

Assessing deepSSF trajectories

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Now that we have generated trajectories using the `deepSSF_simulations.ipynb` script, we can check how well they capture different aspects of the observed data. This includes looking at the distribution of step lengths and turning angles, as well as comparing the observed and simulated trajectories in terms of the environmental covariates. We could also further summarise the trajectories using path-level summaries following a similar approach.

Table of contents

Loading packages	2
Reading in the environmental covariates	2
Import observed buffalo data	3
Calculate step info	4
To compare the observed buffalo data to the simulated data, select a subset of the buffalo data	5
Import multiple deep learning trajectories	5
Calculate step lengths and turning angles etc	6
Combine the observed and simulated datasets	7
Prepare trajectories for plotting	7
Plot the observed and simulated trajectories	8
Plot movement distributions	9
Step lengths	9
Log step lengths	10
Turning angles	11
Density of step lengths for each hour	12
Density of turning angles for each hour	27
Extract covariate values	39

Hourly movement behaviour and selection of covariates	40
Calculate the quantiles	41
Set up the plotting parameters	42
Hourly covariate selection	42
Mean step lengths	42
NDVI	44
Canopy cover	46
Herbaceous vegetation	47
Slope	49
Combining the hourly plots	51
Step lengths instead of slope	51
Slope instead of step lengths	52

Loading packages

```
options(scipen = 999)

library(tidyverse)
packages <- c("amt", "sf", "terra", "beepR", "tictoc", "viridis",
              "scales", "ggpubr", "zoo")
walk(packages, require, character.only = T)
```

Reading in the environmental covariates

```
ndvi <- rast("mapping/cropped rasters/ndvi_GEE_projected_watermask20230207.tif")
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) <- rep("ndvi", terra::nlyr(ndvi))
names(slope) <- "slope"
names(veg_herby) <- "veg_herby"
names(canopy_cover) <- "canopy_cover"

# for ggplot (and arbitrary index)
ndvi_df <- as.data.frame(ndvi[[1]], xy = TRUE)
# create discrete breaks for the NDVI for plotting
ndvi_quantiles <- quantile(ndvi_df$ndvi, probs = c(0.01, 0.99))
```

```
ndvi_breaks <- seq(ndvi_quantiles[1], ndvi_quantiles[2], length.out = 9)
ndvi_df$ndvi_discrete <- cut(ndvi_df$ndvi, breaks=ndvi_breaks, dig.lab = 2)
```

Import observed buffalo data

```
buffalo <- read_csv("data/buffalo_clean.csv")
```

Rows: 115776 Columns: 4

-- Column specification -----

Delimiter: ","

dbl (3): x_, y_, id

dtm (1): t_

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

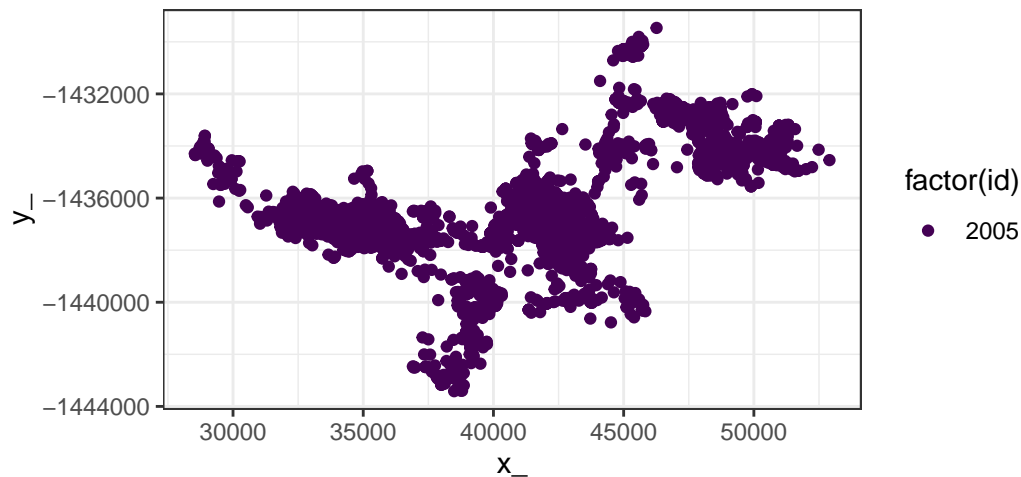
i Specify the column types or set `show_col_types = FALSE` to quiet this message.

```
attr(buffalo$t_, "tzone") <- "Australia/Queensland"
```

plot the data of the buffalo that the deepSSF model was trained with

ggplot() +

```
  geom_point(data = buffalo |> filter(id == 2005),
             aes(x = x_, y = y_, colour = factor(id))) +
  scale_colour_viridis_d() +
  coord_equal() +
  theme_bw()
```



Calculate step info

```
hourly_lag <- 1

buffalo <- buffalo %>% mutate(
  id = id,
  x1 = x_,
  y1 = y_,
  x2 = lead(x1, n = hourly_lag, default = NA),
  y2 = lead(y1, n = hourly_lag, default = NA),
  t1 = t_,
  t2 = lead(t1, n = hourly_lag, default = NA),
  hour_t1 = lubridate::hour(t_),
  hour_t2 = lead(hour_t1, n = hourly_lag, default = NA),
  yday_t1 = lubridate::yday(t_), # day of the year
  yday_t2 = lead(yday_t1, n = hourly_lag, default = NA),
  sl = c(sqrt(diff(y_)^2 + diff(x_)^2), NA), # step lengths
  log_sl = log(sl),
  bearing = c(atan2(diff(y_), diff(x_)), NA),
  ta = c(NA, ifelse(
    diff(bearing) > pi, diff(bearing)-(2*pi), ifelse(
      diff(bearing) < -pi, diff(bearing)+(2*pi), diff(bearing))))), # turning angles
  cos_ta = cos(ta),

  .keep = "none"
)

head(buffalo)
```

```
# A tibble: 6 x 16
   id      x1      y1      x2      y2 t1          t2
<dbl> <dbl>    <dbl> <dbl>    <dbl> <dtm>      <dtm>
1  2005 41941. -1435875. 41969. -1.44e6 2018-07-25 10:04:02 2018-07-25 11:04:23
2  2005 41969. -1435671. 41922. -1.44e6 2018-07-25 11:04:23 2018-07-25 12:04:39
3  2005 41922. -1435654. 41779. -1.44e6 2018-07-25 12:04:39 2018-07-25 13:04:17
4  2005 41779. -1435601. 41841. -1.44e6 2018-07-25 13:04:17 2018-07-25 14:04:39
5  2005 41841. -1435635. 41655. -1.44e6 2018-07-25 14:04:39 2018-07-25 15:04:27
6  2005 41655. -1435604. 41619. -1.44e6 2018-07-25 15:04:27 2018-07-25 16:04:24
# i 9 more variables: hour_t1 <int>, hour_t2 <int>, yday_t1 <dbl>,
#   yday_t2 <dbl>, sl <dbl>, log_sl <dbl>, bearing <dbl>, ta <dbl>,
#   cos_ta <dbl>
```

To compare the observed buffalo data to the simulated data, select a subset of the buffalo data

```
no_subset_locations <- 3000 # to compare to the simulated data

buffalo_id_subset <- buffalo %>%
  filter(id == 2005) %>%
  arrange(t1) |>
  slice(1:no_subset_locations)
```

Import multiple deep learning trajectories

```
# read in multiple csv files with similar filenames and bind them together
sim_data_full_list <-
  list.files("Python/outputs/deepSSF_trajectories/2005", pattern = "*.csv", full.names = T)

# to filter filenames with any string matching conditions
sim_data_filenames <- grep("", sim_data_full_list, value = T) %>%
  grep("3000steps", x = ., value = T)

# read dataframes as a single dataframe with id identifier
sim_data_all <- sim_data_filenames %>%
  map_dfr(read_csv, .id = "id") %>%
  mutate(
    ...1 = NULL
  )

head(sim_data_all)
```

```
# A tibble: 6 x 6
  id      x      y hour yday bearing
<chr> <dbl> <dbl> <dbl> <dbl> <dbl>
1 1    41969. -1435671     0   206  0.745
2 1    41976. -1435666     1   206  0.686
3 1    41970. -1435679     2   206 -1.99
4 1    41919. -1435576     3   206  2.03
5 1    41920. -1435575     4   206  0.919
6 1    41933. -1435575     5   206 -0.0175
```

Calculate step lengths and turning angles etc

```
hourly_lag <- 1

# Nest the data by 'id'
sim_data_nested <- sim_data_all %>%
  group_by(id) %>%
  nest()

# Map the mutate transformation over each nested tibble
sim_data_nested <- sim_data_nested %>%
  mutate(data = map(data, ~ .x %>%
    mutate(
      x1 = x,
      y1 = y,
      x2 = lead(x1, n = hourly_lag, default = NA),
      y2 = lead(y1, n = hourly_lag, default = NA),
      date = as.Date(yday - 1, origin = "2018-01-01"),
      t1 = as.POSIXct(paste(date, hour), format = "%Y-%m-%d %H"),
      t2 = lead(t1, n = hourly_lag, default = NA),
      yday_t1 = lubridate::yday(t1), # day of the year
      yday_t2 = lead(yday_t1, n = hourly_lag, default = NA),
      hour_t1 = lubridate::hour(t1),
      hour_t2 = lead(hour_t1, n = hourly_lag, default = NA),
      sl = c(sqrt(diff(y)^2 + diff(x)^2), NA), # step lengths
      log_sl = log(sl),
      bearing = c(atan2(diff(y), diff(x)), NA),
      ta = c(NA, ifelse(
        diff(bearing) > pi, diff(bearing) - (2 * pi),
        ifelse(diff(bearing) < -pi, diff(bearing) + (2 * pi), diff(bearing))
      )),
      cos_ta = cos(ta),

      .keep = "none"
    )
  ))

# Unnest the transformed data back into a single data frame
sim_data_all <- sim_data_nested %>%
  unnest(data) %>%
  ungroup() %>%
  mutate(id = as.numeric(id))

head(sim_data_all)
```

```
# A tibble: 6 x 17
  id bearing x1 y1 x2 y2 date t1
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <date> <dtm>
1 1 0.686 41969. -1435671 41976. -1435666. 2018-07-25 2018-07-25 00:00:00
2 1 -1.99 41976. -1435666. 41970. -1435679. 2018-07-25 2018-07-25 01:00:00
3 1 2.03 41970. -1435679. 41919. -1435576. 2018-07-25 2018-07-25 02:00:00
4 1 0.919 41919. -1435576. 41920. -1435575. 2018-07-25 2018-07-25 03:00:00
5 1 -0.0175 41920. -1435575. 41933. -1435575. 2018-07-25 2018-07-25 04:00:00
6 1 1.48 41933. -1435575. 41933. -1435569. 2018-07-25 2018-07-25 05:00:00
# i 9 more variables: t2 <dtm>, yday_t1 <dbl>, yday_t2 <dbl>, hour_t1 <int>,
# hour_t2 <int>, sl <dbl>, log_sl <dbl>, ta <dbl>, cos_ta <dbl>
```

