

SSF Validation

Scott Forrest

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Similar to the deepSSF next-step validation scripts, we can validate the fitted SSF models by assessing the predicted probability values at the location of the next step. We can do this for the movement, habitat selection and next-step probability surfaces, providing information about the accuracy of each of these processes, and how that changes through time.

We fitted the SSF models (with and without temporal dynamics) in the [SSF Model Fitting](#) script, and we can use the fitted parameters to generate the movement, habitat sele

Whilst the realism and emergent properties of simulated trajectories are difficult to assess, we can validate the deepSSF models on their predictive performance at the next step, for each of the habitat selection, movement and next-step probability surfaces. Ensuring that the probability surfaces are normalised to sum to one, they can be compared to the predictions of typical step selection functions when the same probability surfaces are generated for the same local covariates. This approach not only allows for comparison between models, but can be informative as to when in the observed trajectory the model performs well or poorly, which can be analysed across the entire tracking period or for each hour of the day, and can lead to critical evaluation of the covariates that are used by the models and allow for model refinement.

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Loading packages

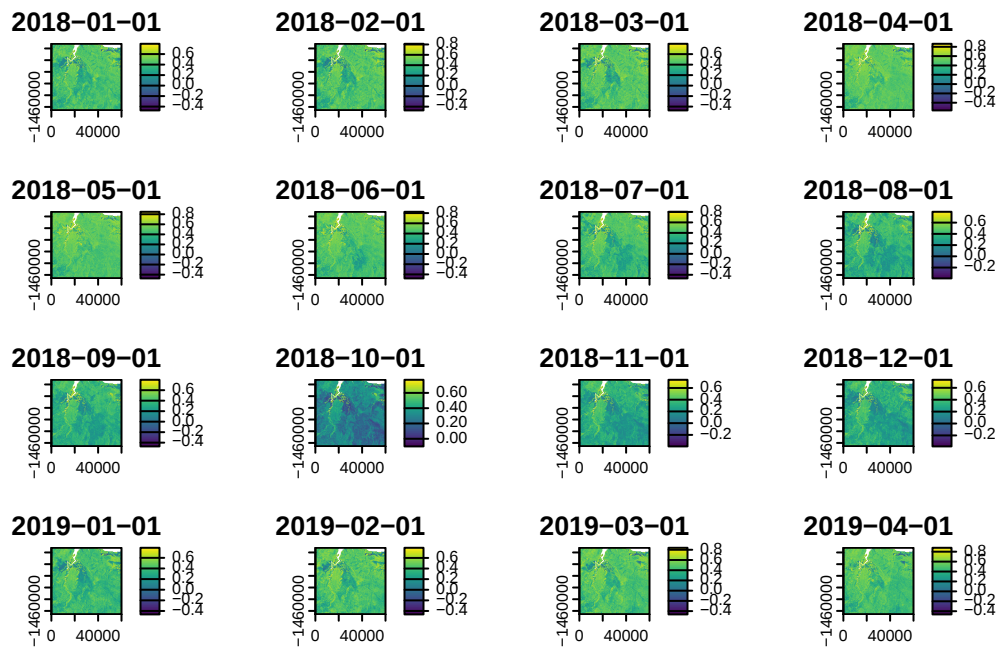
```
library(tidyverse)
packages <- c("amt", "sf", "terra", "beepr", "tictoc", "circular", "matrixStats", "progress")
walk(packages, require, character.only = T)
```

Reading in the environmental covariates

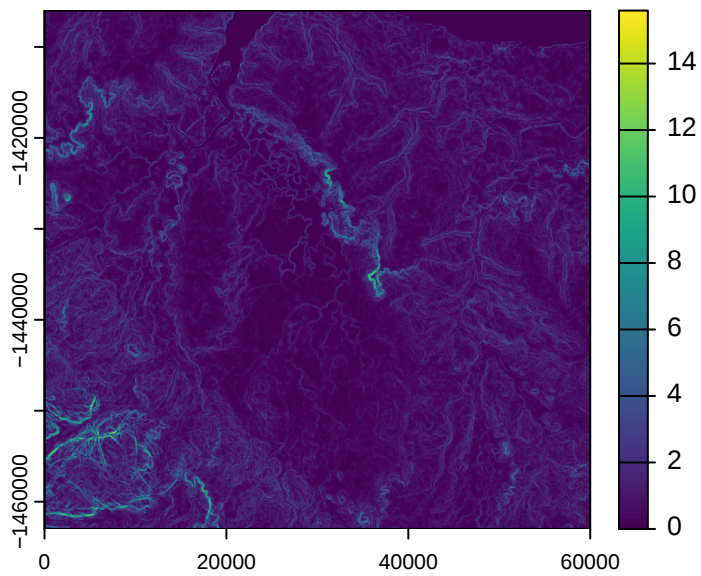
```
ndvi_projected <- rast("mapping/cropped rasters/ndvi_GEE_projected_watermask20230207.tif")
terra::time(ndvi_projected) <- as.POSIXct(lubridate::ymd("2018-01-01") + months(0:23))
slope <- rast("mapping/cropped rasters/slope_raster.tif")
veg_herby <- rast("mapping/cropped rasters/veg_herby.tif")
canopy_cover <- rast("mapping/cropped rasters/canopy_cover.tif")

# change the names (these will become the column names when extracting
# covariate values at the used and random steps)
names(ndvi_projected) <- rep("ndvi", terra::nlyr(ndvi_projected))
names(slope) <- "slope"
names(veg_herby) <- "veg_herby"
names(canopy_cover) <- "canopy_cover"

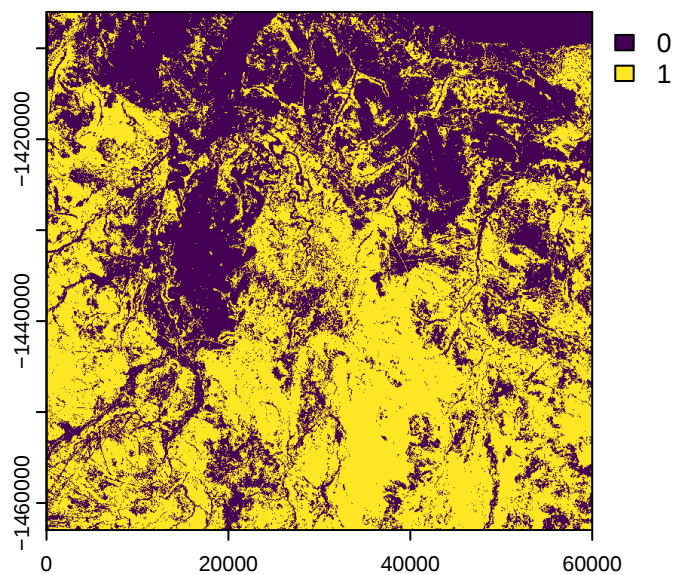
# to plot the rasters
plot(ndvi_projected)
```



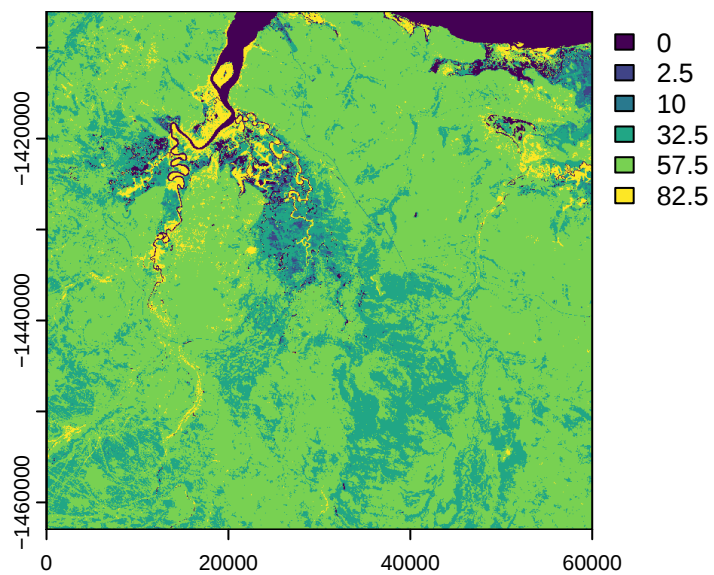
```
plot(slope)
```



```
plot(veg_herby)
```



```
plot(canopy_cover)
```



Generating the data to fit a deepSSF model

Set up the spatial extent of the local covariates

```
# get the resolution from the covariates
res <- terra::res(ndvi_projected)[1]
```

```

# how much to trim on either side of the location,
# this will determine the extent of the spatial inputs to the deepSSF model
buffer <- 1250 + (res/2)
# calculate the number of cells in each axis
nxn_cells <- buffer*2/res

# hourly lag - to set larger time differences between locations
hourly_lag <- 1

```

Evaluate next-step ahead predictions

Create distance and bearing layers for the movement probability

```

image_dim <- 101
pixel_size <- 25
center <- image_dim %/% 2

# Create matrices of indices
x <- matrix(rep(0:(image_dim - 1), image_dim), nrow = image_dim, byrow = TRUE)
y <- matrix(rep(0:(image_dim - 1), each = image_dim), nrow = image_dim, byrow = TRUE)

# Compute the distance layer
distance_layer <- sqrt((pixel_size * (x - center))^2 + (pixel_size * (y - center))^2)

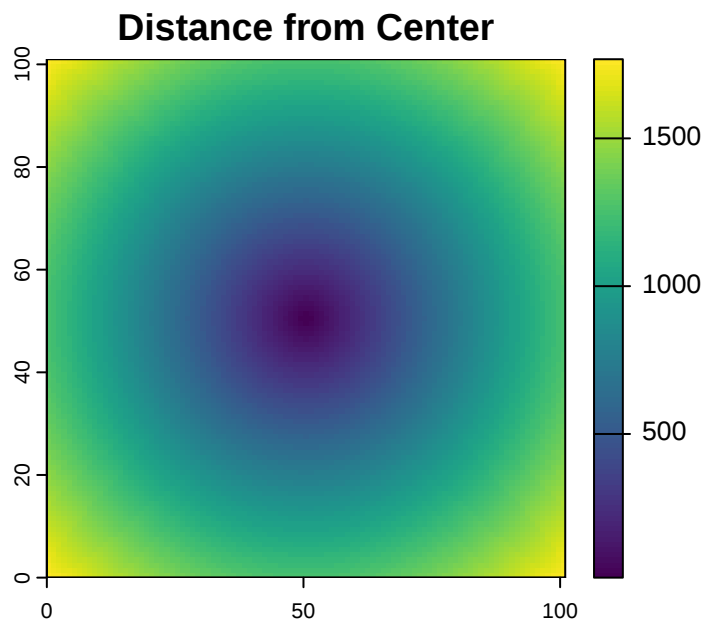
# Change the center cell to the average distance from the center to the edge of the pixel
distance_layer[center + 1, center + 1] <- 0.56 * pixel_size

# Compute the bearing layer
bearing_layer <- atan2(center - y, x - center)

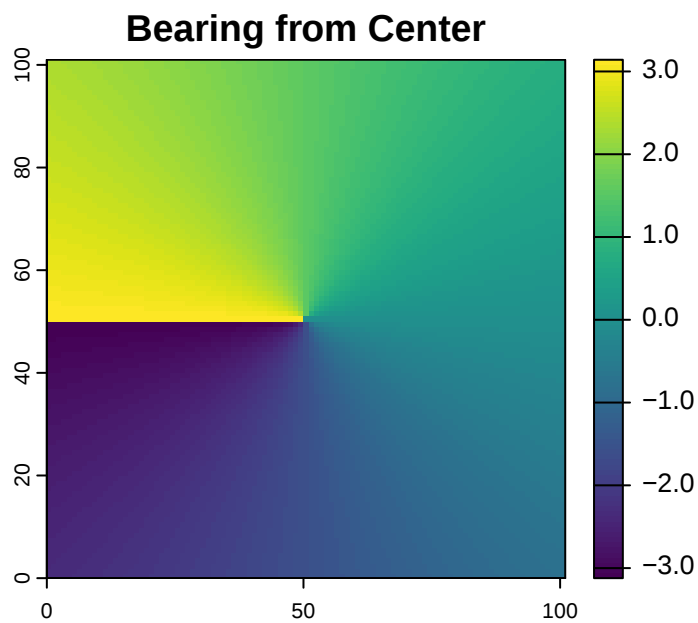
# Convert the distance and bearing matrices to raster layers
distance_layer <- rast(distance_layer)
bearing_layer <- rast(bearing_layer)

# Optional: Plot the distance and bearing rasters
plot(distance_layer, main = "Distance from Center")

```



```
plot(bearing_layer, main = "Bearing from Center")
```



```
distance_values <- terra::values(distance_layer)  
bearing_values <- terra::values(bearing_layer)
```

Calculating the habitat selection probabilities

The habitat selection term of a step selection function is typically modelled analogously to a resource-selection function (RSF), that assumes an exponential (log-linear) form as

$$\omega(\mathbf{X}(s_t); \beta(\tau; \alpha)) = \exp(\beta_1(\tau; \alpha_1)X_1(s_t) + \dots + \beta_n(\tau; \alpha_n)X_n(s_t)),$$

where $\beta(\tau; \alpha) = (\beta_1(\tau; \alpha_1), \dots, \beta_n(\tau; \alpha_n))$ in our case,

$$\beta_i(\tau; \alpha_i) = \alpha_{i,0} + \sum_{j=1}^P \alpha_{i,j} \sin\left(\frac{2j\pi\tau}{T}\right) + \sum_{j=1}^P \alpha_{i,j+P} \cos\left(\frac{2j\pi\tau}{T}\right),$$

and $\alpha_i = (\alpha_{i,0}, \dots, \alpha_{i,2P})$, where P is the number of pairs of harmonics, e.g. for $P = 2$, for each covariate there would be two sine terms and two cosine terms, as well as the linear term denoted by $\alpha_{i,0}$. The $+P$ term in the α index of the cosine term ensures that each α_i coefficient in α_i is unique.

