

# Combining different data types into hidden Markov models of animal movement behaviour with R package momentuHMM

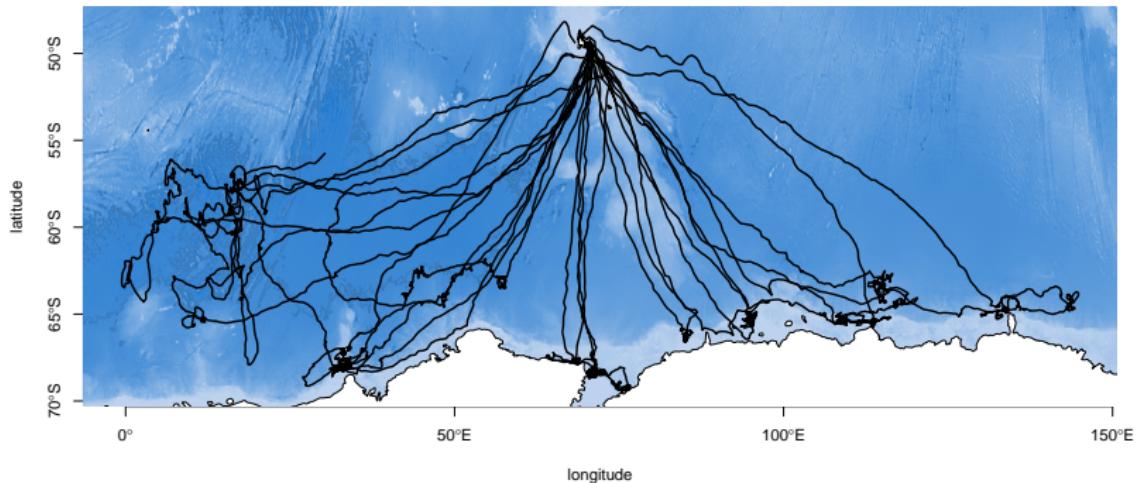
Brett McClintock

NOAA Marine Mammal Lab, Seattle, U.S.A.

29 June 2018

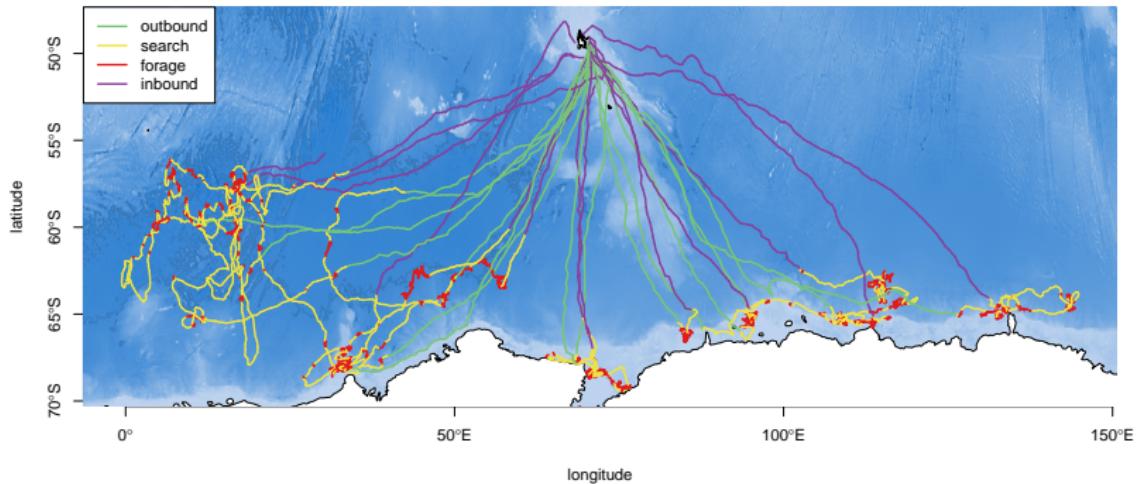
## Background on hidden Markov models

# HMM of animal movement



Data from: Michelot et al. (2017), "Estimation and simulation of foraging trips in land-based marine predators", *Ecology*, 98(7).

# HMM of animal movement



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# Correlated random walk

A correlated random walk includes **persistence in direction**  
→ Correlation between successive directions