Combine the observed and simulated datasets

```
all_data <- bind_rows(buffalo_id_subset, sim_data_all)
head(all_data)
```

```
# A tibble: 6 x 17
  id x1 y1 x2 y2 t1 t2
<dbl> <dbl> <dbl> <dbl> <dbl> <dtm> <dtm>
1 2005 41941. -1435875. 41969. -1.44e6 2018-07-25 10:04:02 2018-07-25 11:04:23
2 2005 41969. -1435671. 41922. -1.44e6 2018-07-25 11:04:23 2018-07-25 12:04:39
3 2005 41922. -1435654. 41779. -1.44e6 2018-07-25 12:04:39 2018-07-25 13:04:17
4 2005 41779. -1435601. 41841. -1.44e6 2018-07-25 13:04:17 2018-07-25 14:04:39
5 2005 41841. -1435635. 41655. -1.44e6 2018-07-25 14:04:39 2018-07-25 15:04:27
6 2005 41655. -1435604. 41619. -1.44e6 2018-07-25 15:04:27 2018-07-25 16:04:24
# i 10 more variables: hour_t1 <int>, hour_t2 <int>, yday_t1 <dbl>,
# yday_t2 <dbl>, sl <dbl>, log_sl <dbl>, bearing <dbl>, ta <dbl>,
# cos_ta <dbl>, date <date>
```

Prepare trajectories for plotting

```
# set the extent of the plot
plot_extent <- sim_data_all %>%
  summarise(min_x = min(x1), min_y = min(y1), max_x = max(x1), max_y = max(y1))

# set a buffer around the minimum and maximum x and y values
buffer <- 2500
```

Plot the observed and simulated trajectories

```
ggplot() +  
  
  geom_raster(data = ndvi_df,  
             aes(x = x, y = y, fill = ndvi_discrete),  
             alpha = 0.75) +  
  scale_fill_brewer("ndvi", palette = "Greys",  
                   guide = guide_legend(reverse = TRUE)) +  
  
  geom_path(data = all_data %>% filter(id %in% 1:5),  
           aes(x = x1, y = y1, colour = as.factor(id)),  
           alpha = 0.75, linewidth = 0.25) +  
  
  scale_colour_viridis_d() +  
  
  geom_path(data = all_data %>% filter(id == 2005),  
           aes(x = x1, y = y1),  
           alpha = 0.75, linewidth = 0.25, colour = "red") +  
  
  geom_point(data = all_data %>% slice(1),  
            aes(x = x1, y = y1), fill = "blue", shape = 23) +  
  
  scale_x_continuous("Easting (m)",  
                     limits = c(min(plot_extent[[1]])-buffer,  
                                max(plot_extent[[3]])+buffer)) +  
  scale_y_continuous("Northing (m)",  
                     limits = c(min(plot_extent[[2]])-buffer,  
                                max(plot_extent[[4]])+buffer)) +  
  
  coord_equal() +  
  theme_bw() +  
  theme(legend.position = "none")
```

Warning: Removed 106502 rows containing missing values or values outside the scale range (``geom_raster()``).



Plot movement distributions

The skyblue density plot represents the observed data and the orange density plot represents the simulated data.

Step lengths

```
ggplot() +
  geom_density(data = all_data %>% filter(id == 2005),
    aes(x = sl),
    fill = "skyblue", colour = "skyblue", alpha = 0.5) +
  geom_density(data = all_data,
    aes(x = sl),
    fill = "orange", colour = "orange", alpha = 0.5) +
  scale_x_continuous("Step length (m)", limits = c(0, 1500)) +
  scale_y_continuous("Density") +
  theme_bw()
```

Warning: Removed 24 rows containing non-finite outside the scale range (`stat_density()`).

Warning: Removed 162 rows containing non-finite outside the scale range (`stat_density()`).



Log step lengths

```
ggplot() +
  geom_density(data = all_data %>% filter(id == 2005),
    aes(x = sl),
    fill = "skyblue", colour = "skyblue", alpha = 0.5) +
  geom_density(data = all_data,
    aes(x = sl),
    fill = "orange", colour = "orange", alpha = 0.5) +
  scale_x_log10("log Step length (m)") +
  scale_y_continuous("Density") +
  theme_bw()
```

Warning: Removed 51 rows containing non-finite outside the scale range (``stat_density()``).



Turning angles

```
ggplot() +
  geom_density(data = all_data %>% filter(id == 2005),
    aes(x = ta),
    fill = "skyblue", colour = "skyblue", alpha = 0.5) +
  geom_density(data = all_data,
    aes(x = ta),
    fill = "orange", colour = "orange", alpha = 0.5) +
  scale_x_continuous("Turning angle (radians)") +
  scale_y_continuous("Density") +
  theme_bw()
```

Warning: Removed 1 row containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 103 rows containing non-finite outside the scale range
(`stat_density()`).

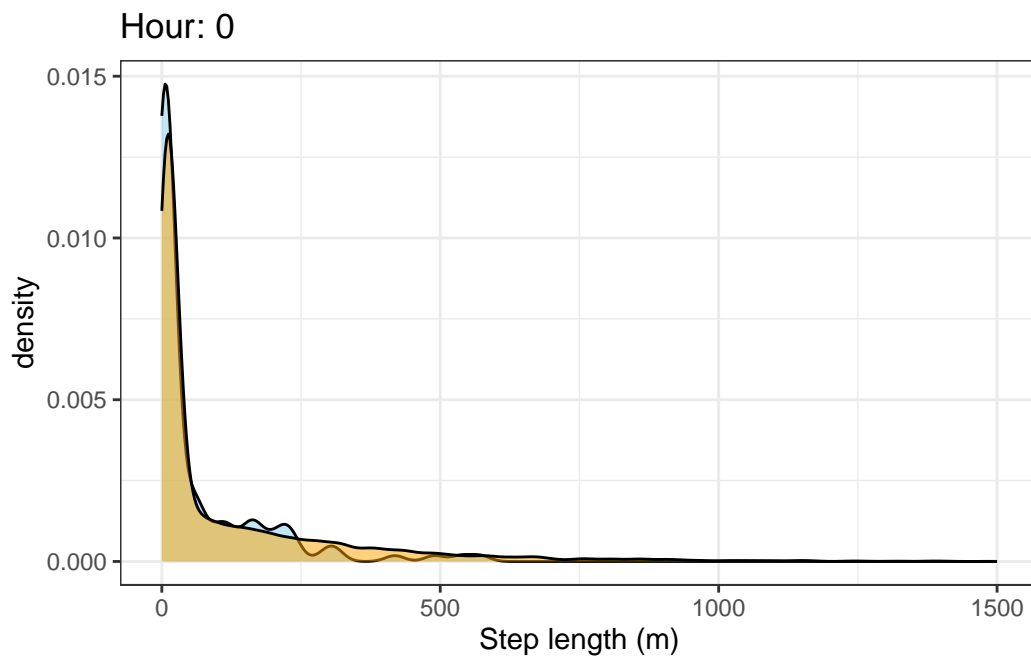


Density of step lengths for each hour

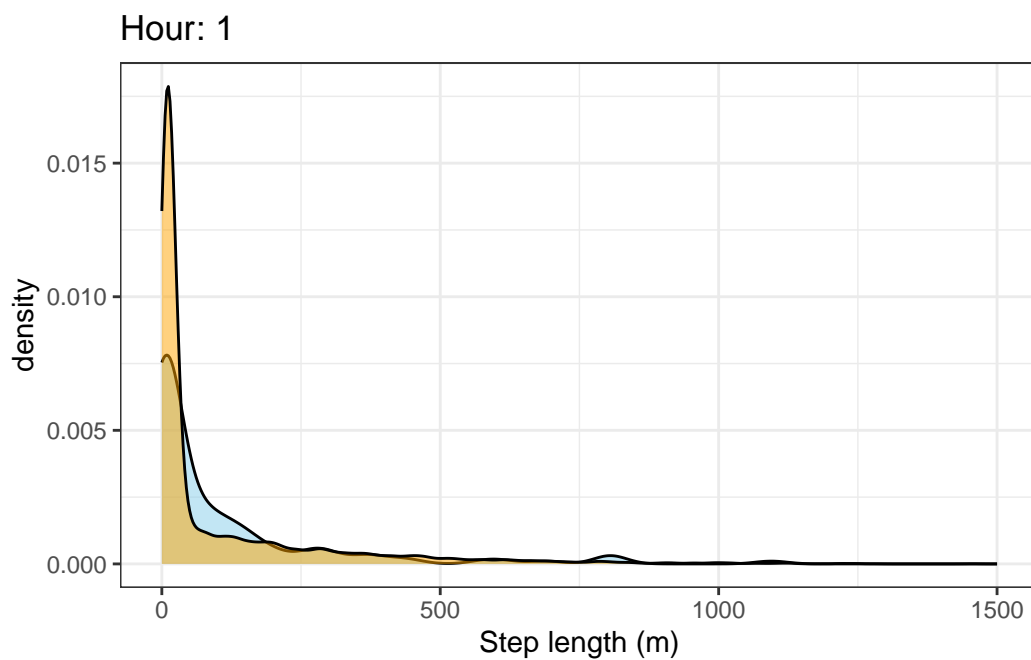
```
for(i in 0:23) {
  print(ggplot() +
    geom_density(data = all_data %>% filter(id == 2005 & hour_t1 == i),
      aes(x = sl),
      fill = "skyblue", colour = "black", alpha = 0.5) +
    geom_density(data = all_data %>% filter(hour_t1 == i),
      aes(x = sl),
      fill = "orange", colour = "black", alpha = 0.5) +
    scale_x_continuous("Step length (m)", limits = c(0, 1500)) +
    ggtitle(paste0("Hour: ", i)) +
    theme_bw())
}
```

Warning: Removed 1 row containing non-finite outside the scale range (`stat_density()`).

