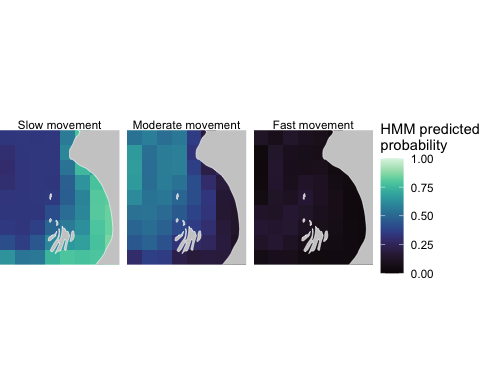
Format the data for plotting.

newfish\_long <- newfish %>%  
 tidyr::pivot\_longer(cols = hmm\_state1:hmm\_state3,   
 names\_to = "model", values\_to = "prediction") %>%  
 mutate(dplyr::across(model, factor, levels=  
 c("hmm\_state1", "hmm\_state2", "hmm\_state3")))

## Warning: There was 1 warning in `mutate()`.  
## ℹ In argument: `dplyr::across(...)`.  
## Caused by warning:  
## ! The `...` argument of `across()` is deprecated as of dplyr 1.1.0.  
## Supply arguments directly to `.fns` through an anonymous function instead.  
##   
## # Previously  
## across(a:b, mean, na.rm = TRUE)  
##   
## # Now  
## across(a:b, \(x) mean(x, na.rm = TRUE))

Visualize the results.

map\_hmm <- ggplot() +   
 geom\_tile(data = newfish\_long, aes(x = x, y = y, fill = prediction)) +  
 scale\_fill\_viridis(option = "mako", limits = c(0,1)) +  
 labs(fill = 'HMM predicted\nprobability') +  
 geom\_sf(data = nat\_trans, fill = "grey80", color = "white") +   
 coord\_sf(xlim = ext(fish\_raster)[1:2], ylim = ext(fish\_raster)[3:4], expand = F) +  
 facet\_wrap(~model, labeller = as\_labeller(c('hmm\_state1' = "Slow movement",  
 'hmm\_state2' = "Moderate movement",  
 'hmm\_state3' = "Fast movement"))) +  
 theme\_void()  
  
map\_hmm



We can see that the slow movement state, which was positively related to prey diversity, showed a similar restricted spatial pattern to the RSF, whereas the moderate movement state, which had a negative relationship with prey diversity, showed the opposite pattern to the RSF prediction map. The fast movement state did not show as much spatial variation, due to its non significant relationship with prey diversity.

# References

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# Session

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