simple random walk



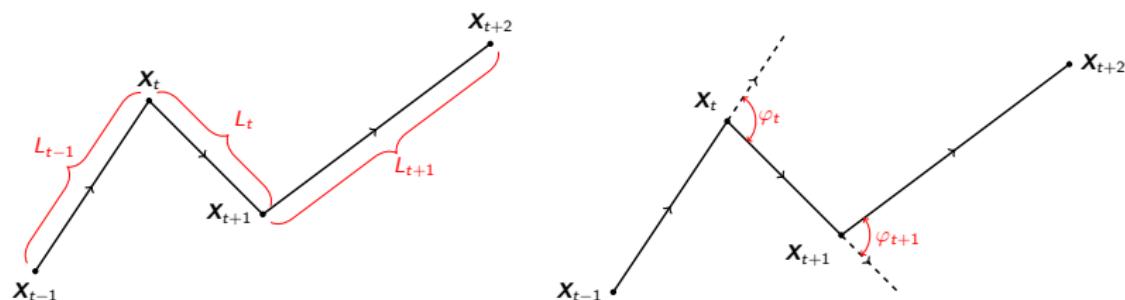
correlated random walk



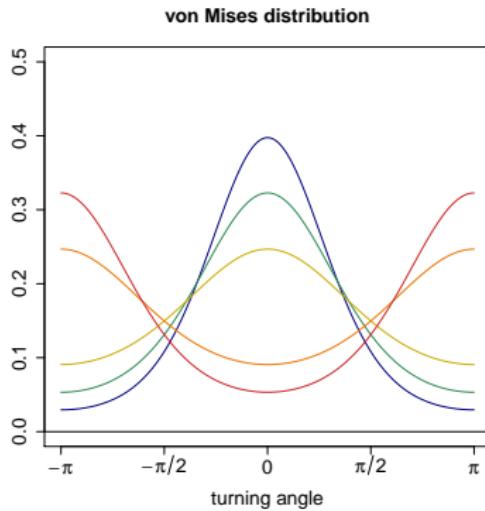
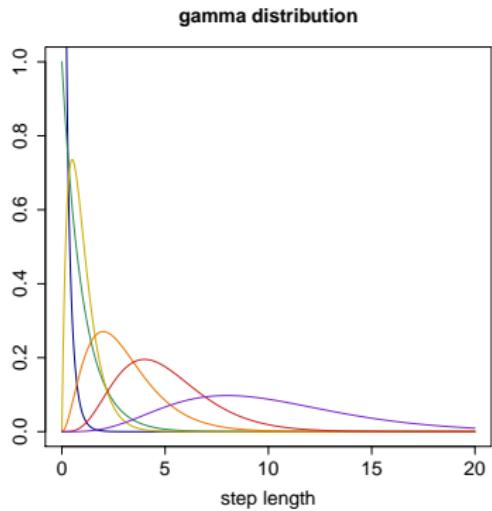
# Movement metrics

In a correlated random walk, we can model:

- ▶ step lengths ( $L_t$ );
- ▶ turning angles ( $\varphi_t$ ).



# Modelling the steps and angles



## Multistate random walk

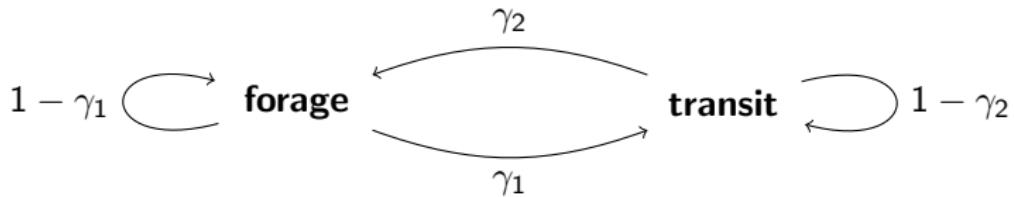
Idea: the animal switches between several movement processes, corresponding to several **behaviours**.  
→ Behavioural process = unobserved Markov chain ( $S_t$ ).

# Multistate random walk

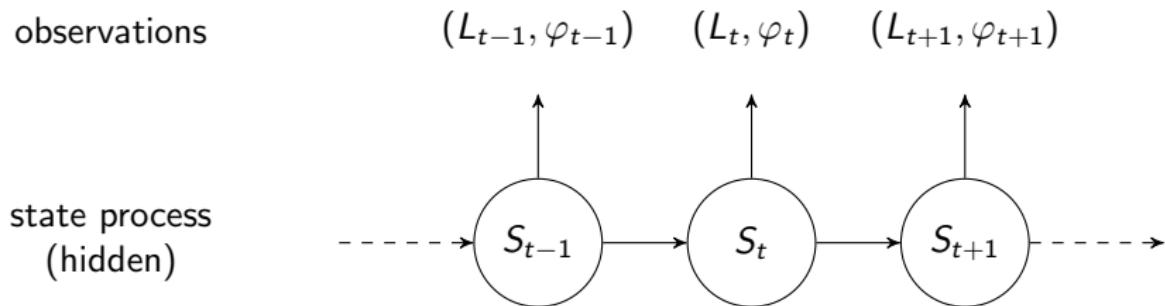
Idea: the animal switches between several movement processes, corresponding to several **behaviours**.

→ Behavioural process = unobserved Markov chain ( $S_t$ ).

Example:



# Hidden Markov model for animal movement



The steps and angles are modelled by state-dependent distributions. For example:

$$L_t | S_t = j \sim \text{gamma}(\alpha_j, \beta_j)$$

$$\varphi_t | S_t = j \sim \text{von Mises}(\mu_j, \kappa_j)$$

## Covariates

Does [insert covariate] have an effect on the probability that the animal is [insert behaviour]?

→ Time-varying transition probabilities.

In a 2-state model:

$$\begin{cases} \Pr(S_{t+1} = 2 | S_t = 1) = \text{logit}^{-1}(\beta_0^{(12)} + \sum_{i=1}^m \beta_i^{(12)} w_{i,t}) \\ \Pr(S_{t+1} = 1 | S_t = 2) = \text{logit}^{-1}(\beta_0^{(21)} + \sum_{i=1}^m \beta_i^{(21)} w_{i,t}) \end{cases}$$

momentuHMM

# Introduction to momentuHMM

- ▶ Extension of moveHMM (Michelot et al. 2016)  
→ Same core functions with more options
- ▶ Available on CRAN since June 2017
- ▶ To get started: the vignette presents eight case studies to illustrate all the functionalities of the package.



Michelot, Langrock, Patterson (2016). moveHMM: An R package for the statistical modelling of animal movement data using hidden Markov models, *Methods Ecol Evol.*

McClintock and Michelot (2018). momentuHMM: R package for generalized hidden Markov models of animal movement, *Methods Ecol Evol.*

moveHMM is easier to use, but momentuHMM is much more flexible

Additional capabilities of momentuHMM include:

- ▶ biased and correlated random walks
- ▶ unlimited number of data streams
- ▶ larger choice of distributions for data streams
- ▶ covariates on all parameters
- ▶ parameter constraints
- ▶ seamless integration of spatio-temporal covariate raster data
- ▶ centres of attraction
- ▶ group dynamic models
- ▶ cosinor (i.e. cyclic) and spline models for complex patterns
- ▶ multiple imputation (irregular sampling, measurement error)
- ▶ parallel processing
- ▶ ...