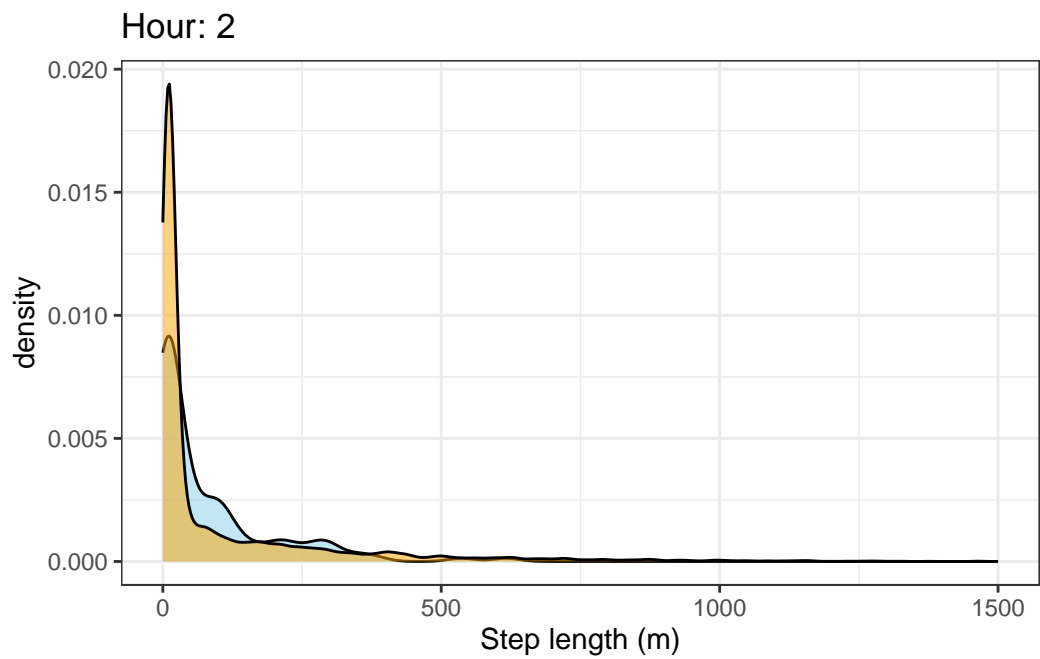
Removed 1 row containing non-finite outside the scale range (`stat_density()`).



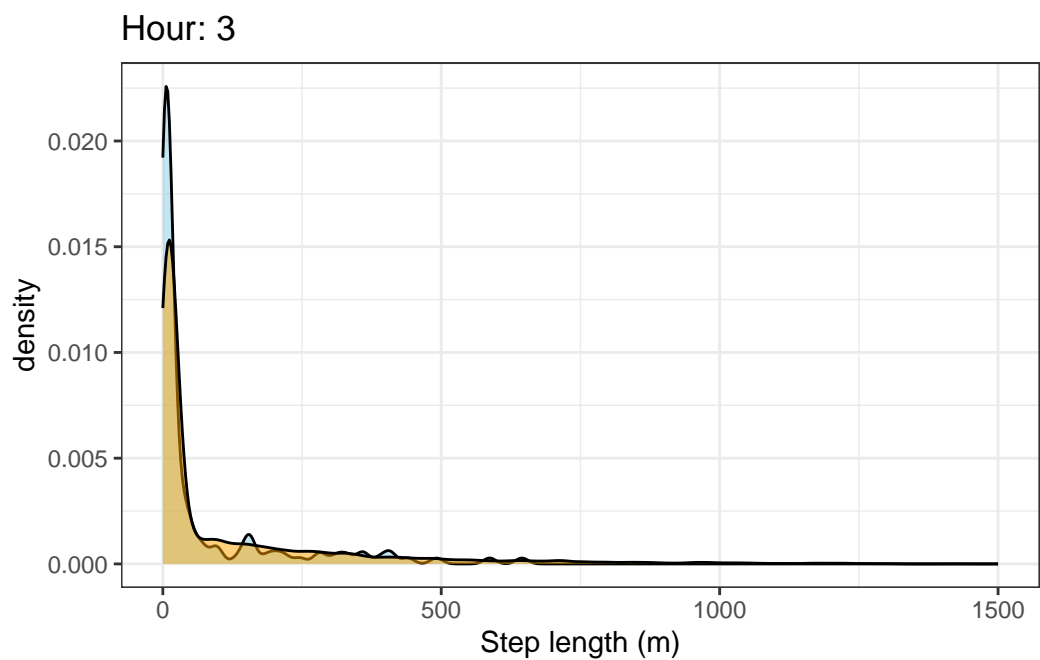
Warning: Removed 2 rows containing non-finite outside the scale range (``stat_density()``).



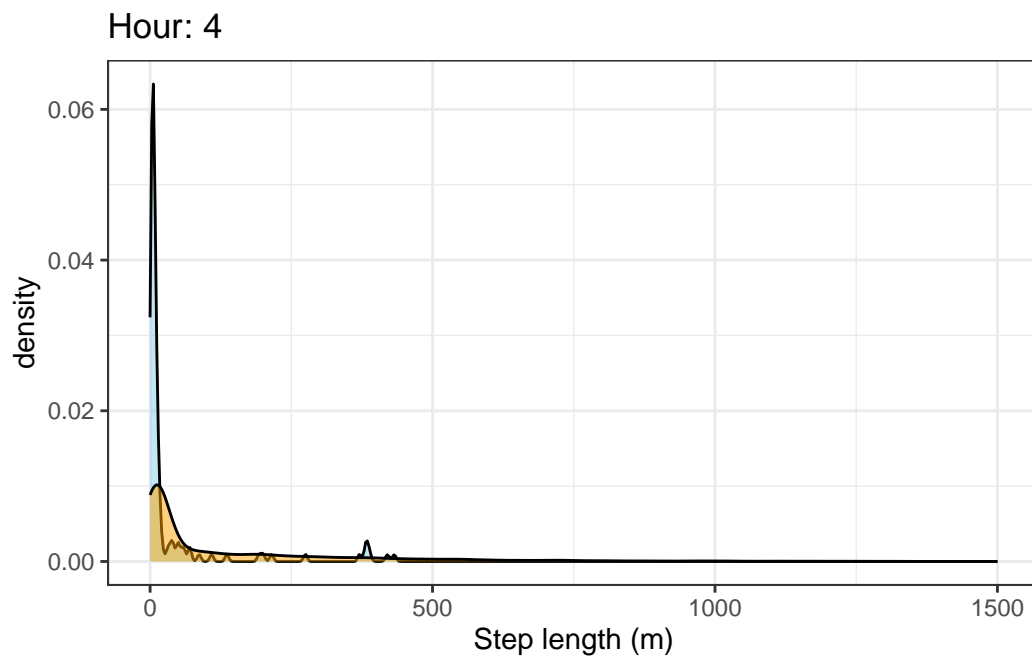
Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).
Removed 1 row containing non-finite outside the scale range (``stat_density()``).



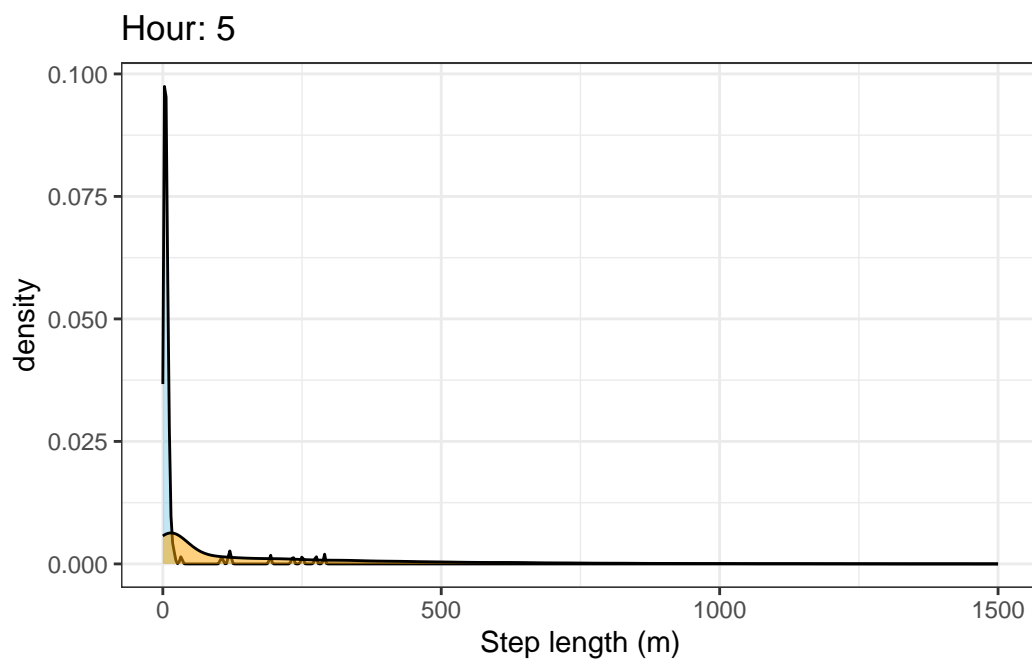
Warning: Removed 2 rows containing non-finite outside the scale range (``stat_density()``).



Warning: Removed 3 rows containing non-finite outside the scale range (``stat_density()``).



Warning: Removed 4 rows containing non-finite outside the scale range (``stat_density()``).



Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).

Warning: Removed 5 rows containing non-finite outside the scale range
(`stat_density()`).



Warning: Removed 3 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 7 rows containing non-finite outside the scale range
(`stat_density()`).