To aid the computation of the simulations, we can precompute $\omega(\mathbf{X}(s_t); \beta(\tau; \alpha))$ for each hour prior to running the simulations.

In the dataframe of temporally varying coefficients, for each covariate we have reconstructed $\beta_i(\tau; \alpha_i)$ and discretised for each hour of the day, resulting in $\beta_{i,\tau}$ for $i = 1, \dots, n$ where n is the number of covariates and $\tau = 1, \dots, 24$.

Given these, we can solve $\omega(\mathbf{X}(s_t); \beta(\tau; \alpha))$ for every hour of the day. This will result in an RSF map for each hour of the day, which we will use in the simulations.

Then, when we do our step selection simulations, we can just subset these maps by the current hour of the day, and extract the values of $\omega(\mathbf{X}(s_t); \beta(\tau; \alpha))$ for each proposed step location, rather than solving $\omega(\mathbf{X}(s_t); \beta(\tau; \alpha))$ for every step location.

Calculating the next-step probabilities for the 0p and 2p models

Select model coefficients

```
model_date <- "2025-04-10"
focal_id <- 2005
```

Setting up the data

Read in the data of all individuals, which includes the focal or ‘in-sample’ individual that the model was fitted to, as well as the data of the ‘out-of-sample’ individuals that the model has never seen before, and which is from quite a different environmental space (more on the floodplain and closer to the river system).

```
# create vector of GPS date filenames
buffalo_data_ids <- list.files(path = "buffalo_local_data_id", pattern = ".csv")
print(buffalo_data_ids)
```

```
[1] "buffalo_2005_data_df_lag_1hr_n10297.csv"
[2] "buffalo_2014_data_df_lag_1hr_n6572.csv"
[3] "buffalo_2018_data_df_lag_1hr_n9440.csv"
[4] "buffalo_2021_data_df_lag_1hr_n6928.csv"
[5] "buffalo_2022_data_df_lag_1hr_n9099.csv"
[6] "buffalo_2024_data_df_lag_1hr_n9531.csv"
[7] "buffalo_2039_data_df_lag_1hr_n5569.csv"
[8] "buffalo_2154_data_df_lag_1hr_n10417.csv"
[9] "buffalo_2158_data_df_lag_1hr_n9700.csv"
[10] "buffalo_2223_data_df_lag_1hr_n5310.csv"
[11] "buffalo_2327_data_df_lag_1hr_n8983.csv"
[12] "buffalo_2387_data_df_lag_1hr_n10409.csv"
[13] "buffalo_2393_data_df_lag_1hr_n5299.csv"
[14] "buffalo_temporal_cont_2005_data_df_lag_1hr_n10.csv"
[15] "buffalo_temporal_cont_2005_data_df_lag_1hr_n100.csv"
[16] "buffalo_temporal_cont_2005_data_df_lag_1hr_n10297.csv"
[17] "fixed_buffalo_2005_data_df_lag_1hr_n10297.csv"
```

```
ids <- substr(buffalo_data_ids, 9, 12)

# import data
buffalo_id_list <- vector(mode = "list", length = length(buffalo_data_ids))

# read in the data
for(i in 1:length(buffalo_data_ids)){

  buffalo_id_list[[i]] <- read.csv(paste("buffalo_local_data_id/",
                                         buffalo_data_ids[[i]],
                                         sep = ""))

  buffalo_id_list[[i]]$id <- ids[i]

}
```

Calculating the next-step probabilities

This scrip takes a long time to run. As we have already calculated the next-step probabilities for all individuals and all steps we will just calculate a subset of the next-step predictions for illustration.

```
# how many samples to illustrate the approach
n_samples_subset <- 50
```

Loop over all individuals and models

This script loops over all individuals and models, and calculates the next-step probabilities for each step of the individual.

Here's high-level overview of the full chunk below

Outermost loop: `for(k in 1:length(buffalo_id_list)) {...}`

- **Data Preparation and Subsetting**

- Each buffalo's trajectory (`data_id`) is filtered to retain location steps within the local spatial extent ($\pm 1250\text{m}$).
- Any steps with missing data (e.g., turning angle, `ta`) are removed.
- The data is used to define a local bounding box (`template_raster_crop`) for cropping relevant raster datasets. This bounding box covers the extent of all points for that individual, and is for computational efficiency (so the full raster isn't being subsetted at every step). This is only done once per individual and is not the same as the local cropping done at every step.

- **Covariate Rasters Cropped to Bounding Box**

- **NDVI** (Normalized Difference Vegetation Index - including squared term)
- **Canopy Cover** (including squared term)
- **Herbaceous Vegetation**
- **Slope**

Middle loop: `for(j in 1:length(model_harmonics)) {...}`

- **SSF Models**

- The script selects one of the two models: `0p` (no temporal harmonics) or `2p` (temporal harmonics), indicated by `model_harmonics`.
- Corresponding coefficients for each model are read from CSV files (e.g., `"ssf_coefficients/id{focal_id}_{model_harmonics[j]}Daily_coefs_{model_date}.csv"`).

- Only integer hours are used (filtered via `hour %% 1 == 0`).

Inner loop: for (i in 2:n) {...}

- **Loop Over Steps**

For each step in the buffalo's trajectory:

- **Extract Local Covariates**
A subset of each covariate raster is cropped to the step's spatial extent.
- **Habitat Selection Probability**
 - * Relevant coefficients (e.g., `ndvi`, `ndvi_2`, `canopy`, `canopy_2`, `herby`, `slope`) for the current hour are retrieved, given the model.
 - * A log-probability (`habitat_log`) is computed from the linear combination of covariates.
 - * The habitat selection probability is calculated by exponentiating the log-probability and normalising it to sum to 1.
- **Movement Probability**
 - * **Step length** is modeled via a Gamma distribution (using `shape` and `scale` parameters).
 - * **Turning angle** is modeled via the von Mises distribution (using `kappa` and a mean angle based on the previous step's bearing).
 - * The log-probability of these components is combined (`move_log`) and normalised.
- **Next-Step Probability**
 - * The **habitat** and **movement** log-probabilities are summed to get the next-step log-probability.
 - * It is normalised to yield the **next-step probability** for each candidate pixel (where all pixels sum to 1).
 - * The script then extracts the probability at the buffalo's actual next location (`prob_next_step_ssf_0p` or `prob_next_step_ssf_2p`).

Outputs

- For each step, the script appends probabilities (`prob_habitat_ssf_0/2p`, `prob_movement_ssf_0/2p`, and `prob_next_step_ssf_0/2p`) to the data frame.

Diagnostic Plots

- For the first few steps of the first buffalo (which is the focal id), the script plots local covariate layers and the log-probability surfaces (habitat, movement, and combined next-step).

```
#-----  
### Select a buffalo's data  
#-----  
  
# for(k in 1:length(buffalo_id_list)) {  
  
for(k in 1:1) {  
  
  data_id <- buffalo_id_list[[k]]  
  attr(data_id$t_, "tzone") <- "Australia/Queensland"  
  attr(data_id$t2_, "tzone") <- "Australia/Queensland"  
  
  data_id <- data_id %>% mutate(  
    year_t2 = year(t2_),  
    yday_t2_2018_base = ifelse(year_t2 == 2018, yday_t2, 365+yday_t2)  
  )  
  
  sample_extent <- 1250  
  
  # remove steps that fall outside of the local spatial extent  
  data_id <- data_id %>%  
    filter(x2_cent > -sample_extent &  
           x2_cent < sample_extent &  
           y2_cent > -sample_extent &  
           y2_cent < sample_extent) %>%  
    drop_na(ta)  
  
  # max(data_id$yday_t2_2018_base)  
  # write_csv(data_id, paste0("buffalo_local_data_id/validation/validation_", buffalo_data_i  
  
  model_harmonics <- c("0p", "2p")  
  
  test_data <- data_id %>% slice(1:100) # test with a subset of the data  
  # test_data <- data_id  
  
  # subset rasters around all of the locations of the current buffalo (speeds up local subse  
  buffer <- 2000
```

```

template_raster_crop <- terra::rast(xmin = min(test_data$x2_) - buffer,
                                   xmax = max(test_data$x2_) + buffer,
                                   ymin = min(test_data$y2_) - buffer,
                                   ymax = max(test_data$y2_) + buffer,
                                   resolution = 25,
                                   crs = "epsg:3112")

## Crop the rasters
ndvi_projected_cropped <- terra::crop(ndvi_projected, template_raster_crop)
ndvi_projected_cropped_sq <- ndvi_projected_cropped^2

canopy_cover_cropped <- terra::crop(canopy_cover, template_raster_crop)
canopy01_cropped <- canopy_cover_cropped/100
canopy01_cropped_sq <- canopy01_cropped^2

veg_herby_cropped <- terra::crop(veg_herby, template_raster_crop)
slope_cropped <- terra::crop(slope, template_raster_crop)

tic()

#-----
### Select a model (without temporal dynamics - 0p, or with temporal dynamics - 2p)
#-----

for(j in 1:length(model_harmonics)) {

  ssf_coefs_file_path <- paste0("ssf_coefficients/id", focal_id, "_", model_harmonics[j],
                                print(ssf_coefs_file_path)

  ssf_coefs <- read_csv(ssf_coefs_file_path)

  # keep only the integer hours using the modulo operator
  ssf_coefs <- ssf_coefs %>% filter(ssf_coefs$hour %% 1 == 0)

  # for the progress bar - uncomment the line depending on if using subset
  # for all data
  n <- nrow(test_data)
  # for the subset
  # n <- n_samples_subset

  pb <- progress_bar$new(
    format = " Progress [:bar] :percent in :elapsed",
    total = n,
    clear = FALSE

```

```

)

tic()

#-----
### Loop over every step in the trajectory
#-----

# to calculate the next step probabilities for all samples
# for (i in 2:n) {

sample_plot <- 1

for (i in sample_plot:(sample_plot+10)) {
# for (i in sample_plot:sample_plot) {

# for the subset
# for (i in 2:(n_samples_subset+1)) {

sample_tm1 <- test_data[i-1, ] # get the step at t - 1 for the bearing of the approach
sample <- test_data[i, ]
sample_extent <- ext(sample$x_min, sample$x_max, sample$y_min, sample$y_max)

#-----
### Extract local covariates
#-----
# NDVI
ndvi_index <- which.min(abs(difftime(sample$t_, terra::time(ndvi_projected_cropped))))
ndvi_sample <- crop(ndvi_projected[[ndvi_index]], sample_extent)
# NDVI ^ 2
ndvi_sq_sample <- crop(ndvi_projected_cropped_sq[[ndvi_index]], sample_extent)
# Canopy cover
canopy_sample <- crop(canopy01_cropped, sample_extent)
# Canopy cover ^ 2
canopy_sq_sample <- crop(canopy01_cropped_sq, sample_extent)
# Herbaceous vegetation
veg_herby_sample <- crop(veg_herby_cropped, sample_extent)
# Slope
slope_sample <- crop(slope_cropped, sample_extent)

# create a SpatVector from the coordinates
next_step_vect <- vect(cbind(sample$x2_, sample$y2_), crs = crs(ndvi_sample))

```

```

#-----
### calculate the next-step probability surfaces
#-----

### Habitat selection probability
#-----

# get the coefficients for the appropriate hour
coef_hour <- which(ssf_coefs$hour == sample$hour_t2)

# multiply covariate values by coefficients
# ndvi
ndvi_linear <- ndvi_sample * ssf_coefs$ndvi[[coef_hour]]
ndvi_quad <- ndvi_sq_sample * ssf_coefs$ndvi_2[[coef_hour]]
# canopy cover
canopy_linear <- canopy_sample * ssf_coefs$canopy[[coef_hour]]
canopy_quad <- canopy_sq_sample * ssf_coefs$canopy_2[[coef_hour]]
# veg_herby
veg_herby_pred <- veg_herby_sample * ssf_coefs$herby[[coef_hour]]
# slope
slope_pred <- slope_sample * ssf_coefs$slope[[coef_hour]]

# combining all covariates (on the log-scale)
habitat_log <- ndvi_linear + ndvi_quad + canopy_linear + canopy_quad + slope_pred + ve

# create template raster
habitat_pred <- habitat_log
# convert to normalised probability
habitat_pred[] <- exp(values(habitat_log) - max(values(habitat_log), na.rm = T)) /
  sum(exp(values(habitat_log) - max(values(habitat_log), na.rm = T)), na.rm = T)
# print(sum(values(habitat_pred)))

# habitat probability value at the next step
prob_habitat <- as.numeric(terra::extract(habitat_pred, next_step_vect)[2])
# print(paste0("Habitat probability: ", prob_habitat))

### Movement Probability
#-----

# step lengths
# calculated on the log scale