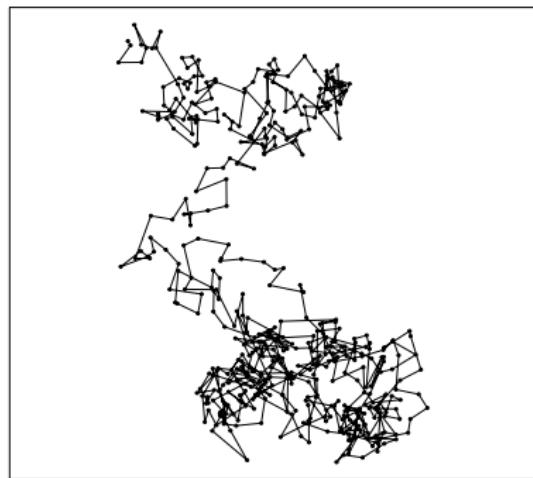
# Biased random walk

A biased random walk includes **bias (or drift) in direction**

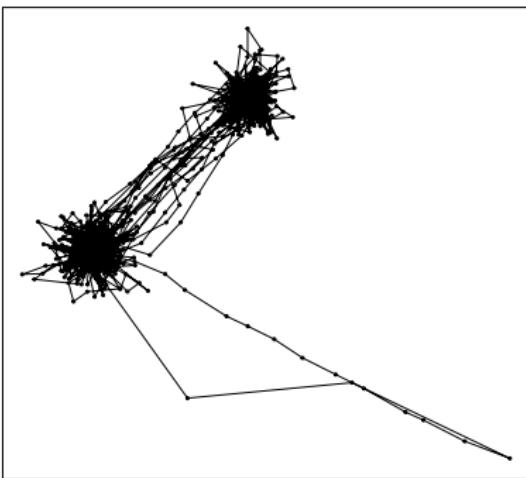
→ along gradients (e.g. ocean currents, wind velocity)

→ towards (or away from) areas of attraction (or repulsion)

simple random walk

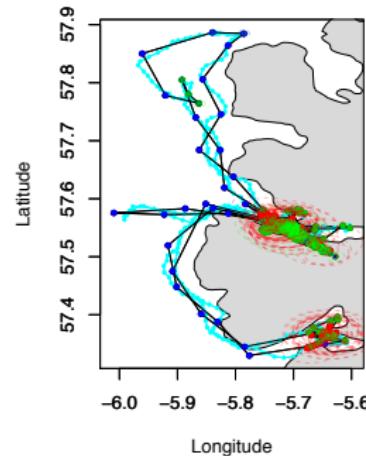
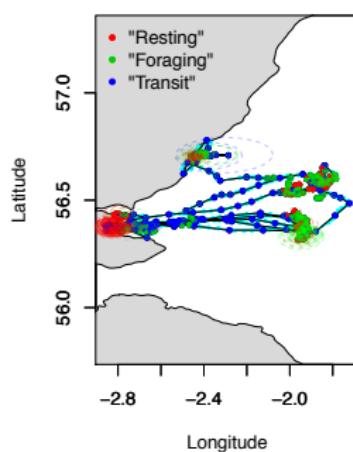


biased random walk

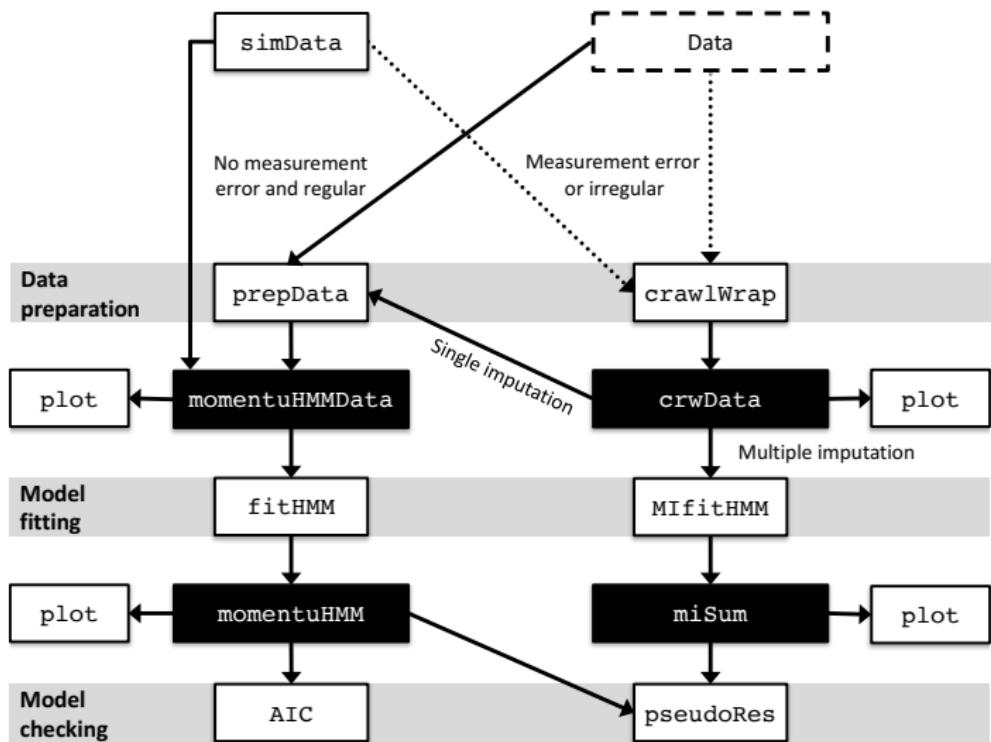


# Auxiliary biotelemetry and environmental data

- ▶ Often difficult to discern > 2 behavior states that are biologically meaningful based solely on horizontal trajectory
- ▶ Additional data streams can help distinguish states that would otherwise be difficult or impossible to discern
- ▶ e.g., proportion of each time step spent diving allows 3 behavior states to be identified in marine mammals:



# momentuHMM workflow



Schematic representing the typical momentuHMM workflow. White boxes indicate package functions and black boxes indicate object classes returned by functions.