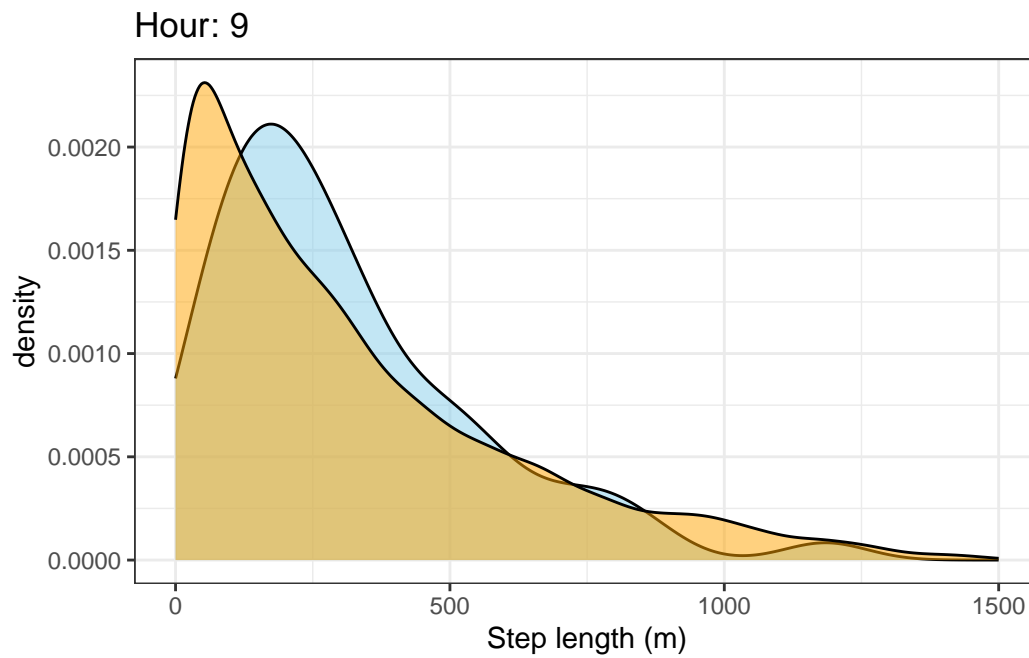


Warning: Removed 4 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 11 rows containing non-finite outside the scale range
(`stat_density()`).



Warning: Removed 9 rows containing non-finite outside the scale range
(`stat_density()`).

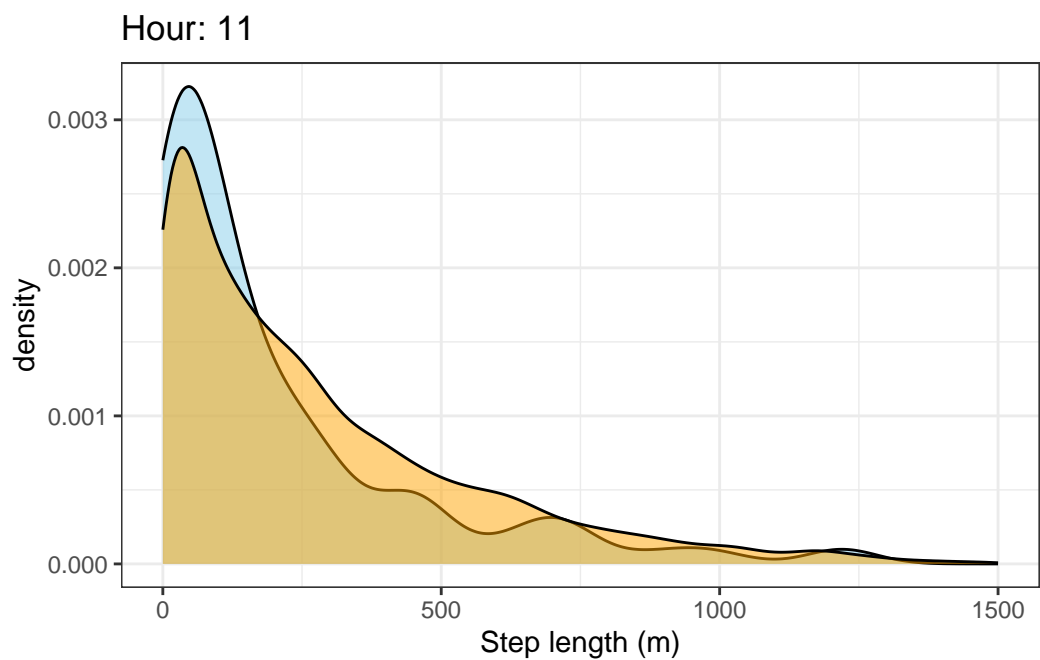


Warning: Removed 2 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 8 rows containing non-finite outside the scale range
(`stat_density()`).



Warning: Removed 5 rows containing non-finite outside the scale range (``stat_density()``).



Warning: Removed 4 rows containing non-finite outside the scale range (``stat_density()``).

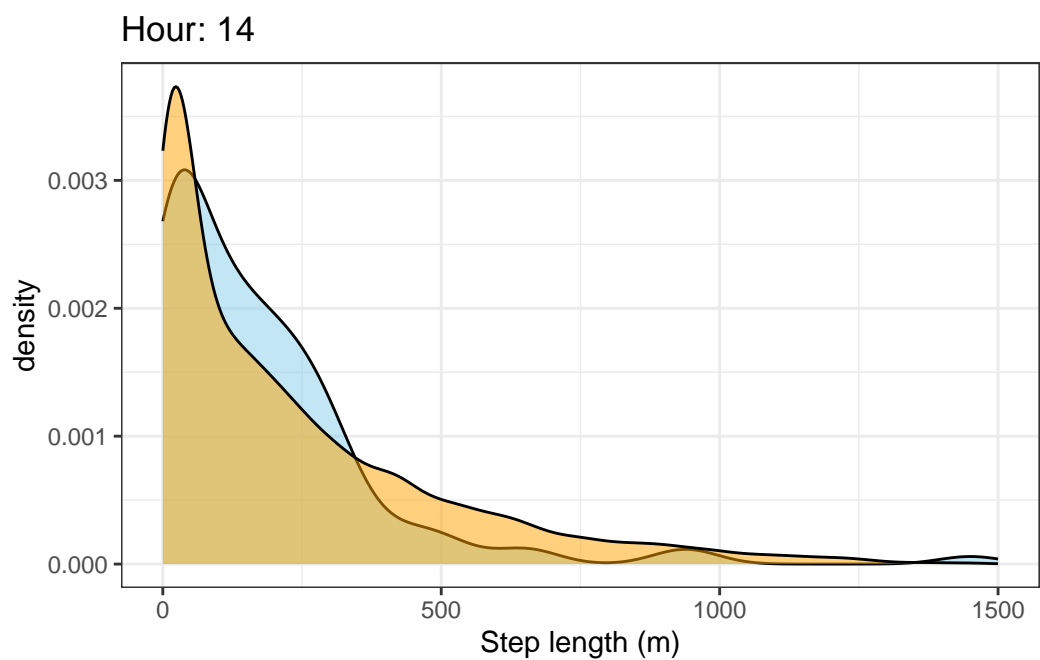


Warning: Removed 6 rows containing non-finite outside the scale range (``stat_density()``).

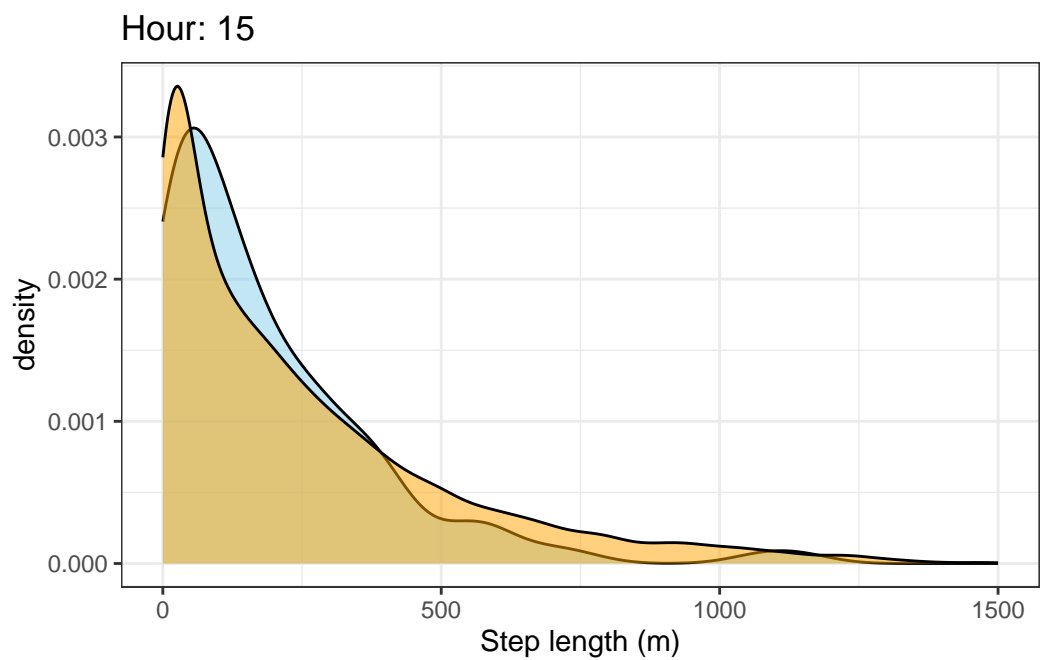


Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).

Warning: Removed 7 rows containing non-finite outside the scale range
(`stat_density()`).