```

```

# subtract the log(distance values to account for the change in movement variables - A
step_log <- habitat_log
step_log[] <- dgamma(distance_values,
                     shape = ssf_coefs$shape[[coef_hour]],
                     scale = ssf_coefs$scale[[coef_hour]], log = TRUE) - log(distance_

# normalise the step length probabilities
# step_log[] <- values(step_log) - max(values(step_log), na.rm = T) -
#   log(sum(exp(values(step_log) - max(values(step_log), na.rm = T))))

# check that they sum to 1
# print(sum(exp(values(step_log))))

# turning angles
ta_log <- habitat_log
vm_mu <- sample$bearing
vm_mu_updated <- ifelse(ssf_coefs$kappa[[coef_hour]] > 0, sample_tm1$bearing, sample_t
ta_log[] <- suppressWarnings(circular::dvonmises(bearing_values,
                                                mu = vm_mu_updated,
                                                kappa = abs(ssf_coefs$kappa[[coef_hou
                                                log = TRUE))

# normalise the turning angle probabilities
# ta_log[] <- values(ta_log) - max(values(ta_log), na.rm = T) -
#   log(sum(exp(values(ta_log) - max(values(ta_log), na.rm = T))))

# check that they sum to 1
# print(sum(exp(values(ta_log))))

# combine the step and turning angle probabilities
move_log <- step_log + ta_log

# create template raster
move_pred <- habitat_log
# convert to normalised probability
move_pred[] <- exp(values(move_log) - max(values(move_log), na.rm = T)) /
  sum(exp(values(move_log) - max(values(move_log), na.rm = T)), na.rm = T)
# print(sum(values(move_pred)))

# movement probability value at the next step
prob_movement <- as.numeric(terra::extract(move_pred, next_step_vect)[2])
# print(prob_movement)

```

```

# Next-step probability
#-----

# calculate the next-step log probability
next_step_log <- habitat_log + move_log

# create template raster
next_step_pred <- habitat_log
# normalise using log-sum-exp trick
next_step_pred[] <- exp(values(next_step_log) - max(values(next_step_log), na.rm = T))
  sum(exp(values(next_step_log) - max(values(next_step_log), na.rm = T)), na.rm = T)
# print(sum(values(next_step_pred)))

# check next-step location
next_step_sample <- terra::mask(next_step_pred, next_step_vect, inverse = T)
# plot(next_step_sample)

# check which cell is NA in rows and columns
# print(rowColFromCell(next_step_pred, which(is.na(values(next_step_sample)))))

# NDVI value at next step (to check against the deepSSF version)
# ndvi_next_step <- as.numeric(terra::extract(ndvi_sample, next_step_vect)[2])
# print(paste("NDVI value = ", ndvi_next_step))

# next-step probability value at the next step
prob_next_step <- as.numeric(terra::extract(next_step_pred, next_step_vect)[2])
# print(prob_next_step)

test_data[i, paste0("prob_habitat_ssf_", model_harmonics[j])] <- prob_habitat
test_data[i, paste0("prob_movement_ssf_", model_harmonics[j])] <- prob_movement
test_data[i, paste0("prob_next_step_ssf_", model_harmonics[j])] <- prob_next_step

# plot a few local covariates and the predictions for the focal buffalo
# if(k == 1 & i < 7){
if(k == 1){

  print(sample)

  png(paste0("outputs/next_step_validation/ndvi_step_", i, ".png"),
      width = 800, height = 750, res = 150)
  plot(ndvi_sample, main = "NDVI")
  dev.off()

  png(paste0("outputs/next_step_validation/canopy_", i, ".png"),

```

```

width = 800, height = 750, res = 150)
plot(canopy_sample, main = "Canopy cover")
dev.off()

png(paste0("outputs/next_step_validation/herby_", i, ".png"),
width = 800, height = 750, res = 150)
plot(veg_herby_sample, main = "Herbaceous vegetation")
dev.off()

png(paste0("outputs/next_step_validation/slope_", i, ".png"),
width = 800, height = 750, res = 150)
plot(slope_sample, main = "Slope")
dev.off()

png(paste0("outputs/next_step_validation/habitat_log_step_", i, "_model_", j, ".png"),
width = 800, height = 750, res = 150)
plot(terra::mask(log(habitat_pred), next_step_vect, inverse = T),
      main = paste0("Habitat selection (log) - Model ", model_harmonics[j]))
# plot(habitat_pred)
dev.off()

png(paste0("outputs/next_step_validation/habitat_step_", i, "_model_", j, ".png"),
width = 800, height = 750, res = 150)
plot(terra::mask(habitat_pred, next_step_vect, inverse = T),
      main = paste0("Habitat selection - Model ", model_harmonics[j]))
dev.off()

# plot(step_log, main = "")
# plot(ta_log, main = "")
plot(terra::mask(log(move_pred), next_step_vect, inverse = T),
      main = paste0("Movement log-probability - Model ", model_harmonics[j]))
# plot(move_pred)

plot(terra::mask(log(next_step_pred), next_step_vect, inverse = T),
      main = paste0("Next-step log-probability - Model ", model_harmonics[j]))
# plot(next_step_pred)

}

pb$tick() # Update progress bar

}

```

```

    toc()

}

# write.csv(test_data, file = paste0("outputs/next_step_validation/next_step_probs_ssf_80-
gc()

}

```

```
[1] "ssf_coefficients/id2005_0pDaily_coefs_80-10-10_2025-04-10.csv"
```

```
Rows: 240 Columns: 13
```

```
-- Column specification -----
```

```
Delimiter: ","
```

```
dbl (13): hour, ndvi, ndvi_2, canopy, canopy_2, slope, herby, sl, log_sl, co...
```

```
i Use `spec()` to retrieve the full column specification for this data.
```

```
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
Warning in max(values(move_log), na.rm = T): no non-missing arguments to max;
returning -Inf
```

```
Warning in max(values(move_log), na.rm = T): no non-missing arguments to max;
returning -Inf
```

```
Warning in max(values(next_step_log), na.rm = T): no non-missing arguments to
max; returning -Inf
```

```
Warning in max(values(next_step_log), na.rm = T): no non-missing arguments to
max; returning -Inf
```

```
Warning: Failed to compute min/max, no valid pixels found in sampling. (GDAL
error 1)
```

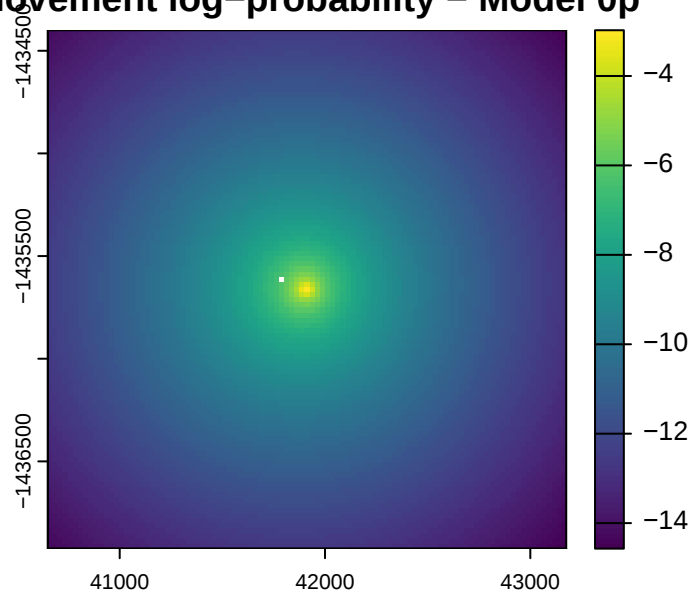
	x_	y_	t_	id	x1_	y1_	x2_													
1	41969.31	-1435671	2018-07-25T01:04:23Z	2005	41969.31	-1435671	41921.52													
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1												
1	-1435654	-47.78894	16.85711	2018-07-25T02:04:39Z		1	11	206												
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos		sl												
1	12	1.224606e-16		-1	206	-0.3913578	-0.9202386	50.67489												
	log_sl	bearing	bearing_sin	bearing_cos		ta	cos_ta	x_min	x_max											
1	3.925431	2.802478	0.3326521	-0.9430496	1.367942	0.201466	40706.81	43231.81												
	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base														
1	-1436934	-1434409		7	NA	2018		206												

Warning: Failed to compute min/max, no valid pixels found in sampling. (GDAL error 1)

Warning: Failed to compute min/max, no valid pixels found in sampling. (GDAL error 1)

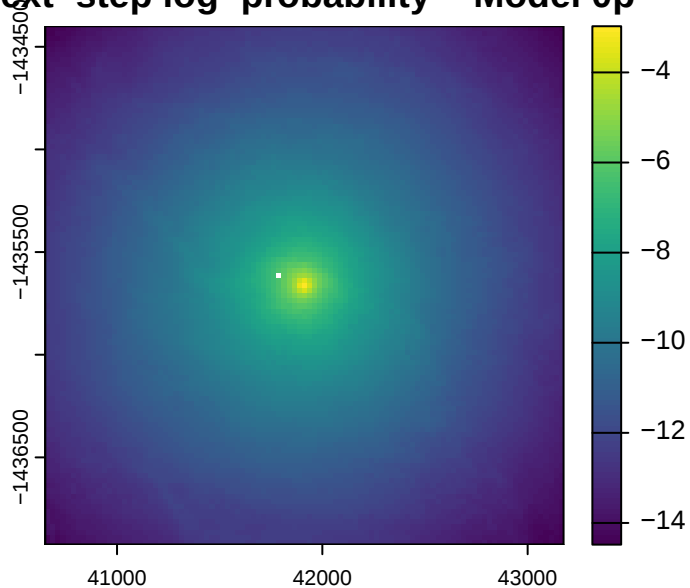
	x_	y_	t_	id	x1_	y1_	x2_	
2	41921.52	-1435654	2018-07-25T02:04:39Z	2005	41921.52	-1435654	41779.44	
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1
2	-1435601	-142.0823	53.56843	2018-07-25T03:04:17Z		1	12	206
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos		s1
2	13	-0.258819	-0.9659258	206	-0.3913578	-0.9202386		151.8452
	log_s1	bearing	bearing_sin	bearing_cos		ta	cos_ta	x_min
2	5.022862	2.781049	0.3527831	-0.9357051	-0.02142933	0.9997704		40659.02
	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2		
2	43184.02	-1436917	-1434392	7	NA	2018		
	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p					
2	206	NA	NA					
	prob_next_step_ssf_0p							
2	NA							

Movement log-probability – Model 0p

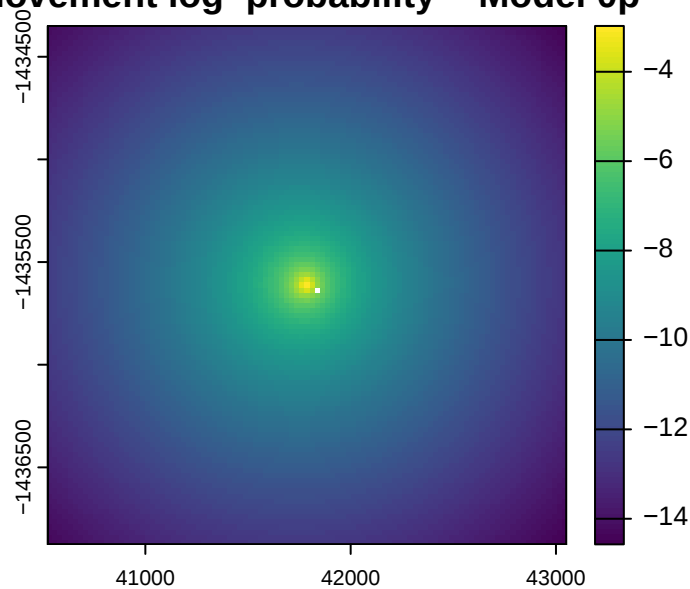


	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	log_s1	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p	prob_next_step_ssf_0p	
3	41779.44	-1435601	2018-07-25T03:04:17Z	2005	41779.44	-1435601	41841.2																																
3		-1435635	61.76368	-34.32294	2018-07-25T04:04:39Z	1	13	206																															
3		14	-0.5	-0.8660254	206	-0.3913578	-0.9202386	70.65986																															
3		4.257878	-0.5072195	-0.4857487	0.8740985	2.994917	-0.9892624	40516.94																															
3		43041.94	-1436863	-1434338	7	NA	2018																																
3			206	NA		NA																																	
3																																							

Next-step log-probability – Model 0p



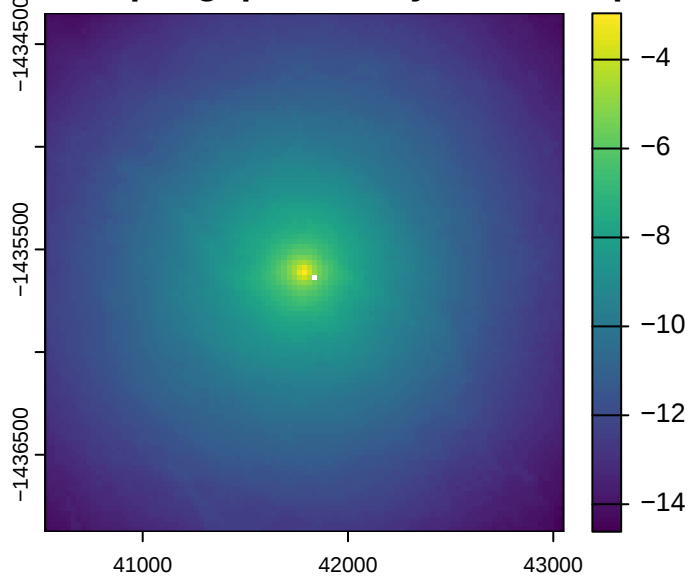
Movement log-probability – Model 0p



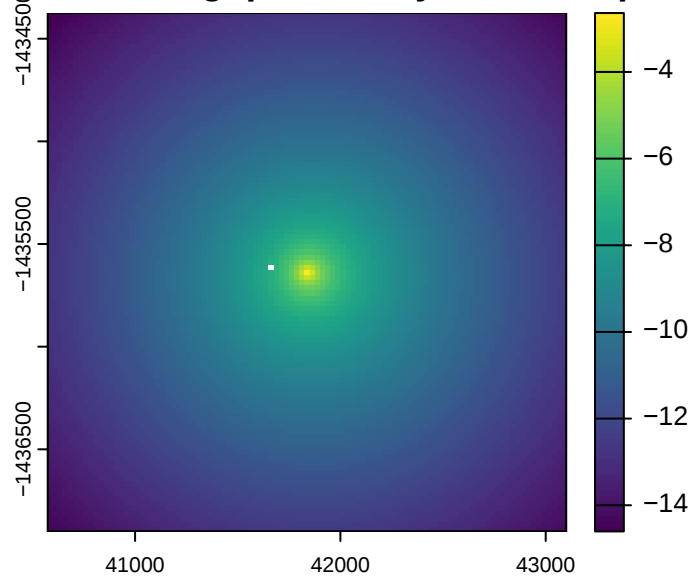
	x_	y_	t_	id	x1_	y1_	x2_	y2_
4	41841.2	-1435635	2018-07-25T04:04:39Z	2005	41841.2	-1435635	41655.46	-1435604
	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	
4	-185.7399	31.00353	2018-07-25T05:04:27Z	1	14	206	15	
	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	log_s1	
4	-0.7071068	-0.7071068	206	-0.3913578	-0.9202386	188.3097	5.238088	
	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	
4	2.976198	0.1646412	-0.9863535	-2.799767	-0.9421444	40578.7	43103.7	
	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base		