# Examples

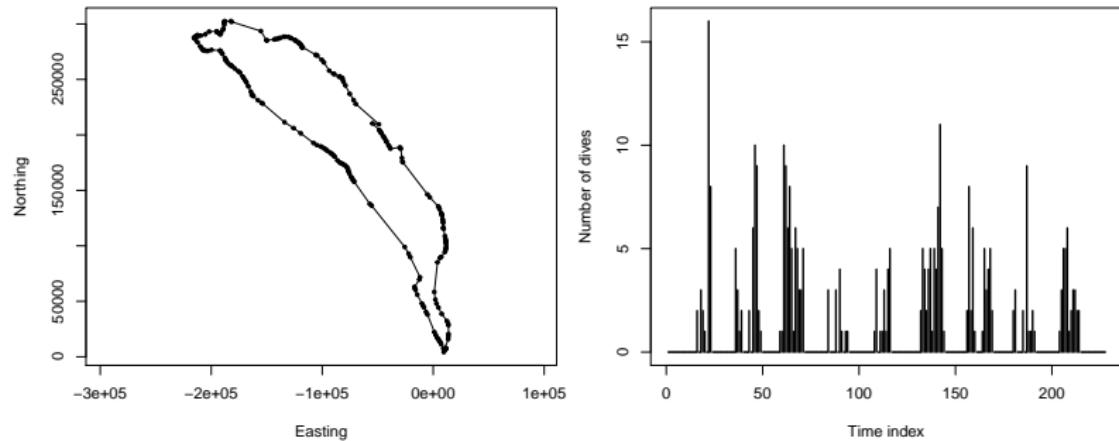
1. Northern fur seal example

2. Bearded seal example

3. Other examples

# Northern fur seal data

- ▶ Locations (irregular sampling frequency)
- ▶ Number of “foraging” dives per hour



Data from McClintock et al. (2014), “When to be discrete: the importance of time formulation in understanding animal movement”, *Movement Ecology*.

# Multiple imputation HMMs

Solution to irregular sampling and measurement error:

- ▶ Fit single-state continuous-time movement model
- ▶ Draw temporally-regular realisations from the fitted model
- ▶ Fit a HMM to each realisation

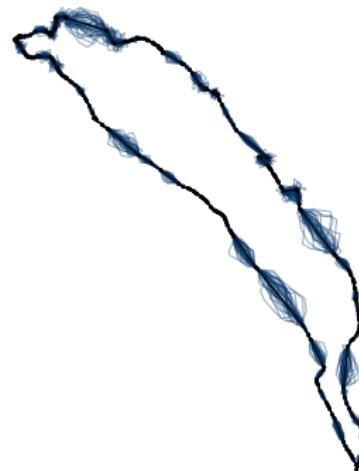


McClintock (2017) "Incorporating telemetry error into hidden Markov models of animal movement using multiple imputation", *JABES*.

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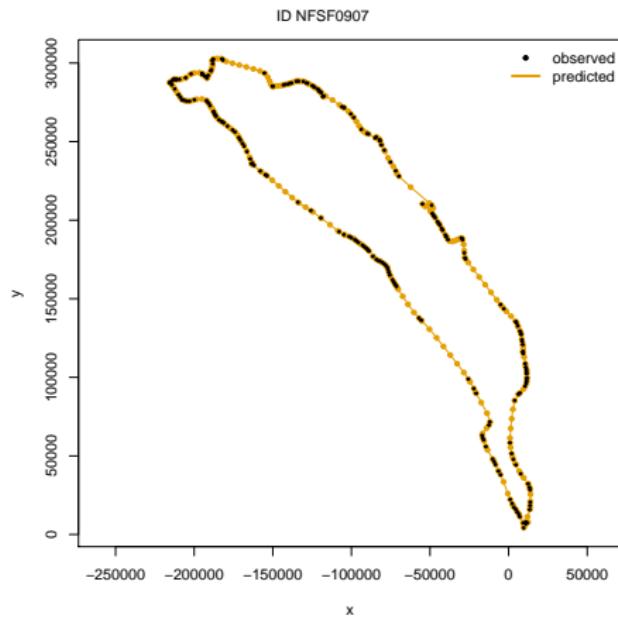


McClintock (2017) "Incorporating telemetry error into hidden Markov models of animal movement using multiple imputation", *JABES*.

# Fit crawl model

```
crwOut <- crawlWrap(obsData=nfsData, predTime="1 hour")
```

```
plot(crwOut, ask=FALSE)
```



# Multiple imputation multivariate HMM

Step length:  $L_t | S_t = s \sim \text{Gamma}(\mu_s, \sigma_s)$

Turn angle:  $\phi_t | S_t = s \sim \text{wCauchy}(0, \rho_s)$

# of dives:  $\delta_t | S_t = s \sim \text{Poisson}(\lambda_s)$

```
# observation distributions
dist <- list(step="gamma", angle="wrpcalpha", dive="pois")

# initial parameters
stepPar0 <- c(500, 1000, 5000, 1000, 1000, 2000)
anglePar0 <- c(0.01, 0.05, 0.75)
divePar0 <- c(10e-4, 2, 10e-4)
Par0 <- list(step=stepPar0, angle=anglePar0, dive=divePar0)
```