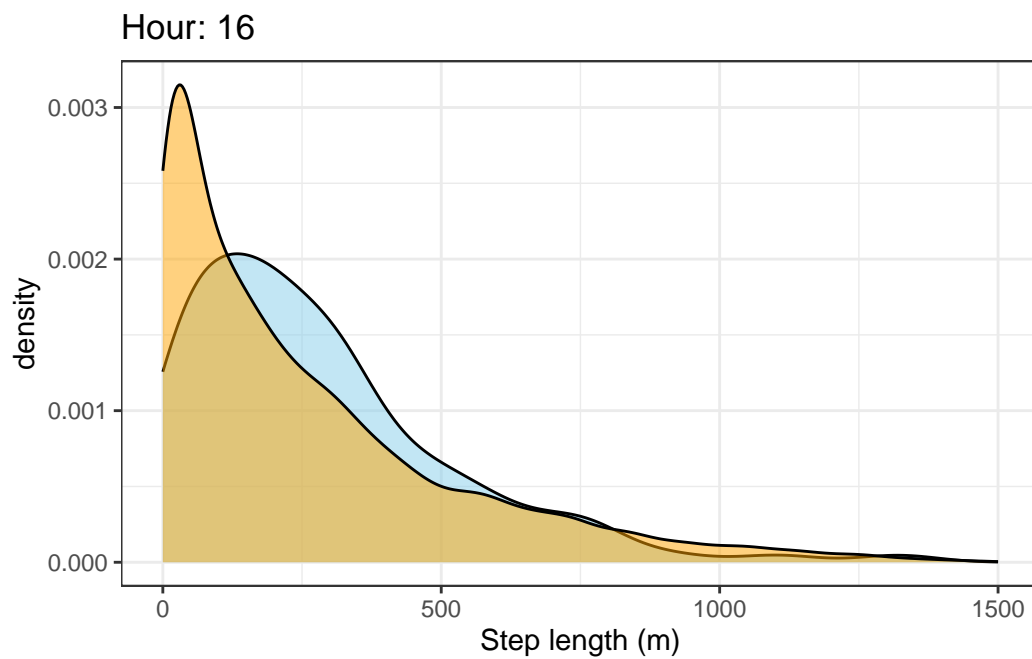


Warning: Removed 8 rows containing non-finite outside the scale range
(`stat_density()`).



Warning: Removed 1 row containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 4 rows containing non-finite outside the scale range
(`stat_density()`).



Warning: Removed 2 rows containing non-finite outside the scale range
(`stat_density()`).

Removed 4 rows containing non-finite outside the scale range
(`stat_density()`).



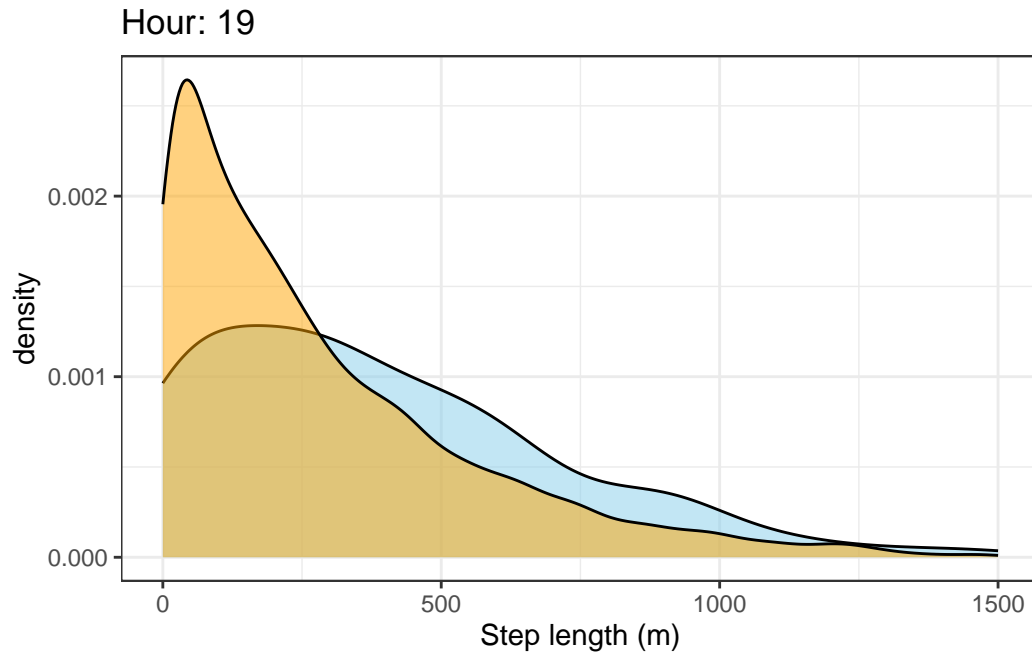
Warning: Removed 4 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 12 rows containing non-finite outside the scale range
(`stat_density()`).

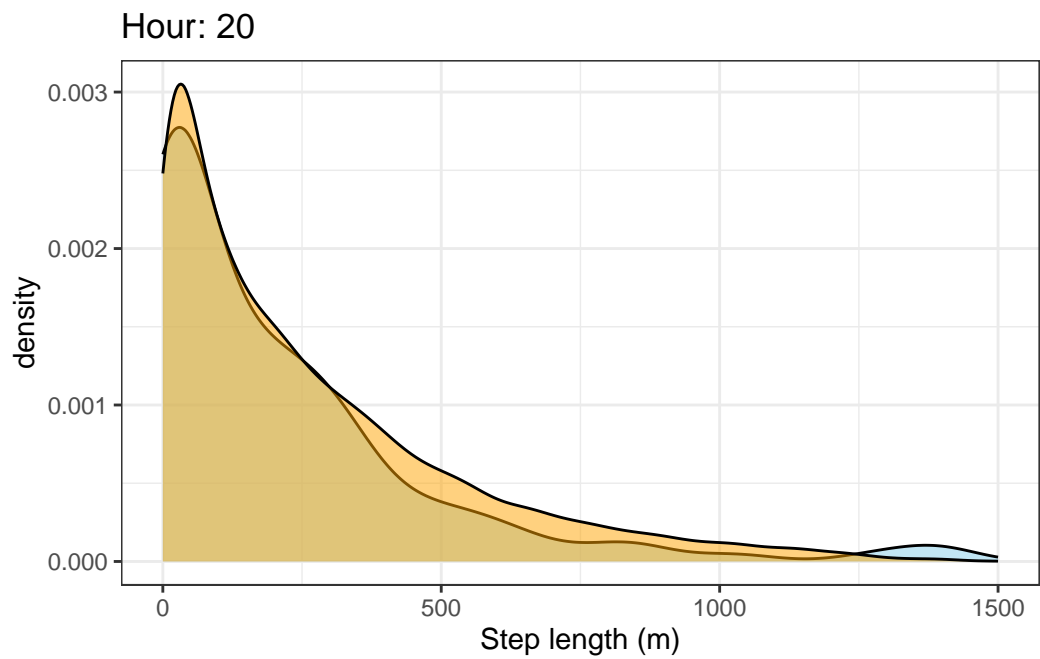


Warning: Removed 2 rows containing non-finite outside the scale range
(`stat_density()`).

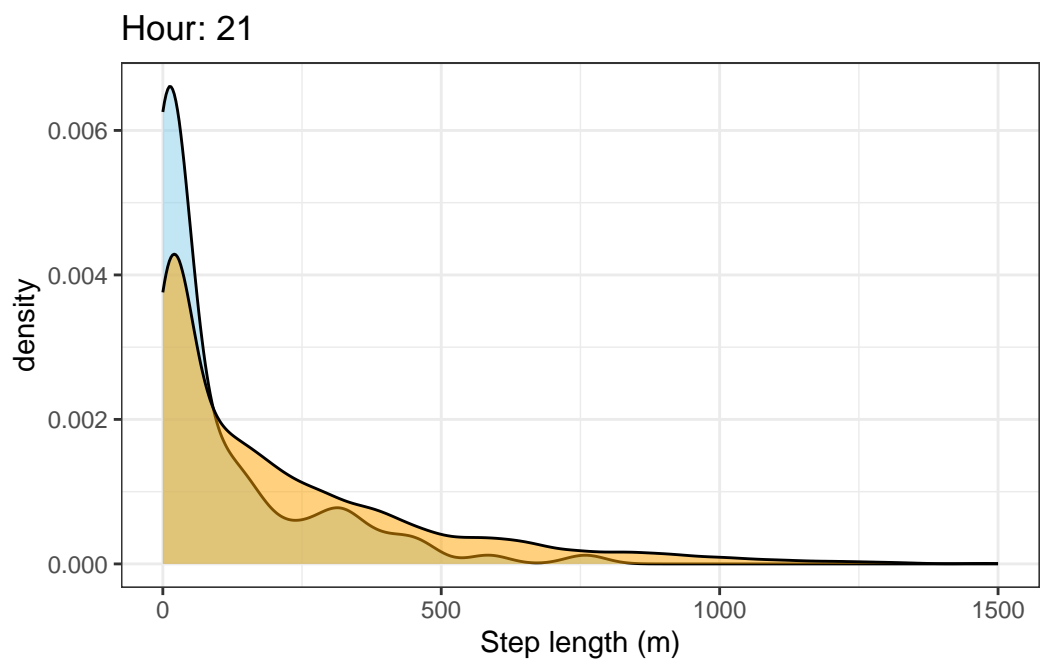
Warning: Removed 3 rows containing non-finite outside the scale range
(`stat_density()`).



Warning: Removed 1 row containing non-finite outside the scale range (`stat_density()`).
Removed 3 rows containing non-finite outside the scale range
(`stat_density()`).

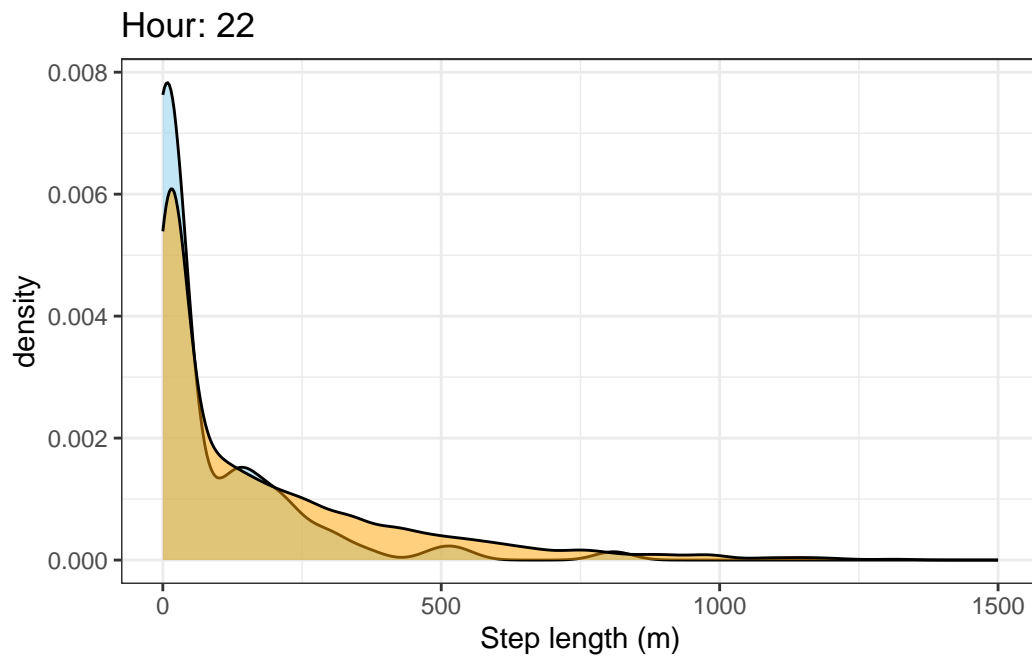


Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).