4	-1436898	-1434373	7	NA	2018	206
	prob_habitat_ssf_0p	prob_movement_ssf_0p	prob_next_step_ssf_0p			
4	NA	NA	NA			

Next-step log-probability – Model 0p



Movement log-probability – Model 0p



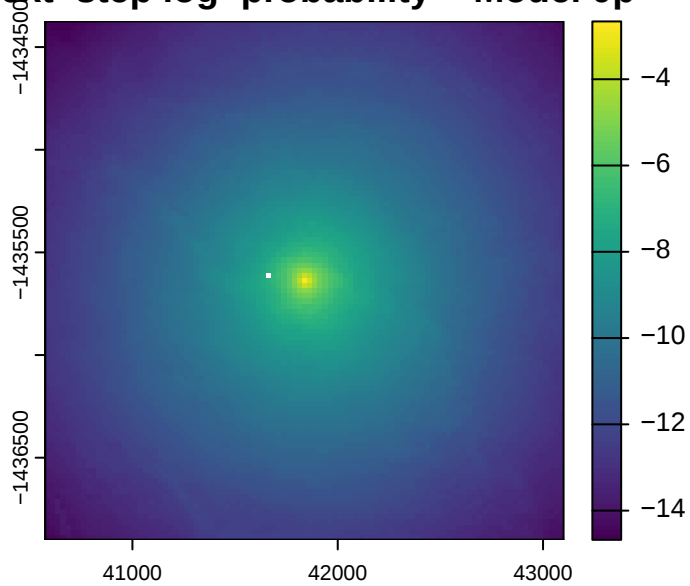
	x_	y_	t_	id	x1_	y1_	x2_	
5	41655.46	-1435604	2018-07-25T05:04:27Z	2005	41655.46	-1435604	41618.65	
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1
5	-1435608	-36.81141	-4.438037		2018-07-25T06:04:24Z		1	15
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos		s1

```

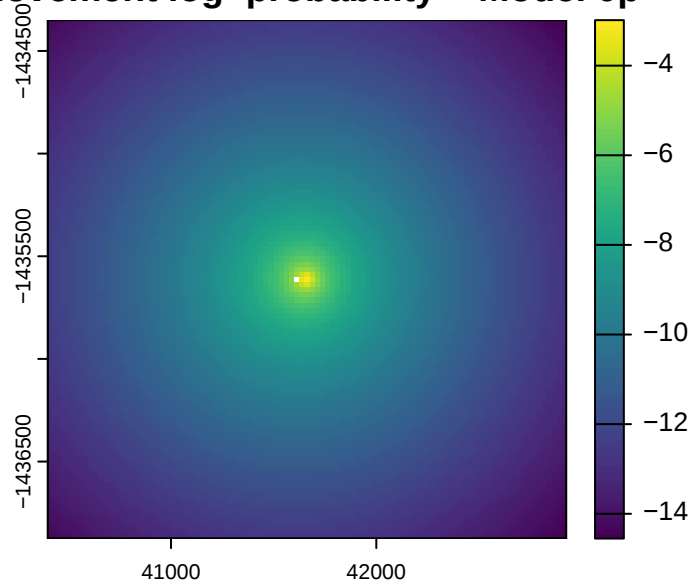
5      16 -0.8660254      -0.5      206 -0.3913578 -0.9202386 37.07797
      log_sl bearing bearing_sin bearing_cos      ta      cos_ta      x_min
5 3.613023 -3.02161 -0.1196947 -0.9928107 0.2853766 0.9595557 40392.96
      x_max      y_min      y_max s2_index points_vect_cent year_t2
5 42917.96 -1436867 -1434342      7      NA      2018
      yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
5      206      NA      NA
      prob_next_step_ssf_0p
5      NA

```

Next-step log-probability – Model 0p

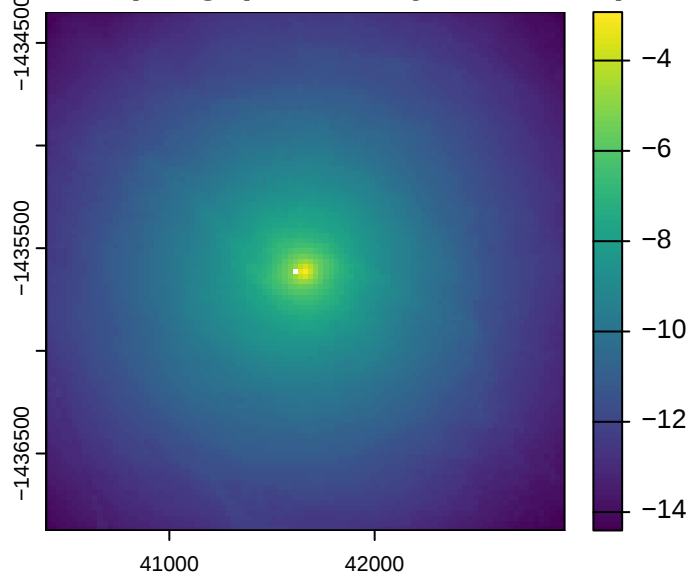


Movement log-probability – Model 0p

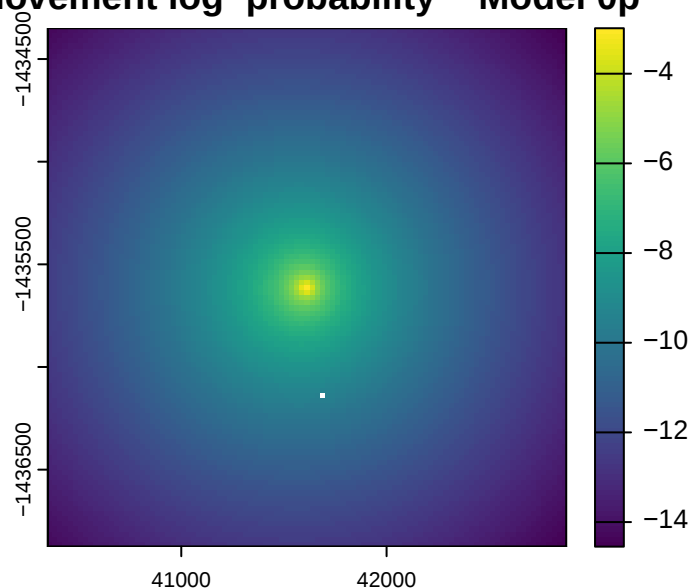


	x_	y_	t_	id	x1_	y1_	x2_	
6	41618.65	-1435608	2018-07-25T06:04:24Z	2005	41618.65	-1435608	41688.44	
	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	
6	-1436126	69.78648	-517.1566	2018-07-25T07:04:28Z	1	16	206	
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	
6	17	-0.9659258	-0.258819	206	-0.3913578	-0.9202386	521.8439	
	log_s1	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	
6	6.257369	-1.436664	-0.9910177	0.1337306	1.584946	-0.01414957	40356.15	
	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2		
6	42881.15	-1436871	-1434346	7	NA	2018		
	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p					
6	206	NA	NA					
	prob_next_step_ssf_0p							
6	NA							

Next-step log-probability – Model 0p

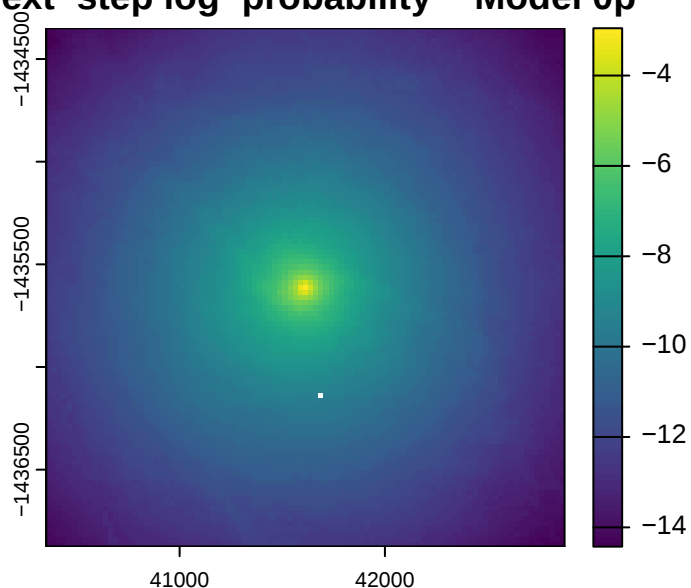


Movement log-probability – Model 0p

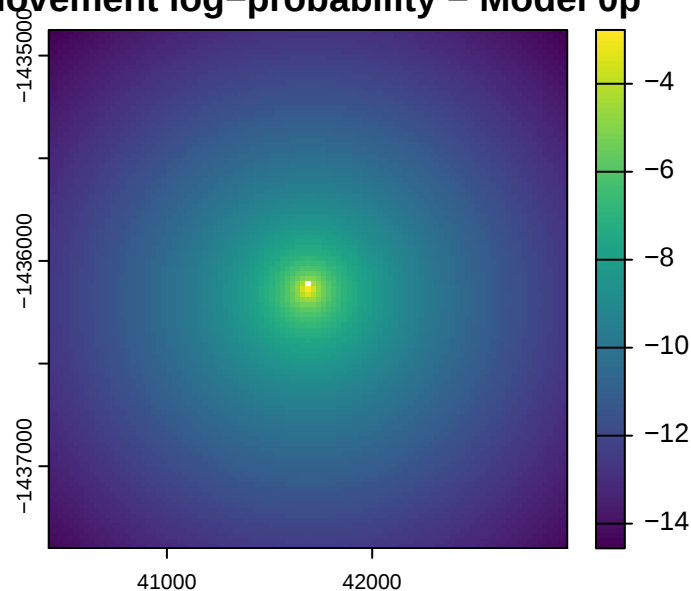


	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	log_s1	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p	prob_next_step_ssf_0p		
7	41688.44	-1436126	2018-07-25T07:04:28Z	2005	41688.44	-1436126	41684.34																																	
7	-1436119	-4.095906	7.020228	2018-07-25T08:04:31Z	1	17	206																																	
7	18	-1	-1.83691e-16	206	-0.3913578	-0.9202386	8.127733																																	
7	2.095282	2.098953	0.8637375	-0.503942	-2.747568	-0.9233716	40425.94																																	
7	42950.94	-1437388	-1434863	7	NA	2018																																		
7		206		NA		NA																																		
7																																								

Next-step log-probability – Model 0p



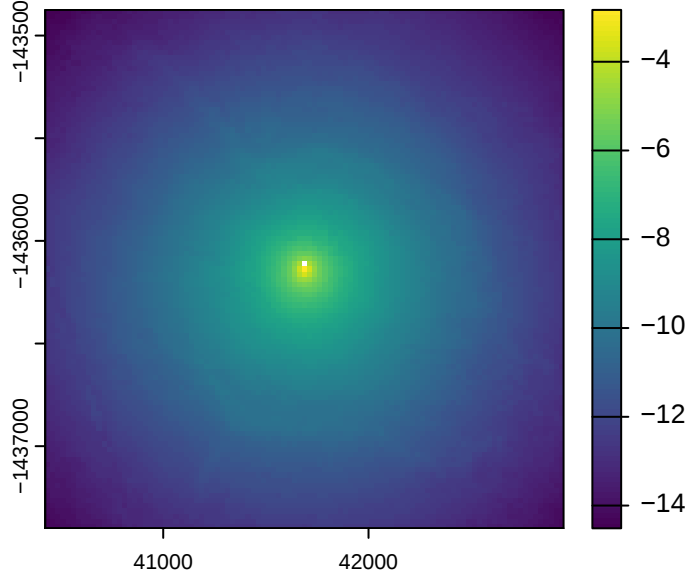
Movement log-probability – Model 0p



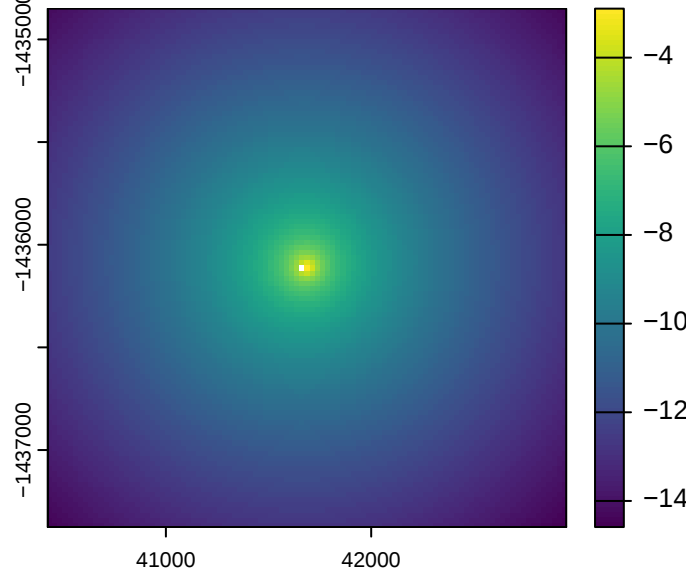
	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	sl	log_sl	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2
8	41684.34	-1436119	2018-07-25T08:04:31Z	2005	41684.34	-1436119	41674.59																											
8		-1436119	-9.754289	-0.08369654	2018-07-25T09:04:33Z	1	18	206																										
8	19	-0.9659258	0.258819	206	-0.3913578	-0.9202386	9.754648																											
8	2.277744	-3.133012	-0.00858017	-0.9999632	1.05122	0.4965124	40421.84																											

```
8 42946.84 -1437381 -1434856      7      NA      2018
  yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
8                206                NA                NA
  prob_next_step_ssf_0p
8                    NA
```