# Multiple imputation multivariate HMM

```
# fit 3-state model
m_nfs <- MIfitHMM(crwOut, nSims = 30,
                     nbStates = 3, dist = dist, Par0 = Par0)

## Drawing 30 realizations from the position process using crawl::crwPostIS...

## 
## Computing importance weights ...

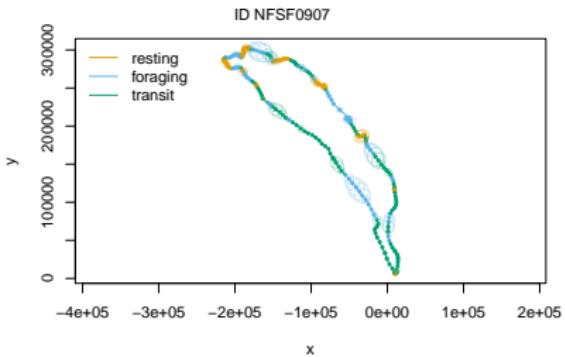
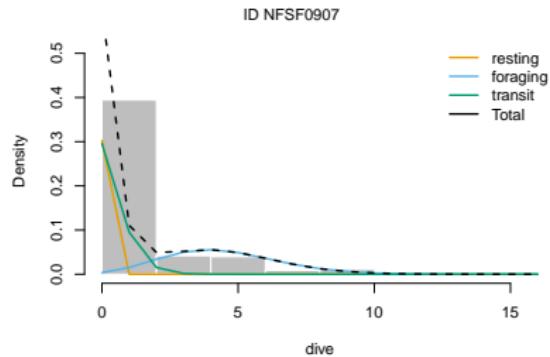
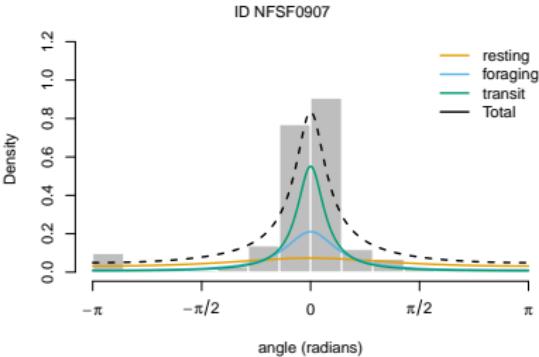
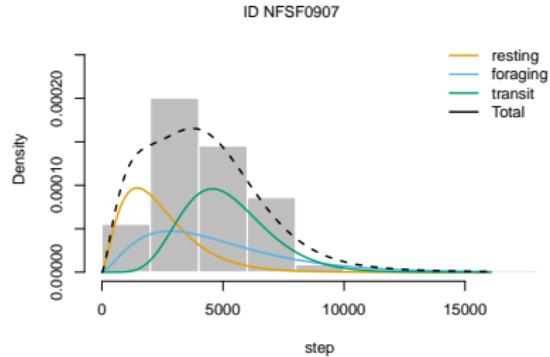
## DONE
## Fitting 30 realizations of the position process using fitHMM...

## =====
## Fitting HMM with 3 states and 3 data streams
## -----
## step ~ gamma(mean=~1, sd=~1)
## angle ~ wrpcauchy(concentration=~1)
## dive ~ pois(lambda=~1)
##
## Transition probability matrix formula: ~1
##
## Initial distribution formula: ~1
## =====

## DONE
## Decoding state sequences and probabilities for each imputation... DONE
## Calculating location 95% error ellipses... DONE
```

# Results – NFS model

```
plot(m_nfs, ask=FALSE)
```

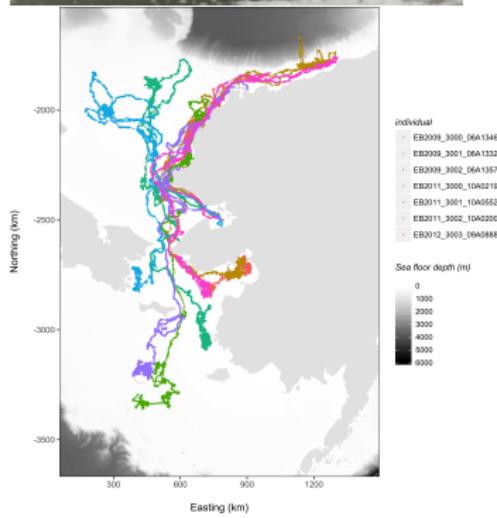


**1.** Northern fur seal example

**2.** Bearded seal example

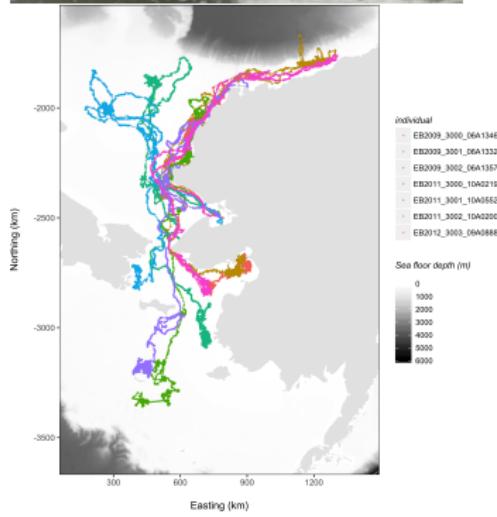
**3.** Other examples

# Bearded seal example



- ▶ 7 seals tagged near Kotzebue, AK
- ▶ 54542 temporally-irregular locations
- ▶ Dive and wet/dry data in 6hr bins
- ▶ 18% of 6hr time steps contain no locations
- ▶ Measurement error (Argos and Fastloc GPS)
- ▶ 7 data streams
- ▶ 6 behavior states:
  - ▶ “Hauled out on ice”
  - ▶ “Resting at sea”
  - ▶ “Hauled out on land”
  - ▶ “Mid-water foraging”
  - ▶ “Benthic foraging”
  - ▶ “Transit”

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  - ▶ “Transit”

# Bearded seal example: data streams

Step length:

$$L_t \mid S_t = s \sim \text{Gamma}(\mu_s, \sigma_s)$$

Turn angle:

$$\phi_t \mid S_t = s \sim \text{wCauchy}(0, \rho_s)$$

Dive time:

$$d_t \mid S_t = s \sim \text{Beta}(\alpha_s^d, \beta_s^d)$$

Dry time:

$$w_t \mid S_t = s \sim \text{Beta}(\alpha_s^w, \beta_s^w)$$

Sea ice cover:

$$c_t \mid S_t = s \sim \text{Beta}(\alpha_s^c, \beta_s^c)$$

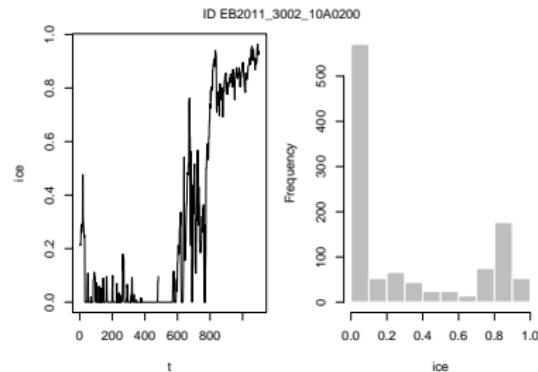
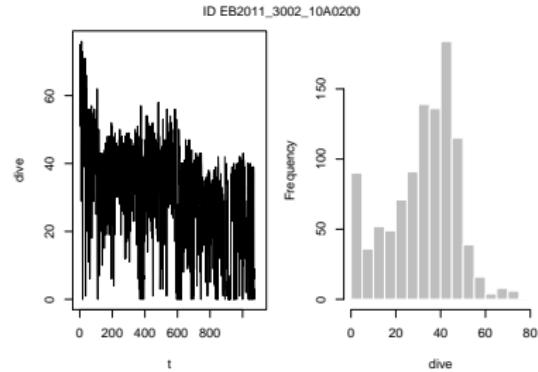
Land cover:

$$l_t \mid S_t = s \sim \text{Beta}(\alpha_s^l, \beta_s^l)$$

Benthic dives:

$$b_t \mid S_t = s \sim \text{Poisson}(\lambda_s)$$

```
plot(data, animals="EB2011_3002_10A0200")
```



## Bearded seal example: behavioral states

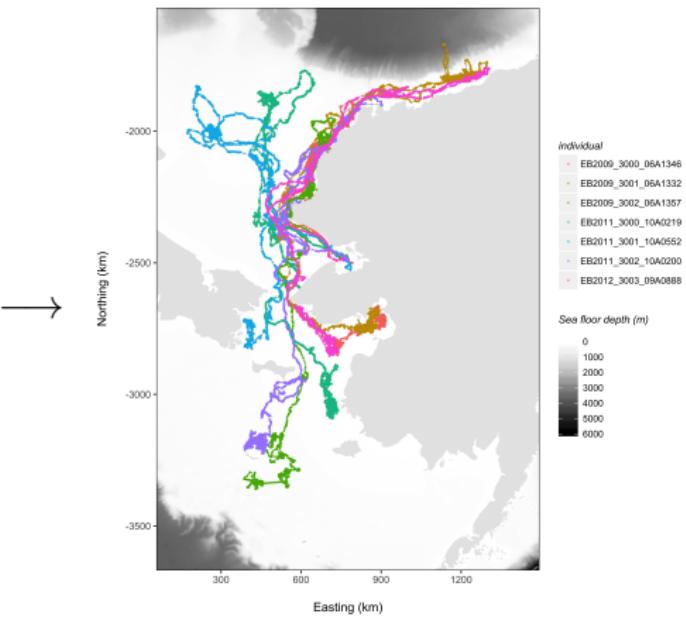
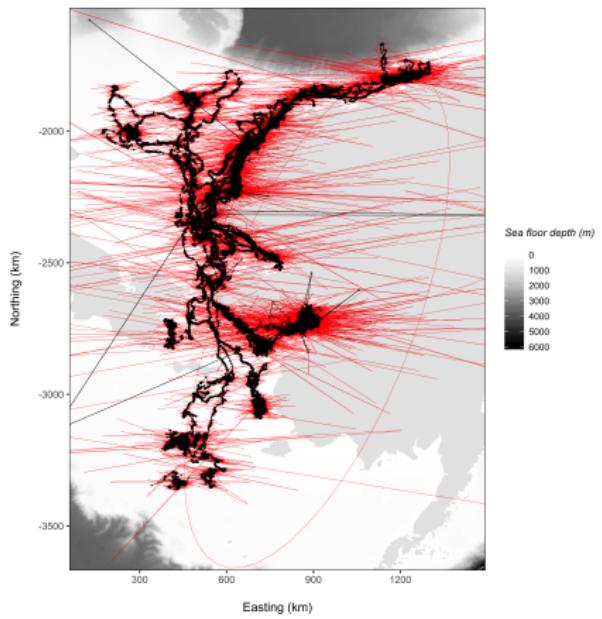
Behavioral state	Horizontal trajectory		Dive	Dry	Benthic	Ice	Land
	Step length	Directional persistence					
"Hauled out on ice"	shorter		lower	higher	lower	higher	lower
"Resting at sea"	shorter		lower	lower	lower	lower	lower
"Hauled out on land"	shorter		lower	higher	lower	lower	higher
"Mid-water foraging"			higher	lower	lower		
"Benthic foraging"			higher	lower	higher		
"Transit"	longer	higher	higher	lower	lower		

Expected characteristics of 6 movement behavior states for a bearded seal movement model incorporating seven data streams. These data streams included horizontal trajectory (Step length and Directional persistence), the proportion of time spent diving below 4 m (Dive), the proportion of time spent dry (Dry), and the number of benthic dives (Benthic) during each 6 h time step. The model incorporated environmental data on the proportion of sea ice and land cover in 25x25km grid cell(s) containing the start and end locations for each time step (Ice and Land), as well as bathymetry data to identify benthic dives. Blank entries indicate no a priori relationships were assumed in the model.

McClintock et al. (2017), "Bridging the gaps in animal movement: hidden behaviors and ecological relationships revealed by integrated data streams", *Ecosphere*.