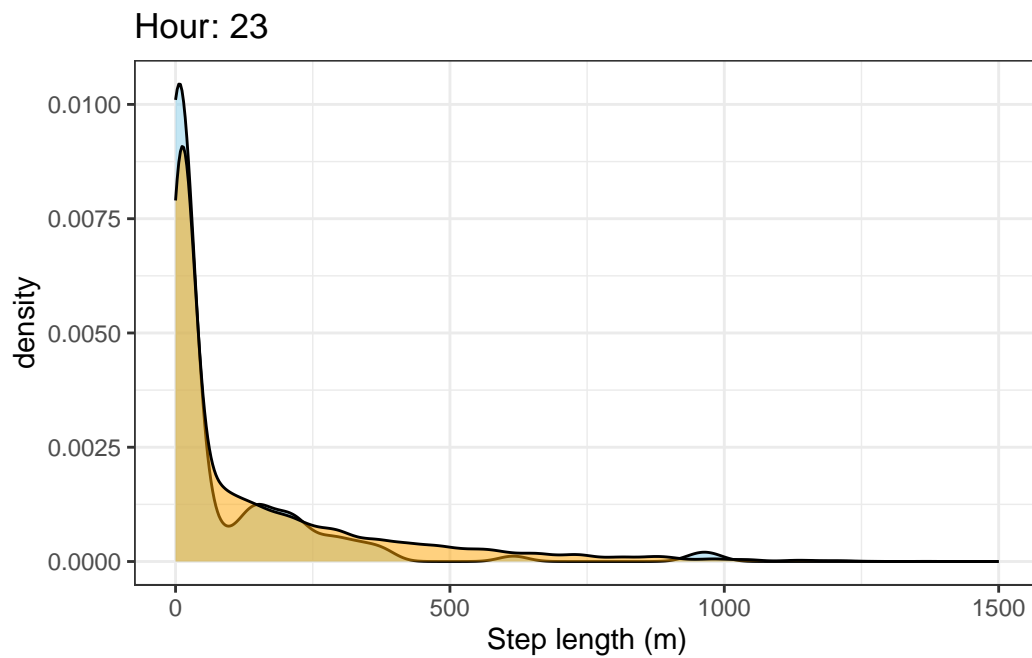


Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).

Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).



Warning: Removed 51 rows containing non-finite outside the scale range (``stat_density()``).

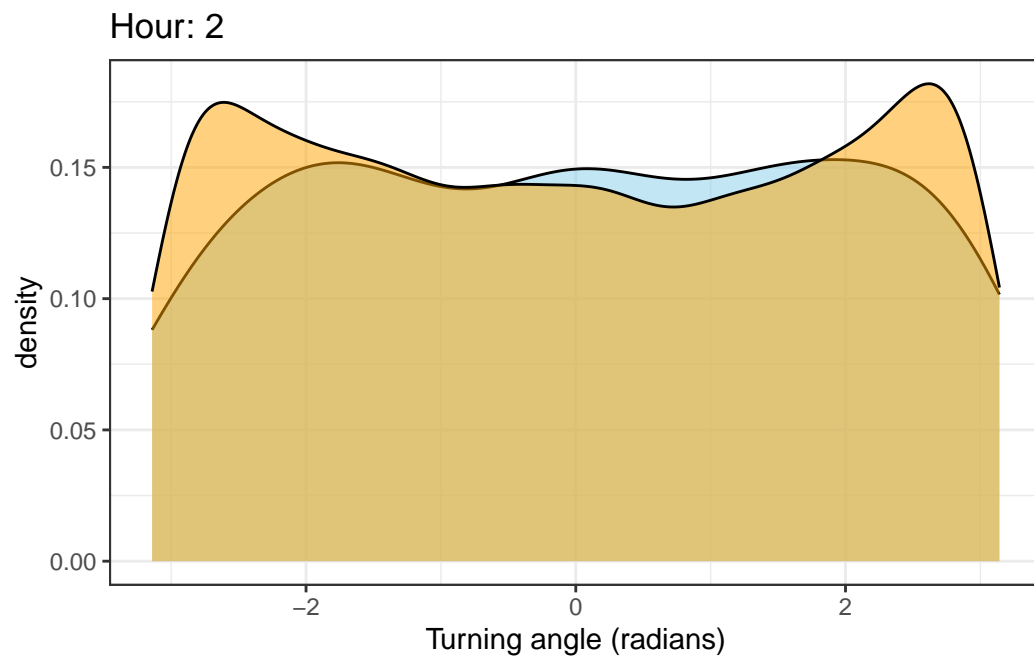
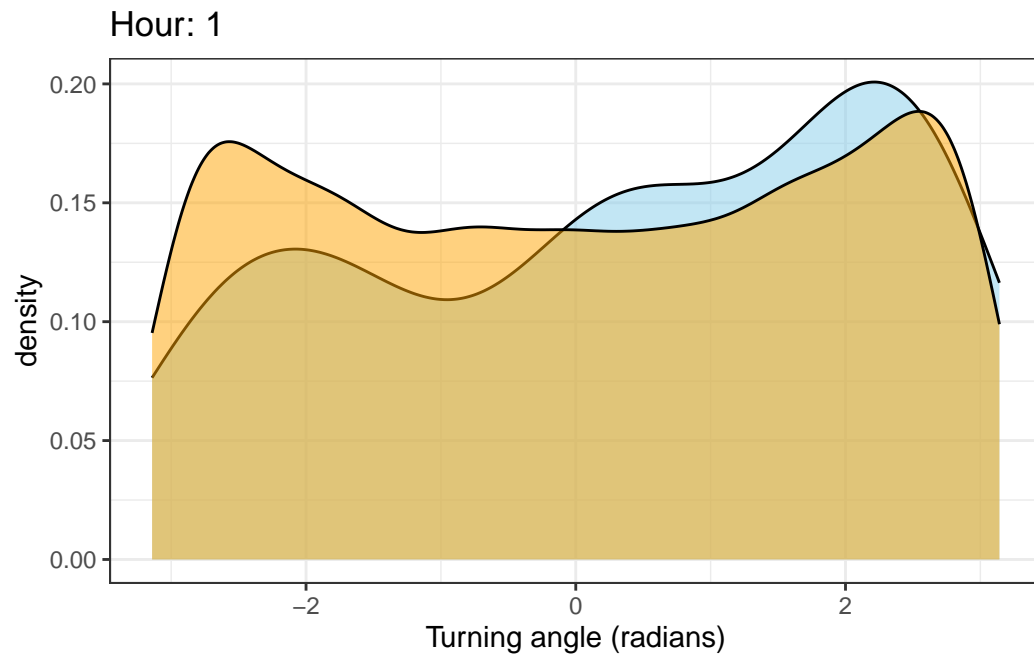


Density of turning angles for each hour

```
for(i in 0:23) {  
  print(ggplot() +  
    geom_density(data = all_data %>% filter(id == 2005 & hour_t1 == i),  
      aes(x = ta),  
      fill = "skyblue", colour = "black", alpha = 0.5) +  
    geom_density(data = all_data %>% filter(hour_t1 == i),  
      aes(x = ta),  
      fill = "orange", colour = "black", alpha = 0.5) +  
    scale_x_continuous("Turning angle (radians)", limits = c(-pi, pi)) +  
    ggtitle(paste0("Hour: ", i)) +  
    theme_bw()  
  }  
}
```

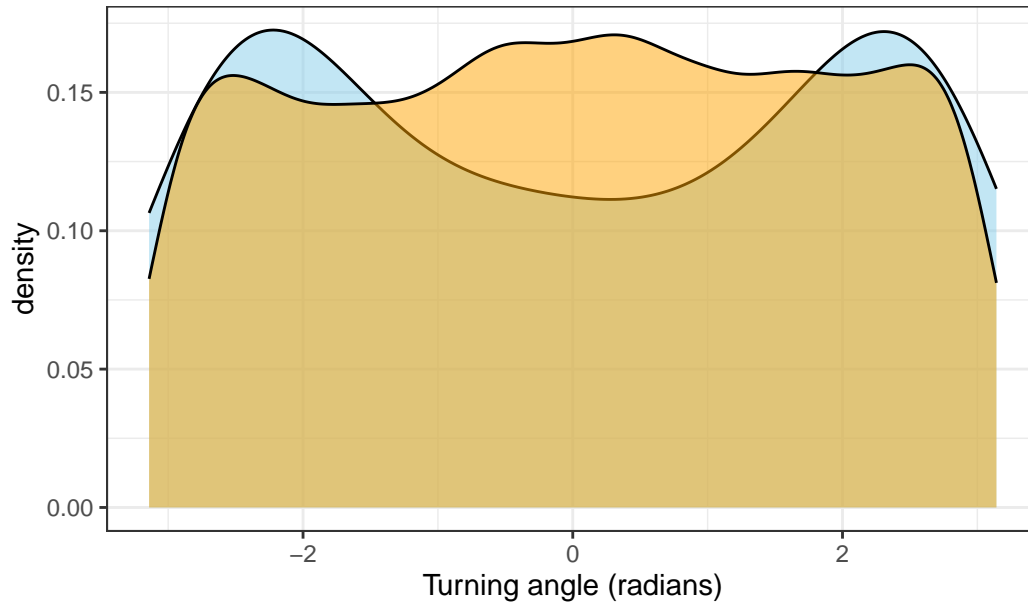
Warning: Removed 51 rows containing non-finite outside the scale range
(`stat_density()`).