Next-step log-probability – Model 0p



Movement log-probability – Model 0p



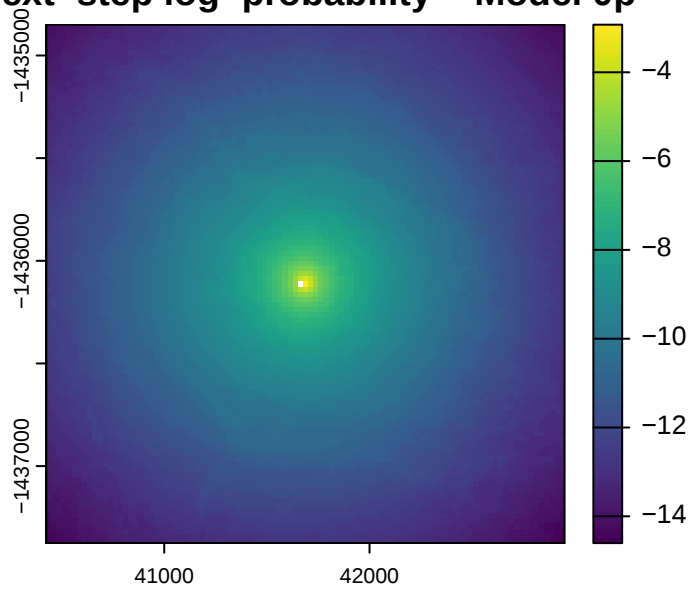
```
          x_      y_      t_   id   x1_   y1_   x2_
9 41674.59 -1436119 2018-07-25T09:04:33Z 2005 41674.59 -1436119 41425.16
  y2_   x2_cent y2_cent      t2_ t_diff hour_t1 yday_t1
```

```

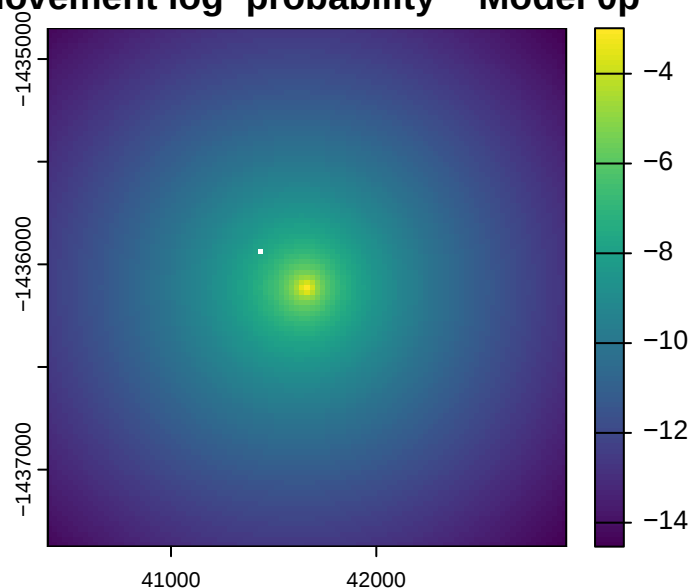
9 -1435938 -249.4296 180.3333 2018-07-25T10:04:02Z      1      19      206
  hour_t2 hour_t2_sin hour_t2_cos yday_t2 yday_t2_sin yday_t2_cos      sl
9      20 -0.8660254      0.5      206 -0.3913578 -0.9202386 307.7908
  log_sl bearing bearing_sin bearing_cos      ta      cos_ta      x_min
9 5.72942 2.515608 0.5858955 -0.8103866 -0.6345649 0.8053297 40412.09
  x_max      y_min      y_max s2_index points_vect_cent year_t2
9 42937.09 -1437381 -1434856      7      NA      2018
  yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
9      206      NA      NA
  prob_next_step_ssf_0p
9      NA

```

Next-step log-probability – Model 0p

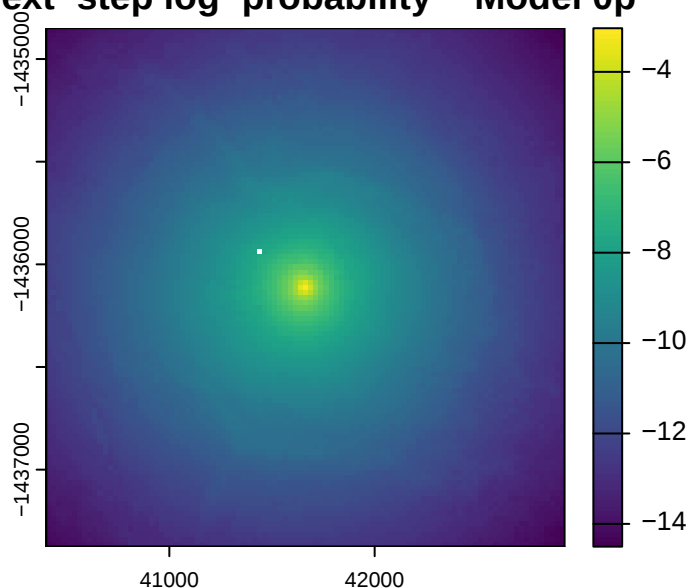


Movement log-probability – Model 0p

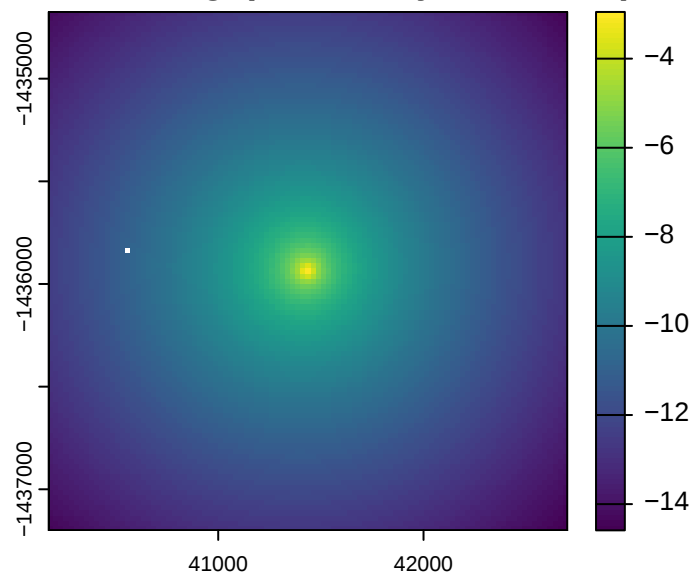


	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	sl	log_sl	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p	prob_next_step_ssf_0p	
10	41425.16	-1435938	2018-07-25T10:04:02Z	2005	41425.16	-1435938	40563.21																																
10	-1435841	-861.9445	97.45269	2018-07-25T11:04:04Z	1	20	206																																
10	21	-0.7071068	0.7071068	206	-0.3913578	-0.9202386	867.4361																																
10	6.765542	3.029009	0.1123457	-0.9936692	0.5134012	0.8710791	40162.66																																
10	42687.66	-1437201	-1434676	7	NA	2018																																	
10		206		NA		NA																																	
10																																							

Next-step log-probability – Model 0p



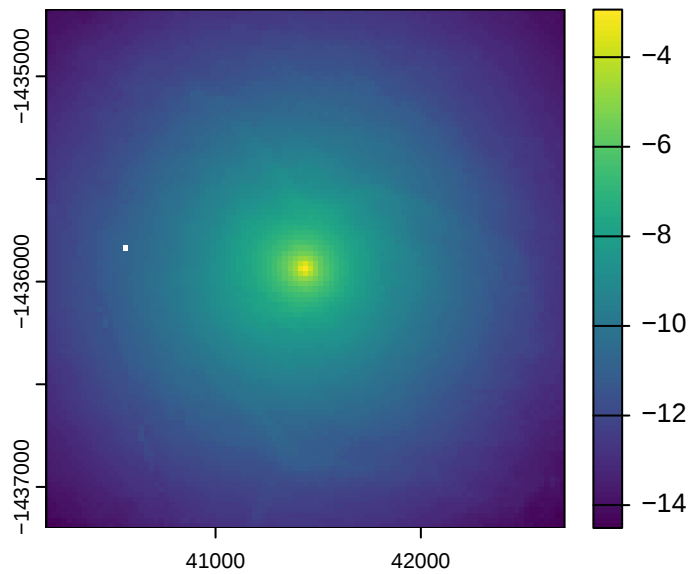
Movement log-probability – Model 0p



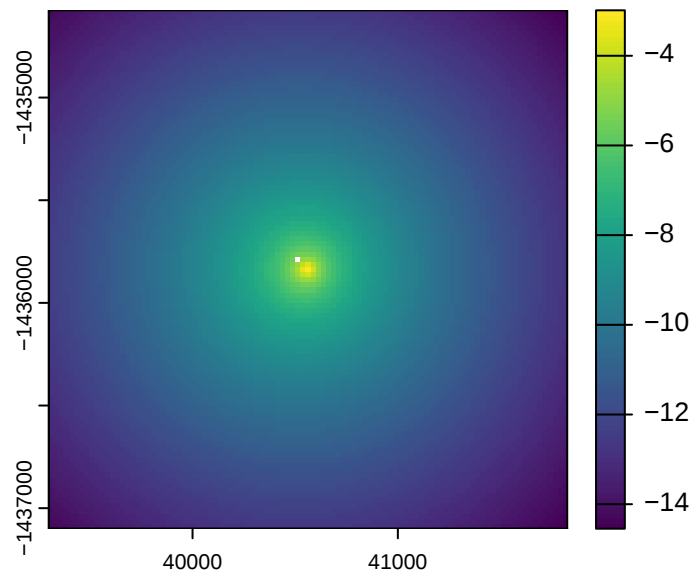
	x_	y_	t_	id	x1_	y1_	x2_	
11	40563.21	-1435841	2018-07-25T11:04:04Z	2005	40563.21	-1435841	40512.76	
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1
11	-1435777	-50.44988	63.87376	2018-07-25T12:05:13Z	1	21	206	
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	
11	22	-0.5	0.8660254	206	-0.3913578	-0.9202386	81.39439	
	log_s1	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	
11	4.399306	2.23931	0.784744	-0.61982	-0.7896996	0.7040587	39300.71	
	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2		

11	41825.71	-1437103	-1434578	7	NA	2018
	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p			
11		206		NA		NA
	prob_next_step_ssf_0p					
11		NA				

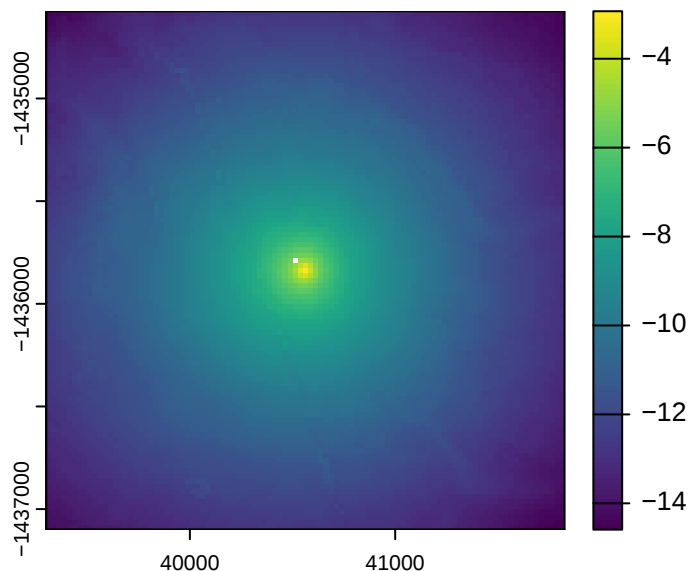
Next-step log-probability – Model 0p



Movement log-probability – Model 0p



Next-step log-probability – Model 0p



33.56 sec elapsed

```
[1] "ssf_coefficients/id2005_2pDaily_coefs_80-10-10_2025-04-10.csv"
```

Rows: 240 Columns: 13

-- Column specification -----

Delimiter: ","

dbl (13): hour, ndvi, ndvi_2, canopy, canopy_2, slope, herby, sl, log_sl, co...

i Use `spec()` to retrieve the full column specification for this data.

i Specify the column types or set `show\_col\_types = FALSE` to quiet this message.