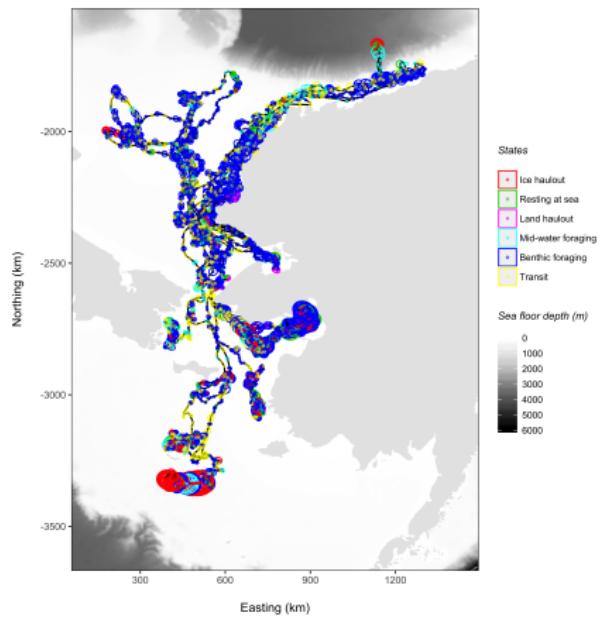
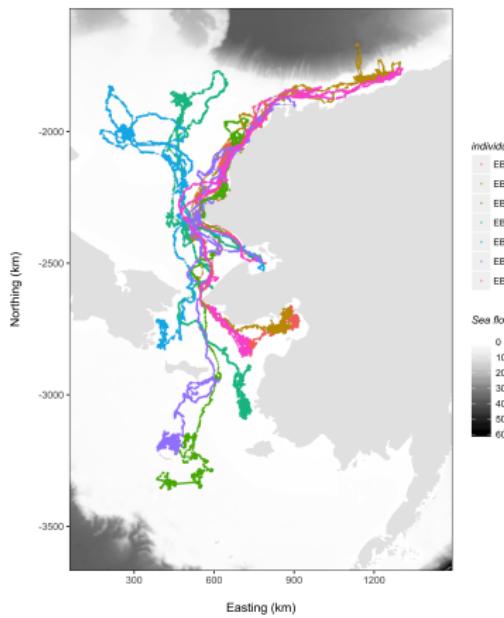
# Bearded seal example: location uncertainty

```
crwOut <- crawlWrap(data, timeStep = "6 hours",  
                      err.model = err.model)
```



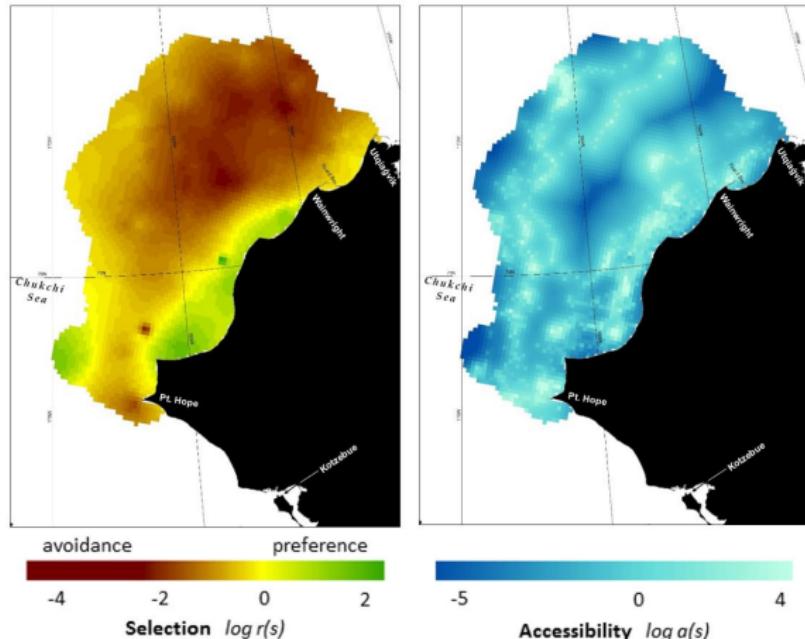
# Bearded seal example: multiple imputation HMM

```
miFits <- MIfitHMM(crwOut, nSims,  
nbStates=6, dist, Par0, DM)
```



## Bearded seal example: state assignments

## Bearded seal example: resource selection



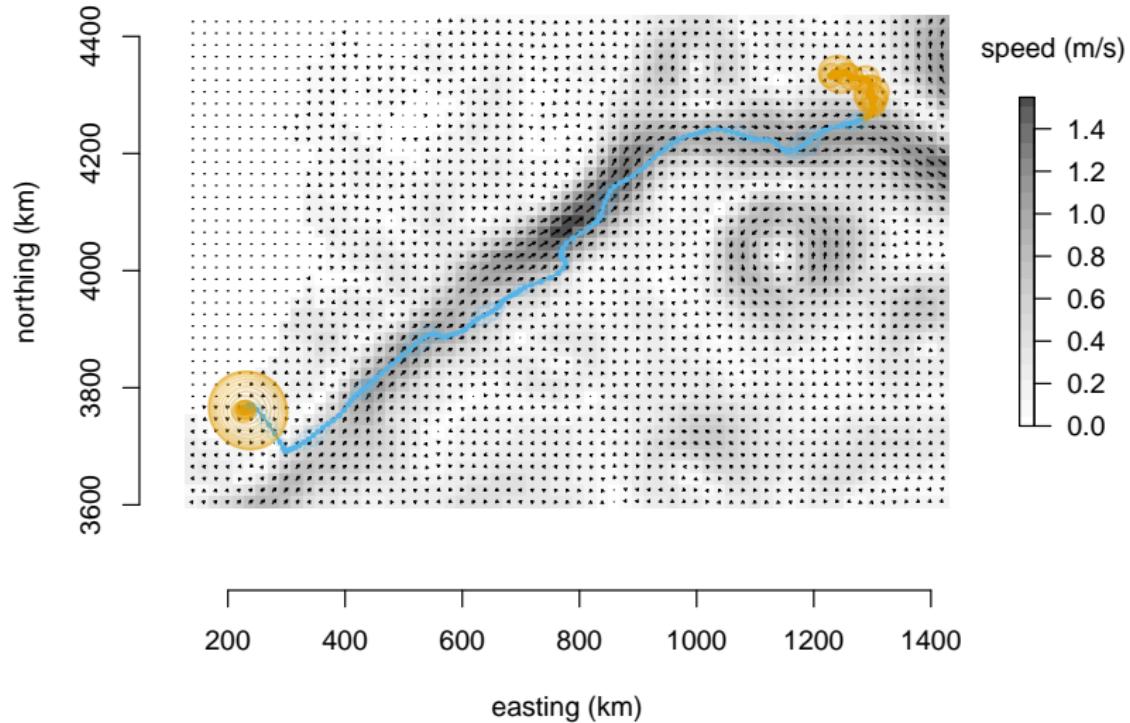
→ Positive selection for bivalves, large shrimp, cod, sculpins, etc.