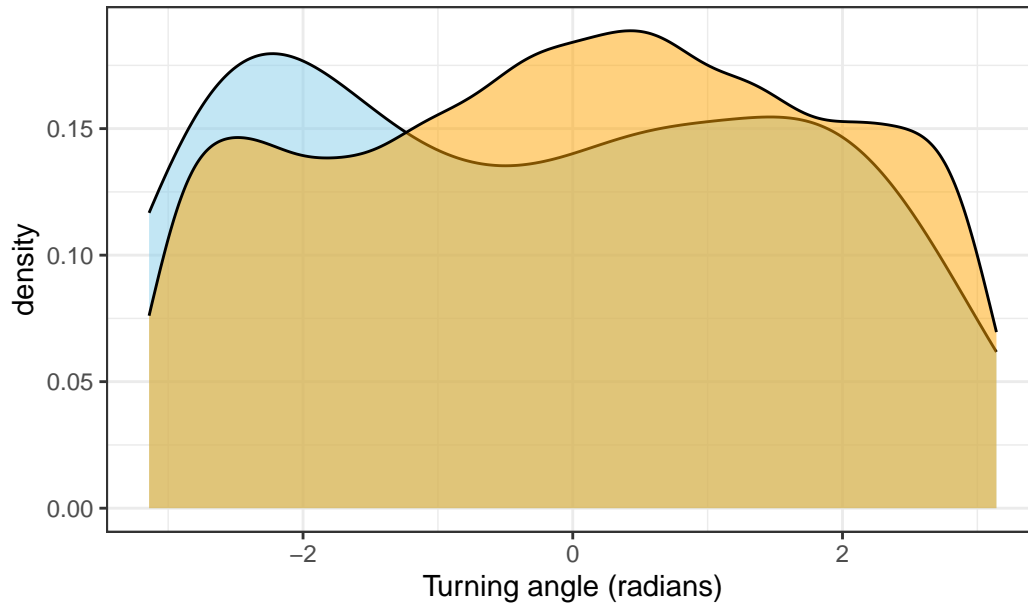




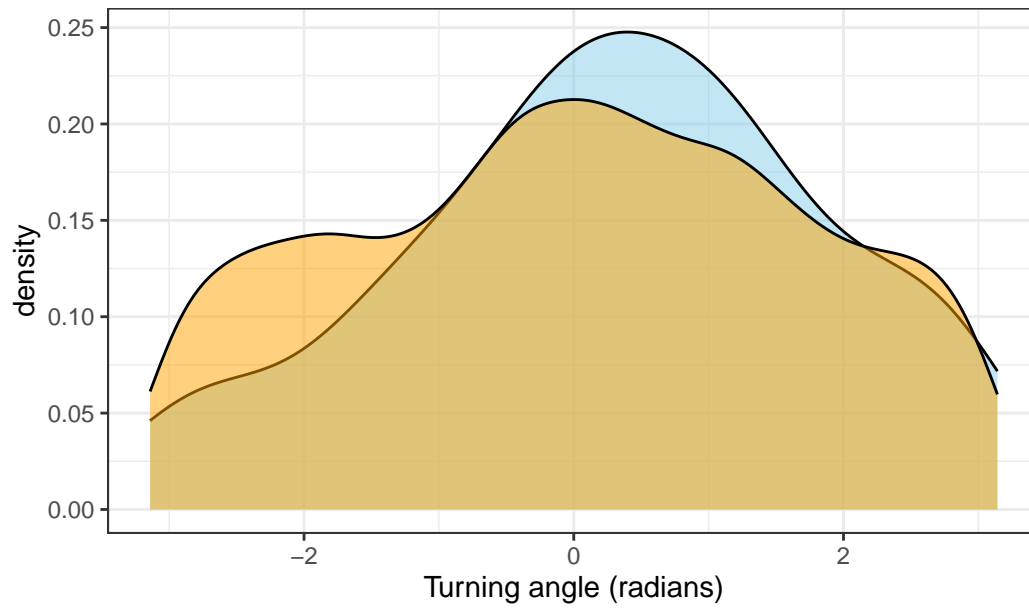
Hour: 5



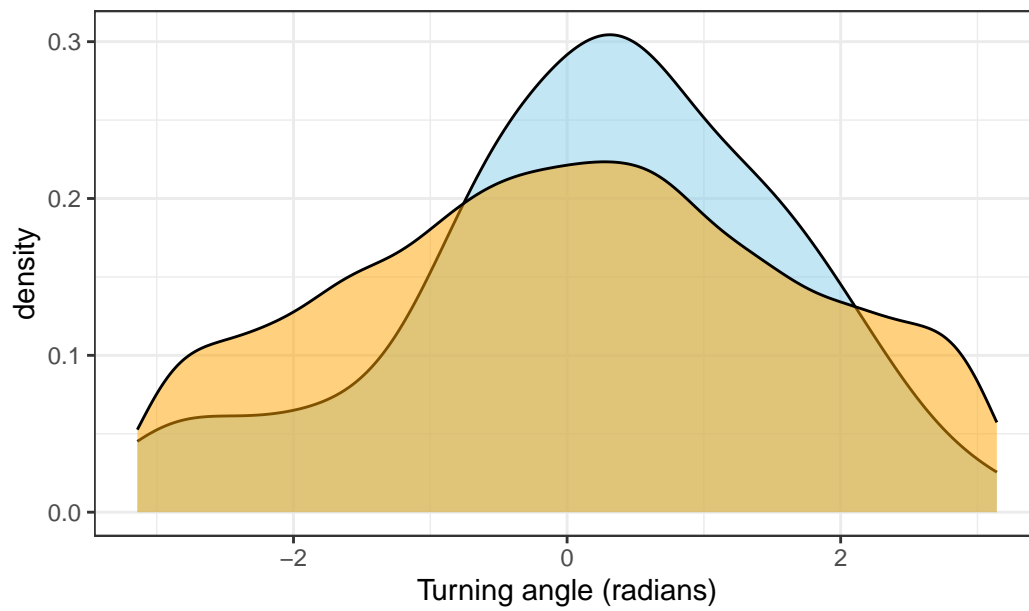
Hour: 6



Hour: 7



Hour: 8



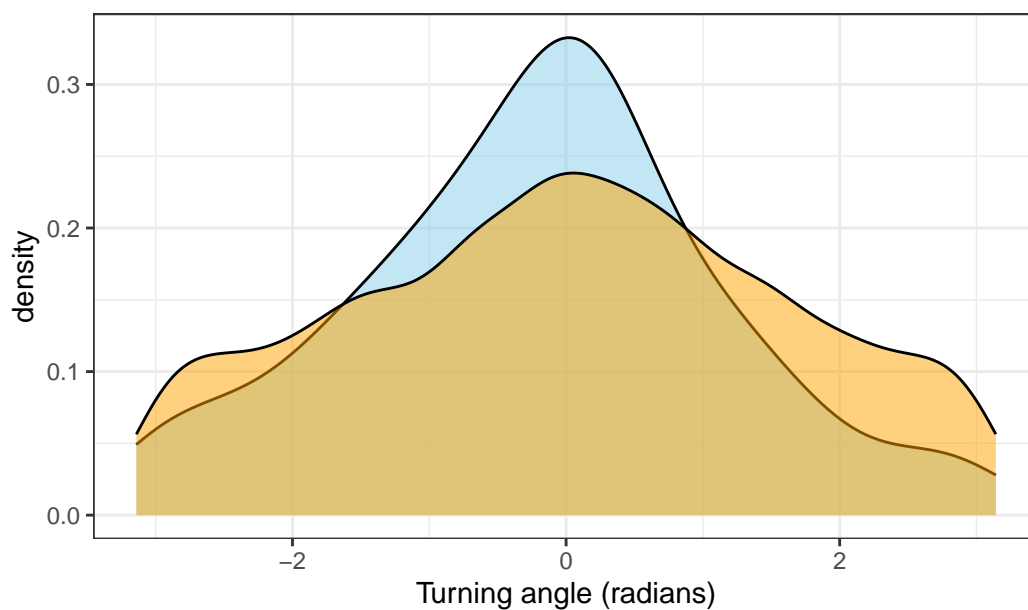
Hour: 9



Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).

Warning: Removed 1 row containing non-finite outside the scale range (``stat_density()``).