Warning in max(values(move_log), na.rm = T): no non-missing arguments to max;
returning -Inf

Warning in max(values(move_log), na.rm = T): no non-missing arguments to max;
returning -Inf

Warning in max(values(next_step_log), na.rm = T): no non-missing arguments to
max; returning -Inf

Warning in max(values(next_step_log), na.rm = T): no non-missing arguments to
max; returning -Inf

Warning: Failed to compute min/max, no valid pixels found in sampling. (GDAL
error 1)

	x_	y_	t_	id	x1_	y1_	x2_	
1	41969.31	-1435671	2018-07-25T01:04:23Z	2005	41969.31	-1435671	41921.52	
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1
1	-1435654	-47.78894	16.85711	2018-07-25T02:04:39Z	1	11	206	
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos		s1
1	12	1.224606e-16	-1	206	-0.3913578	-0.9202386	50.67489	
	log_sl	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max
1	3.925431	2.802478	0.3326521	-0.9430496	1.367942	0.201466	40706.81	43231.81
	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base		
1	-1436934	-1434409	7	NA	2018	206		
	prob_habitat_ssf_0p	prob_movement_ssf_0p	prob_next_step_ssf_0p					
1	9.615473e-05	NA	NA					

Warning: Failed to compute min/max, no valid pixels found in sampling. (GDAL error 1)

Warning: Failed to compute min/max, no valid pixels found in sampling. (GDAL error 1)

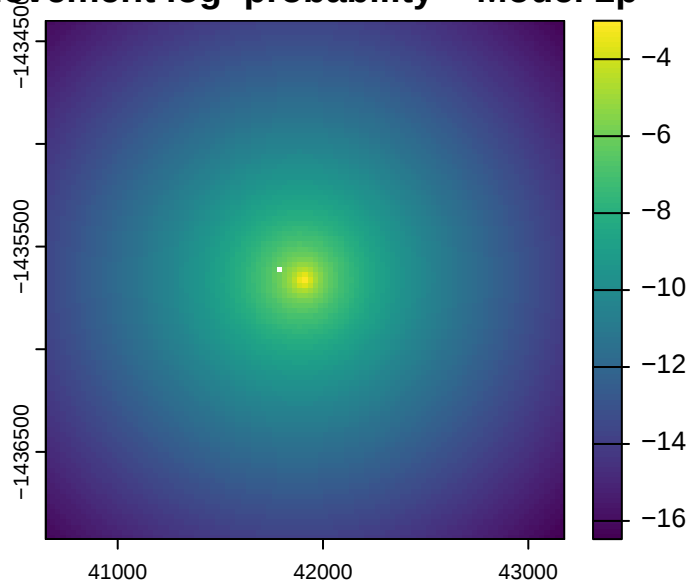
	x_	y_	t_	id	x1_	y1_	x2_	
2	41921.52	-1435654	2018-07-25T02:04:39Z	2005	41921.52	-1435654	41779.44	
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1
2	-1435601	-142.0823	53.56843	2018-07-25T03:04:17Z	1	12	206	
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos		s1

```

2      13  -0.258819 -0.9659258    206 -0.3913578 -0.9202386 151.8452
      log_sl  bearing bearing_sin bearing_cos      ta  cos_ta  x_min
2 5.022862 2.781049  0.3527831 -0.9357051 -0.02142933 0.9997704 40659.02
      x_max  y_min  y_max s2_index points_vect_cent year_t2
2 43184.02 -1436917 -1434392      7      NA    2018
      yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
2      206      9.65375e-05      0.001913733
      prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
2      0.001924442      NA      NA
      prob_next_step_ssf_2p
2      NA

```

Movement log-probability – Model 2p

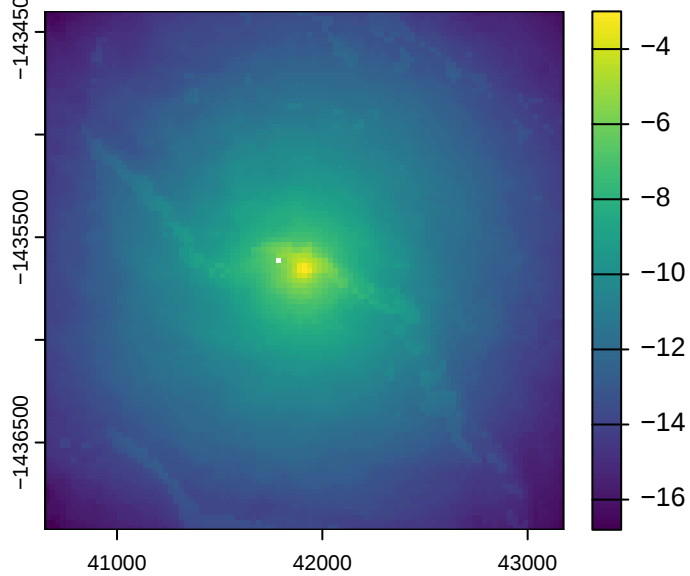


```

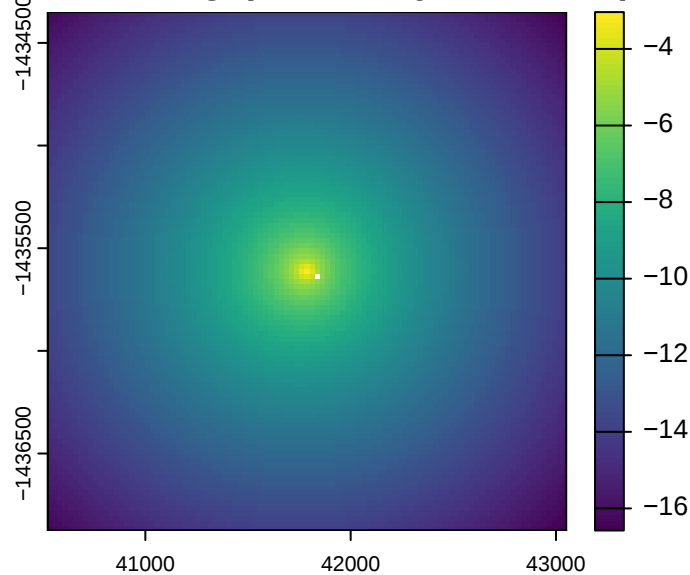
      x_      y_      t_  id      x1_      y1_      x2_
3 41779.44 -1435601 2018-07-25T03:04:17Z 2005 41779.44 -1435601 41841.2
      y2_ x2_cent  y2_cent      t2_ t_diff hour_t1 yday_t1
3 -1435635 61.76368 -34.32294 2018-07-25T04:04:39Z      1      13      206
      hour_t2 hour_t2_sin hour_t2_cos yday_t2 yday_t2_sin yday_t2_cos      sl
3      14      -0.5 -0.8660254      206 -0.3913578 -0.9202386 70.65986
      log_sl  bearing bearing_sin bearing_cos      ta  cos_ta  x_min
3 4.257878 -0.5072195 -0.4857487  0.8740985 2.994917 -0.9892624 40516.94
      x_max  y_min  y_max s2_index points_vect_cent year_t2
3 43041.94 -1436863 -1434338      7      NA    2018
      yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
3      206      9.361172e-05      0.005811244
      prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
3      0.005718225      NA      NA
      prob_next_step_ssf_2p

```

Next-step log-probability – Model 2p



Movement log-probability – Model 2p



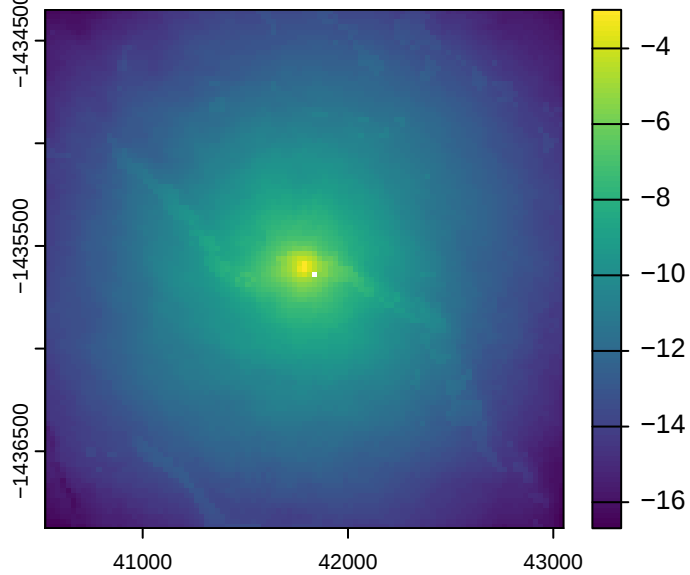
	x_	y_	t_	id	x1_	y1_	x2_	y2_
4	41841.2	-1435635	2018-07-25T04:04:39Z	2005	41841.2	-1435635	41655.46	-1435604
	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	
4	-185.7399	31.00353	2018-07-25T05:04:27Z	1	14	206	15	
	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	log_s1	
4	-0.7071068	-0.7071068	206	-0.3913578	-0.9202386	188.3097	5.238088	
	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	

```

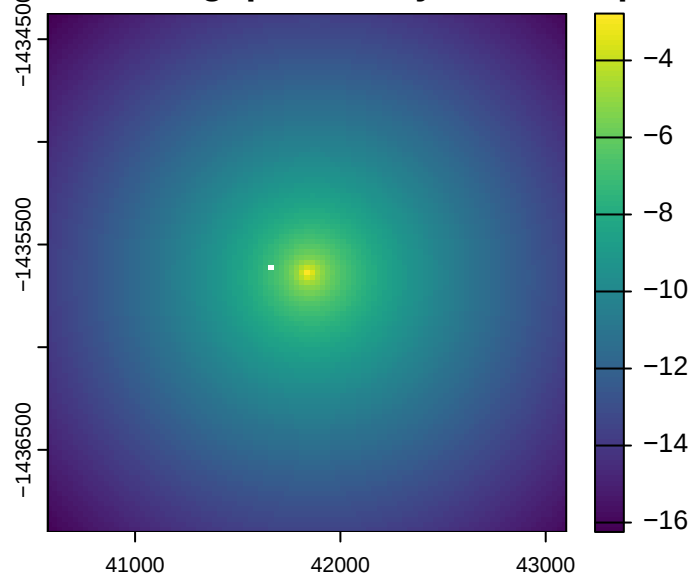
4 2.976198    0.1646412 -0.9863535 -2.799767 -0.9421444 40578.7 43103.7
    y_min    y_max s2_index points_vect_cent year_t2 yday_t2_2018_base
4 -1436898 -1434373      7      NA      2018      206
    prob_habitat_ssf_0p prob_movement_ssf_0p prob_next_step_ssf_0p
4      9.907641e-05      0.0007681248      0.000797917
    prob_habitat_ssf_2p prob_movement_ssf_2p prob_next_step_ssf_2p
4      NA      NA      NA

```

Next-step log-probability – Model 2p



Movement log-probability – Model 2p



```

x_      y_      t_      id      x1_      y1_      x2_

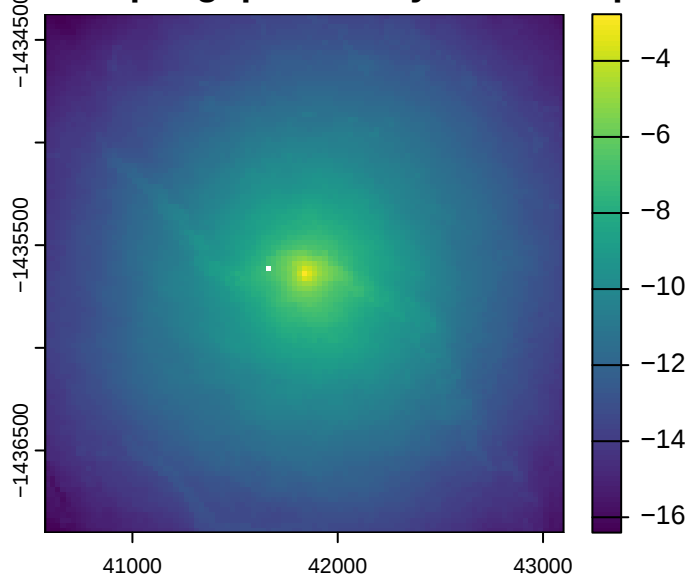
```

```

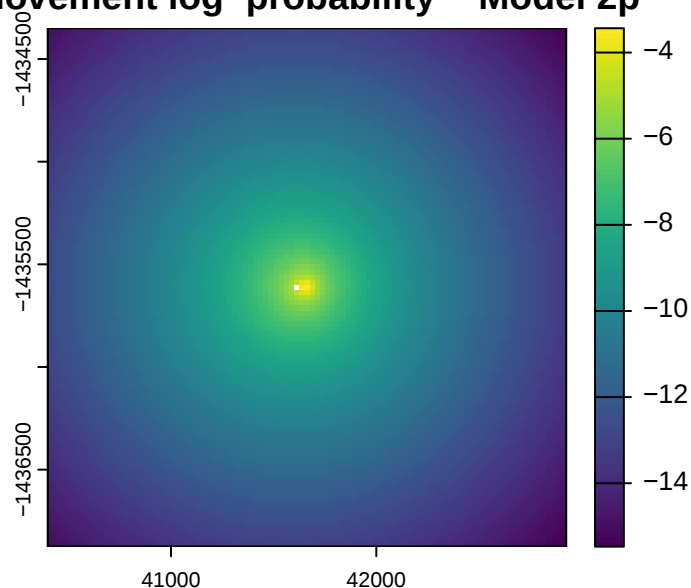
5 41655.46 -1435604 2018-07-25T05:04:27Z 2005 41655.46 -1435604 41618.65
    y2_    x2_cent    y2_cent    t2_ t_diff hour_t1 yday_t1
5 -1435608 -36.81141 -4.438037 2018-07-25T06:04:24Z    1    15    206
    hour_t2 hour_t2_sin hour_t2_cos yday_t2 yday_t2_sin yday_t2_cos    sl
5    16 -0.8660254    -0.5    206 -0.3913578 -0.9202386 37.07797
    log_sl    bearing bearing_sin bearing_cos    ta    cos_ta    x_min
5 3.613023 -3.02161 -0.1196947 -0.9928107 0.2853766 0.9595557 40392.96
    x_max    y_min    y_max s2_index points_vect_cent year_t2
5 42917.96 -1436867 -1434342    7    NA    2018
    yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
5    206    9.602568e-05    0.01028661
    prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
5    0.01055869    NA    NA
    prob_next_step_ssf_2p
5    NA