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**2.** Bearded seal example

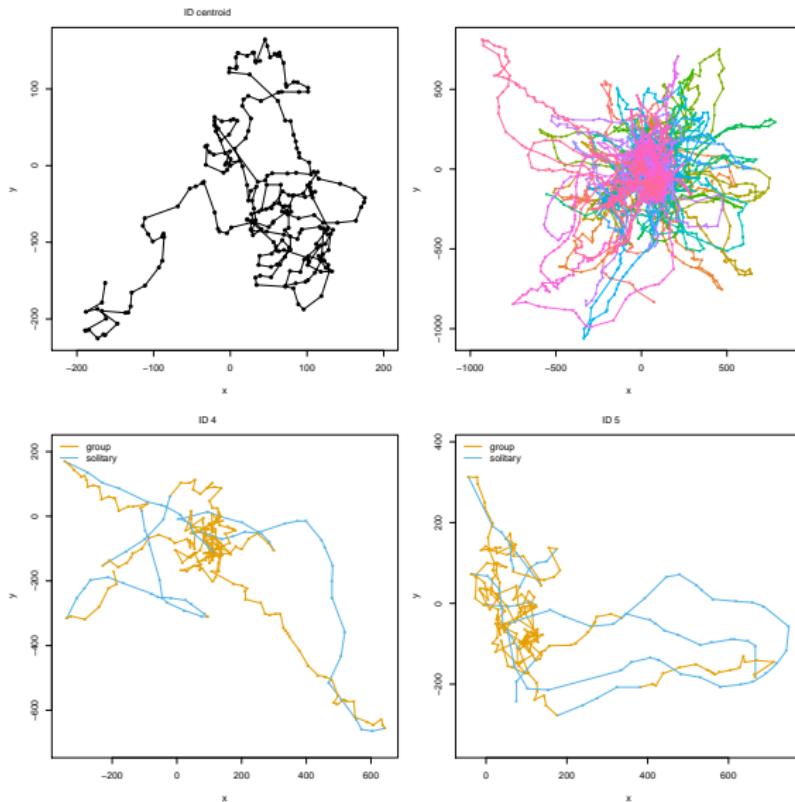
**3.** Other examples

# Loggerhead turtle movement relative to ocean currents



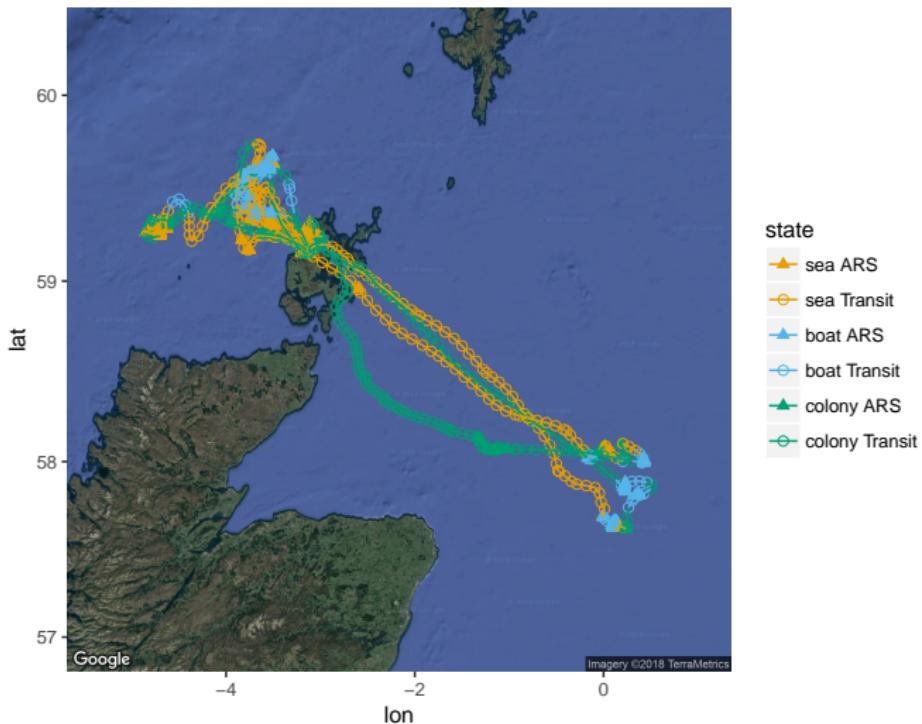
McClintock and Michelot (2018), “momentuHMM: R package for generalized hidden Markov models of animal movement”, *Methods Ecol Evol.*

# Group dynamic models



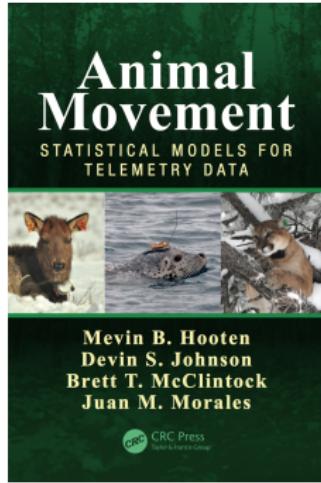
Langrock et al. (2014), "Modelling group dynamic animal movement", *Methods Ecol Evol.*

# Northern fulmar movement relative to fishing vessels



Data from: Pirotta et al. (2018), "Central place foragers and moving stimuli: A hidden-state model to discriminate the processes affecting movement", *J Anim Ecol.*

# Questions?



- ▶ *Animal Movement* book now available from CRS Press and Amazon
- ▶ 1-day workshop during ISEC2018
- ▶ [github.com/bmcclintock/  
momentuHMM](https://github.com/bmcclintock/momentuHMM)

# Practical session

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- ▶ Northern fur seal example
- ▶ Northern fulmar example
- ▶ Loggerhead turtle example