```

Next-step log-probability – Model 2p

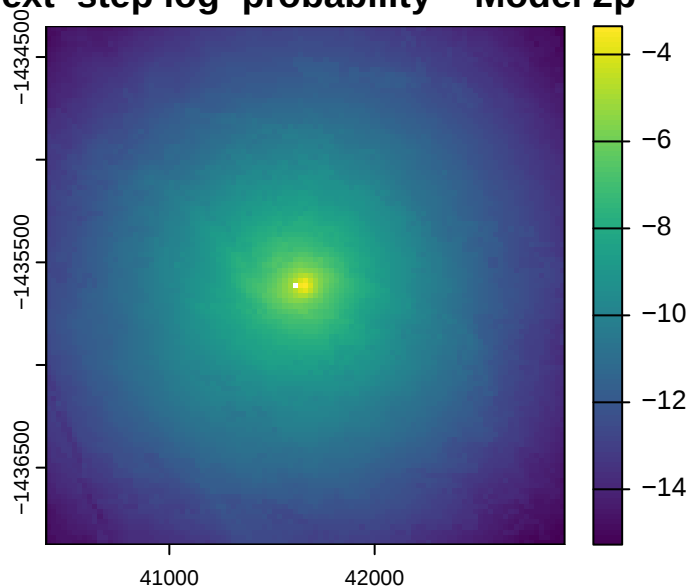


Movement log-probability – Model 2p

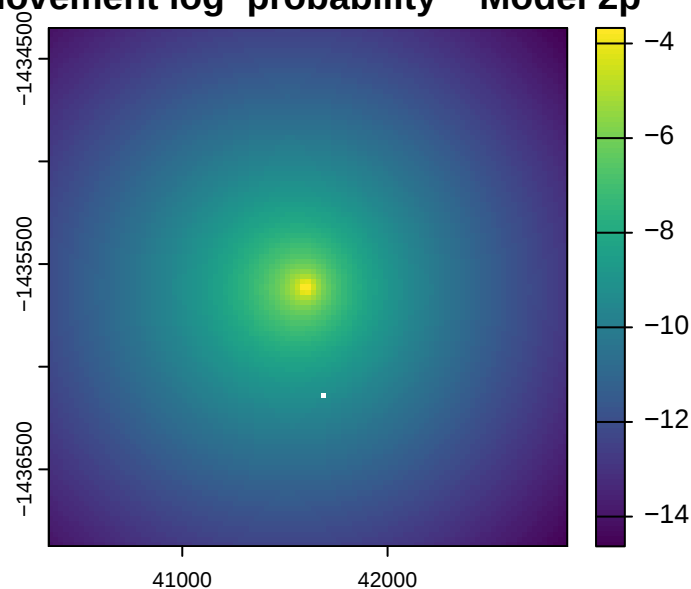


	x_	y_	t_	id	x1_	y1_	x2_	
6	41618.65	-1435608	2018-07-25T06:04:24Z	2005	41618.65	-1435608	41688.44	
	y2_	x2_cent	y2_cent		t2_	t_diff	hour_t1	yday_t1
6	-1436126	69.78648	-517.1566	2018-07-25T07:04:28Z	1	16	206	
	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	
6	17	-0.9659258	-0.258819	206	-0.3913578	-0.9202386	521.8439	
	log_s1	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	
6	6.257369	-1.436664	-0.9910177	0.1337306	1.584946	-0.01414957	40356.15	
	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2		
6	42881.15	-1436871	-1434346	7	NA	2018		
	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p					
6	206	9.083069e-05	7.547135e-05					
	prob_next_step_ssf_0p	prob_habitat_ssf_2p	prob_movement_ssf_2p					
6	7.375487e-05	NA	NA					
	prob_next_step_ssf_2p							
6	NA							

Next-step log-probability – Model 2p



Movement log-probability – Model 2p



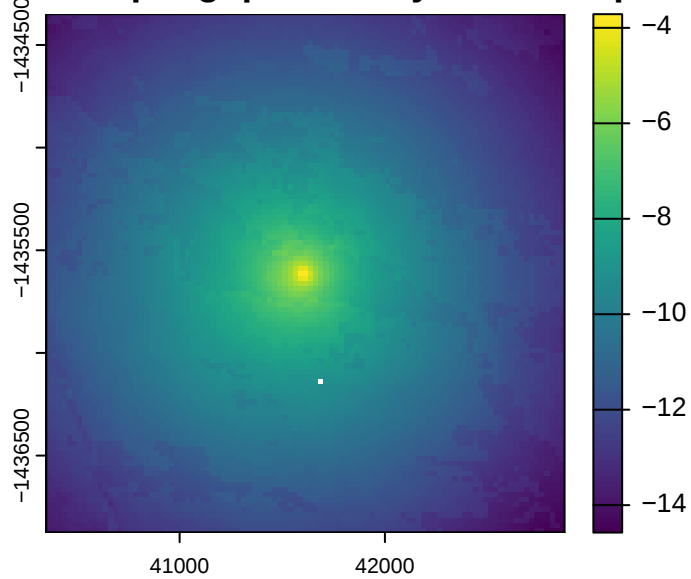
	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1
7	41688.44	-1436126	2018-07-25T07:04:28Z	2005	41688.44	-1436126	41684.34														
7																					
7	-1436119	-4.095906	7.020228	2018-07-25T08:04:31Z		1	17	206													
7																					
7	18	-1	-1.83691e-16	206	-0.3913578	-0.9202386	8.127733														
7																					
7	2.095282	2.098953	0.8637375	-0.503942	-2.747568	-0.9233716	40425.94														
	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2															

```

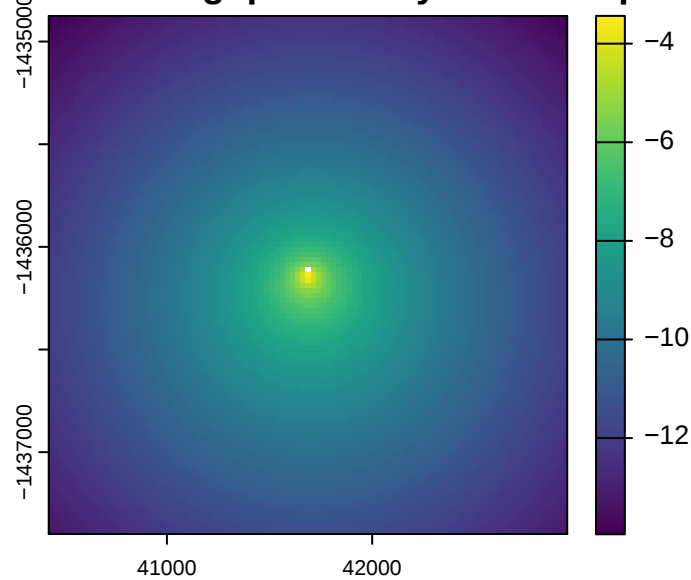
7 42950.94 -1437388 -1434863      7      NA      2018
  yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
7              206      9.167352e-05      0.02051778
  prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
7      0.01968547      NA      NA
  prob_next_step_ssf_2p
7      NA

```

Next-step log-probability – Model 2p



Movement log-probability – Model 2p



```

x_      y_      t_      id      x1_      y1_      x2_

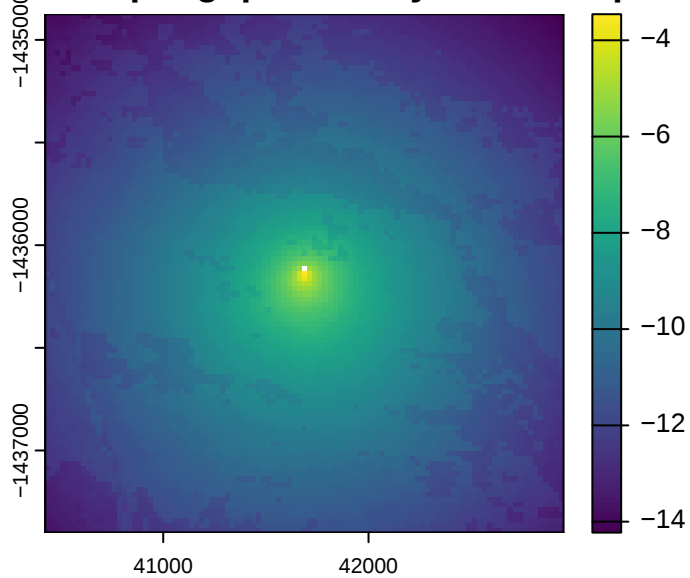
```

```

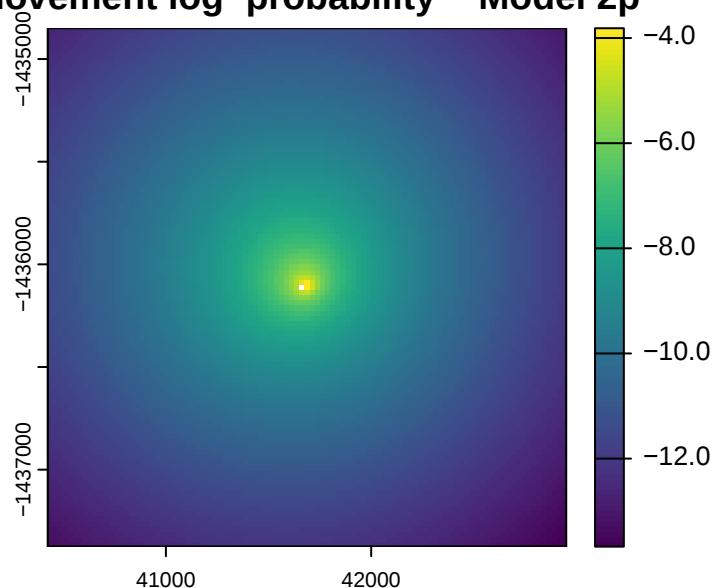
8 41684.34 -1436119 2018-07-25T08:04:31Z 2005 41684.34 -1436119 41674.59
      y2_   x2_cent   y2_cent   t2_ t_diff hour_t1 yday_t1
8 -1436119 -9.754289 -0.08369654 2018-07-25T09:04:33Z      1      18      206
      hour_t2 hour_t2_sin hour_t2_cos yday_t2 yday_t2_sin yday_t2_cos      sl
8      19 -0.9659258      0.258819      206 -0.3913578 -0.9202386 9.754648
      log_sl   bearing bearing_sin bearing_cos      ta      cos_ta      x_min
8 2.277744 -3.133012 -0.00858017 -0.9999632 1.05122 0.4965124 40421.84
      x_max      y_min      y_max s2_index points_vect_cent year_t2
8 42946.84 -1437381 -1434856      7      NA      2018
      yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
8      206      9.007231e-05      0.02774303
      prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
8      0.02635727      NA      NA
      prob_next_step_ssf_2p
8      NA

```

Next-step log-probability – Model 2p

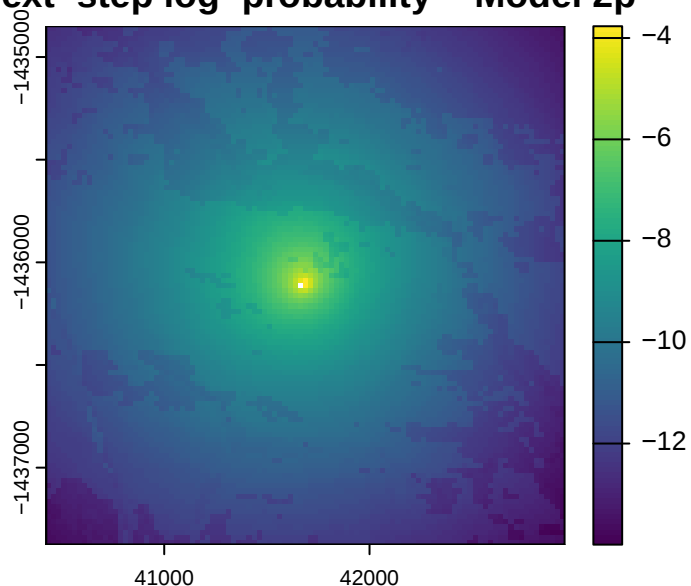


Movement log-probability – Model 2p

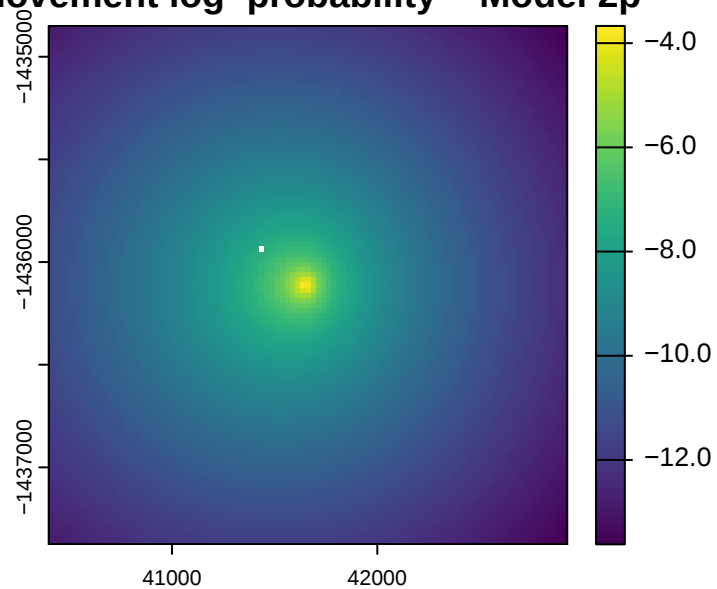


	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	sl	log_sl	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2	yday_t2_2018_base	prob_habitat_ssf_0p	prob_movement_ssf_0p	prob_next_step_ssf_0p	prob_habitat_ssf_2p	prob_movement_ssf_2p	prob_next_step_ssf_2p			
9	41674.59	-1436119	2018-07-25T09:04:33Z	2005	41674.59	-1436119	41425.16																																					
9	-1435938	-249.4296	180.3333	2018-07-25T10:04:02Z	1	19	206																																					
9	20	-0.8660254	0.5	206	-0.3913578	-0.9202386	307.7908																																					
9	5.72942	2.515608	0.5858955	-0.8103866	-0.6345649	0.8053297	40412.09																																					
9	42937.09	-1437381	-1434856	7	NA	2018																																						
9		206	9.566552e-05			0.0004125345																																						
9		0.0004177971		NA		NA																																						
9			NA																																									

Next-step log-probability – Model 2p



Movement log-probability – Model 2p



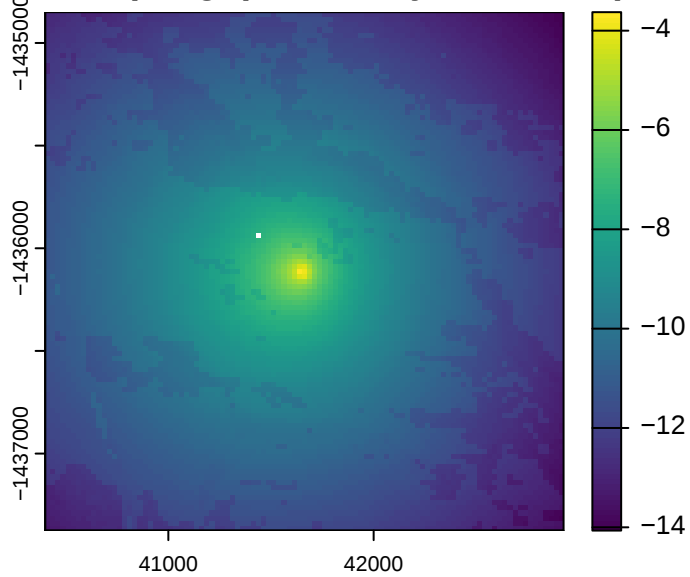
	x_	y_	t_	id	x1_	y1_	x2_	y2_	x2_cent	y2_cent	t2_	t_diff	hour_t1	yday_t1	hour_t2	hour_t2_sin	hour_t2_cos	yday_t2	yday_t2_sin	yday_t2_cos	s1	log_s1	bearing	bearing_sin	bearing_cos	ta	cos_ta	x_min	x_max	y_min	y_max	s2_index	points_vect_cent	year_t2
10	41425.16	-1435938	2018-07-25T10:04:02Z	2005	41425.16	-1435938	40563.21																											
10	-1435841	-861.9445	97.45269	2018-07-25T11:04:04Z	1	20	206																											
10	21	-0.7071068	0.7071068	206	-0.3913578	-0.9202386	867.4361																											
10	6.765542	3.029009	0.1123457	-0.9936692	0.5134012	0.8710791	40162.66																											

```

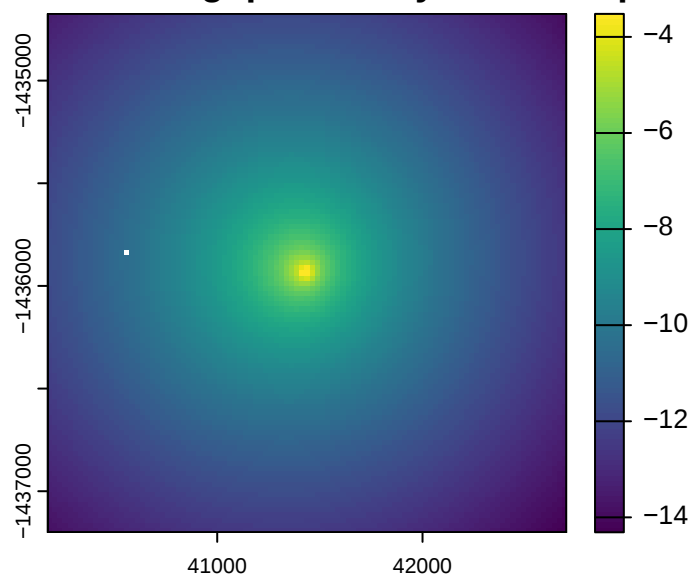
10 42687.66 -1437201 -1434676      7      NA      2018
   yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
10                206      0.000109441      1.74964e-05
   prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
10      2.029205e-05      NA      NA
   prob_next_step_ssf_2p
10      NA

```

Next-step log-probability – Model 2p



Movement log-probability – Model 2p



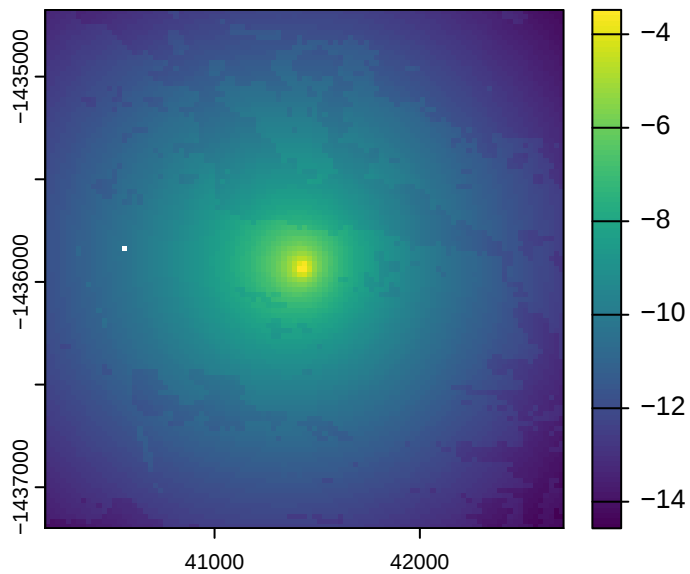
x_ y_ t_ id x1_ y1_ x2_

```

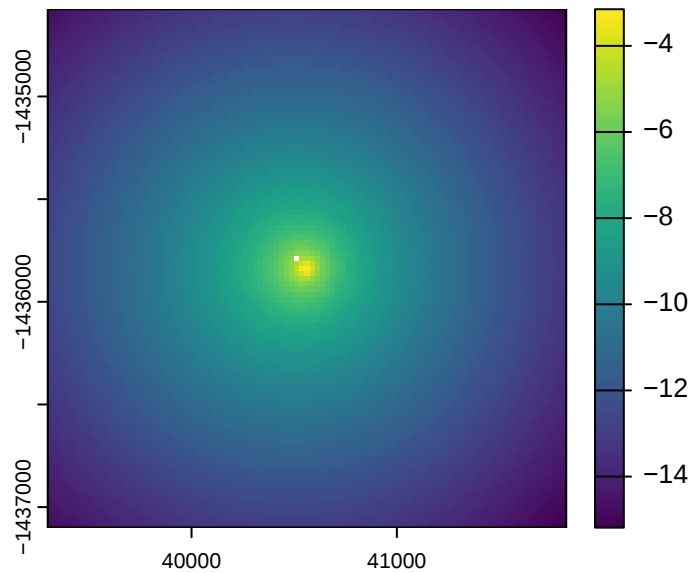
11 40563.21 -1435841 2018-07-25T11:04:04Z 2005 40563.21 -1435841 40512.76
      y2_   x2_cent   y2_cent           t2_ t_diff hour_t1 yday_t1
11 -1435777 -50.44988 63.87376 2018-07-25T12:05:13Z      1      21      206
      hour_t2 hour_t2_sin hour_t2_cos yday_t2 yday_t2_sin yday_t2_cos      sl
11      22      -0.5   0.8660254      206 -0.3913578 -0.9202386 81.39439
      log_sl bearing bearing_sin bearing_cos      ta   cos_ta   x_min
11 4.399306 2.23931   0.784744   -0.61982 -0.7896996 0.7040587 39300.71
      x_max   y_min   y_max s2_index points_vect_cent year_t2
11 41825.71 -1437103 -1434578      7      NA      2018
      yday_t2_2018_base prob_habitat_ssf_0p prob_movement_ssf_0p
11      206      0.0001102691      0.005606582
      prob_next_step_ssf_0p prob_habitat_ssf_2p prob_movement_ssf_2p
11      0.005993663      NA      NA
      prob_next_step_ssf_2p
11      NA

```

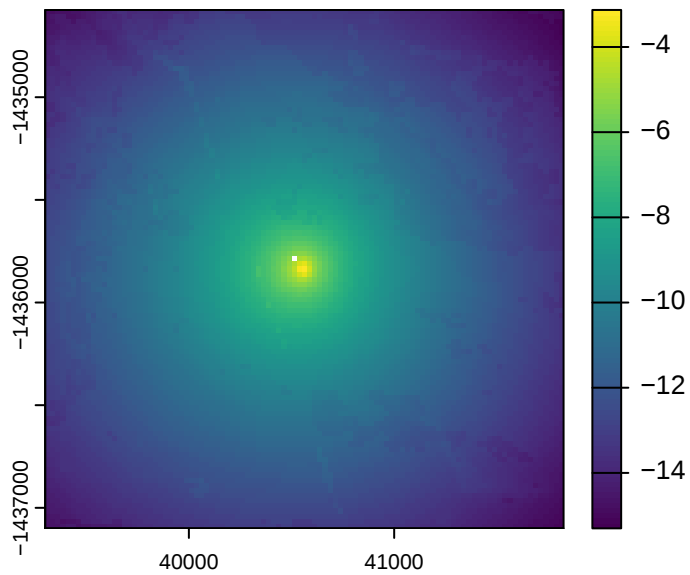
Next-step log-probability – Model 2p



Movement log-probability – Model 2p



Next-step log-probability – Model 2p



22.34 sec elapsed

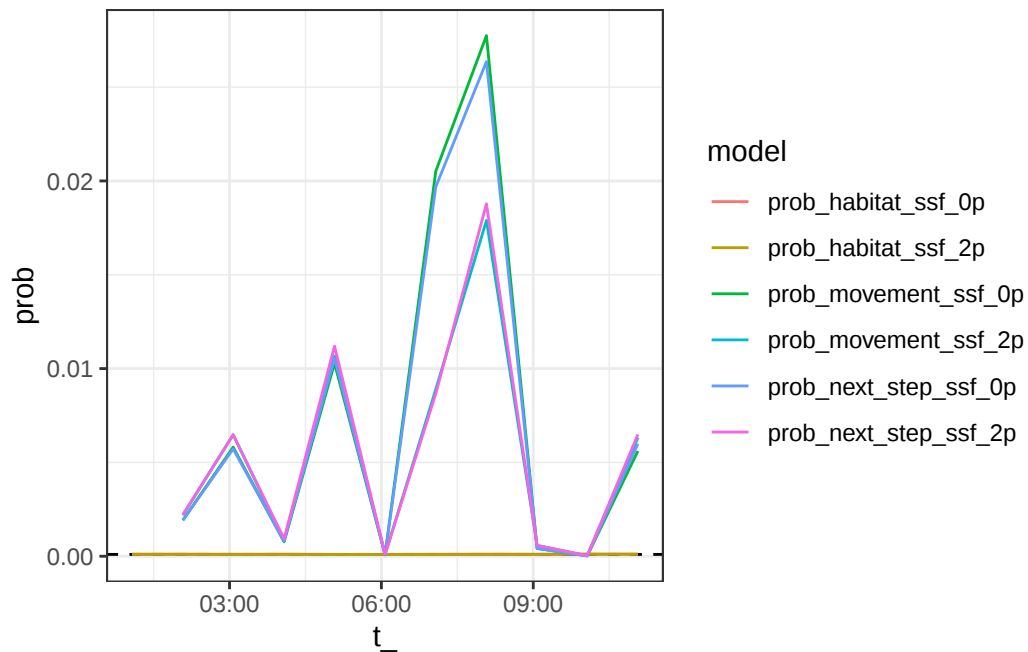
```
toc()
```

59.37 sec elapsed

```
test_data_correction <- test_data %>% drop_na(prob_habitat_ssf_0p) %>%
  select(t_,
         prob_habitat_ssf_0p, prob_habitat_ssf_2p,
         prob_movement_ssf_0p, prob_movement_ssf_2p,
         prob_next_step_ssf_0p, prob_next_step_ssf_2p
        ) %>%
  mutate(t_ = lubridate::as_datetime(t_)) %>%
  pivot_longer(cols = !c(t_),
               names_to = "model", values_to = "prob")

ggplot() +
  geom_hline(yintercept = 0.000098, linetype = "dashed") +
  geom_line(data=test_data_correction %>% filter(),
           aes(x = t_, y = prob, colour = model)) +
  theme_bw()
```

Warning: Removed 4 rows containing missing values or values outside the scale range (`geom\_line()`).



```
test_data_correction <- test_data %>% drop_na(prob_habitat_ssf_0p) %>%
  select(t_,
         prob_habitat_ssf_0p, prob_habitat_ssf_2p
        # prob_movement_ssf_0p, prob_movement_ssf_2p,
        # prob_next_step_ssf_0p, prob_next_step_ssf_2p
       )
```

```

    ) %>%
mutate(t_ = lubridate::as_datetime(t_)) %>%
pivot_longer(cols = !c(t_),
              names_to = "model", values_to = "prob")

ggplot() +
  geom_hline(yintercept = 0.000098, linetype = "dashed") +
  geom_line(data=test_data_correction %>% filter(),
            aes(x = t_, y = prob, colour = model)) +
  theme_bw()

```