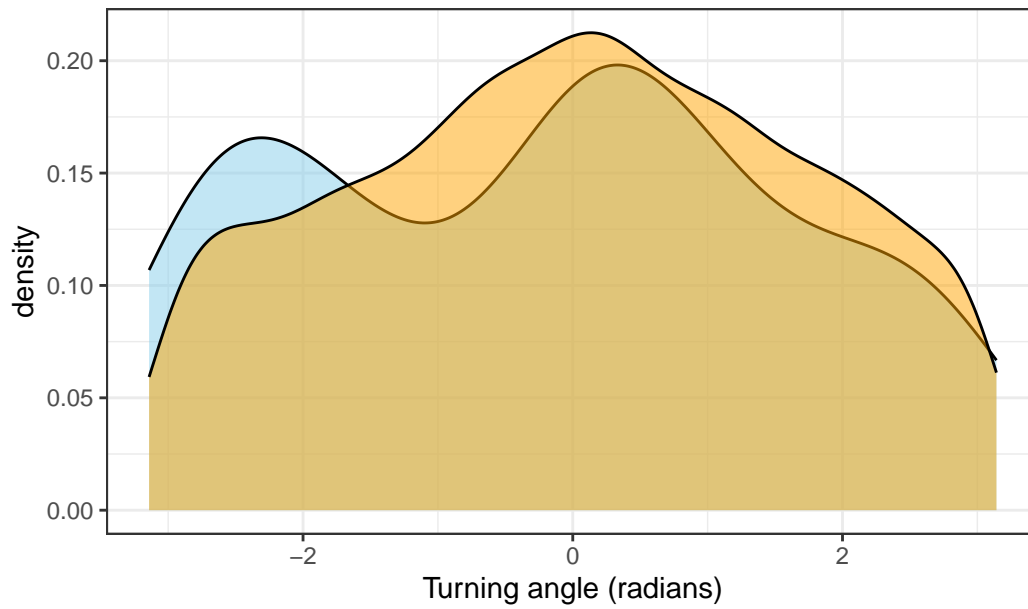
Hour: 10



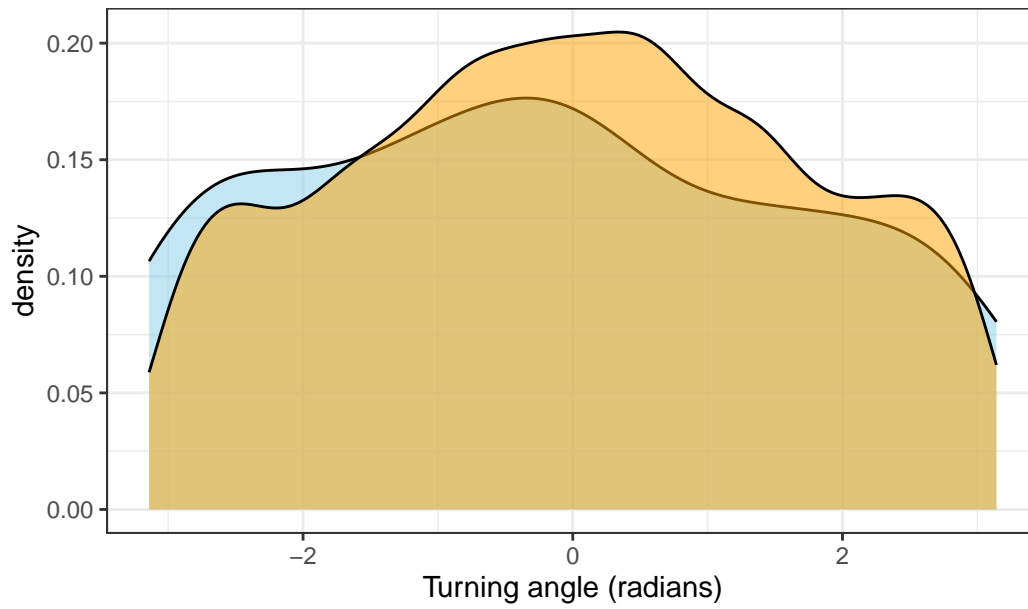
Hour: 11



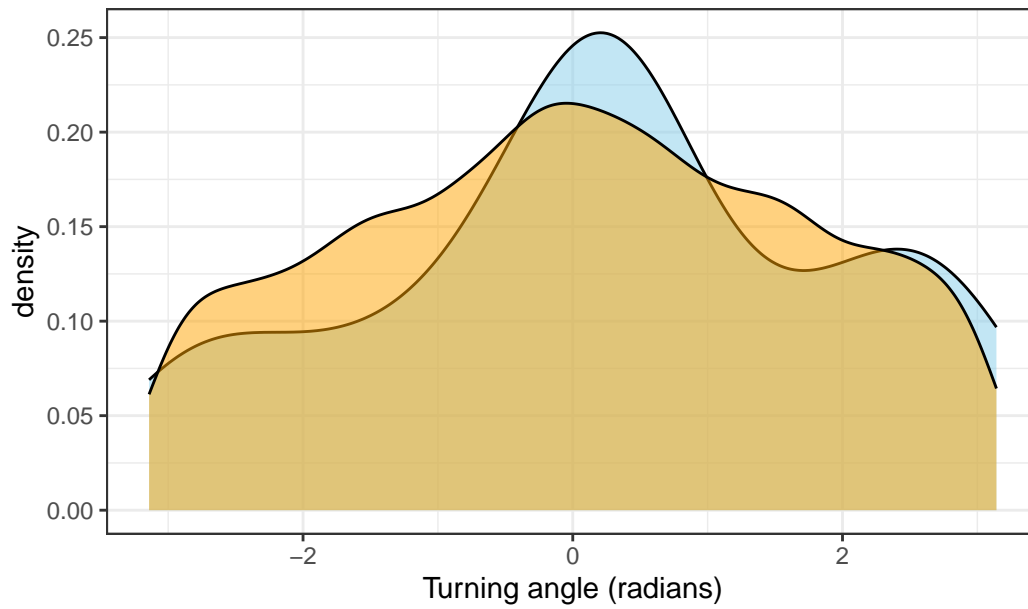
Hour: 12



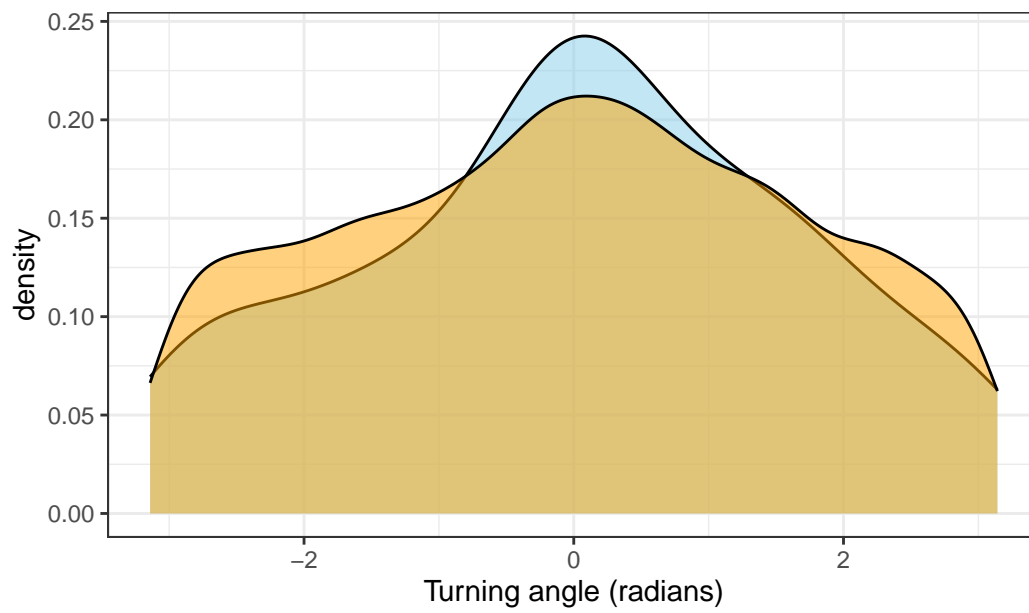
Hour: 13



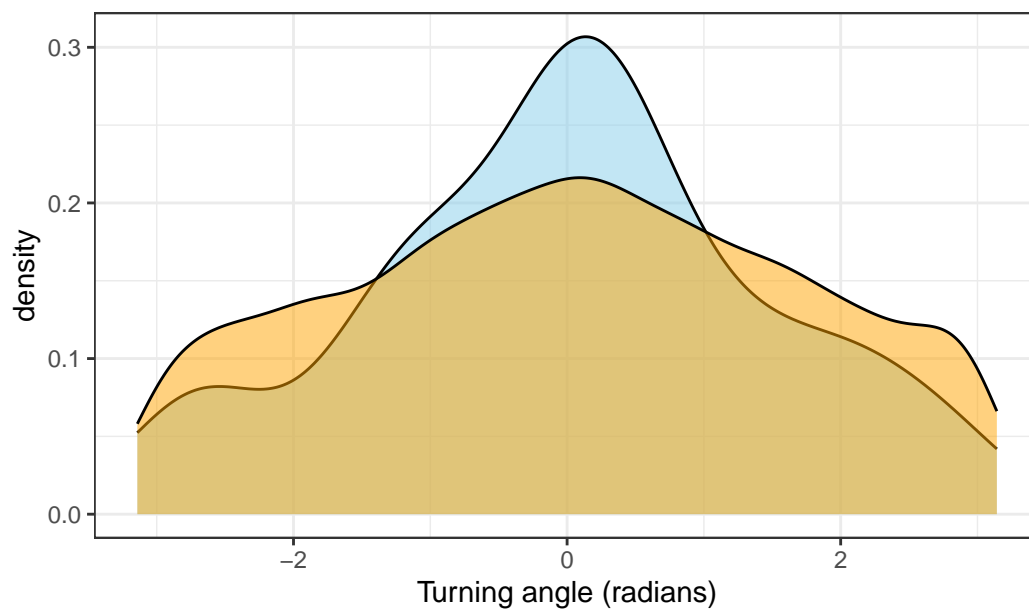
Hour: 14



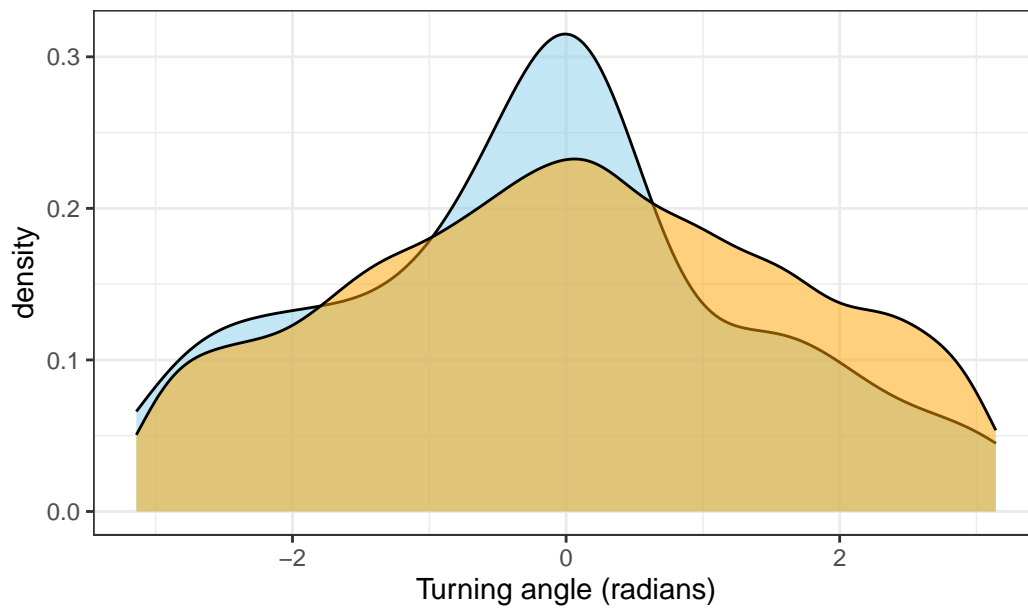
Hour: 15



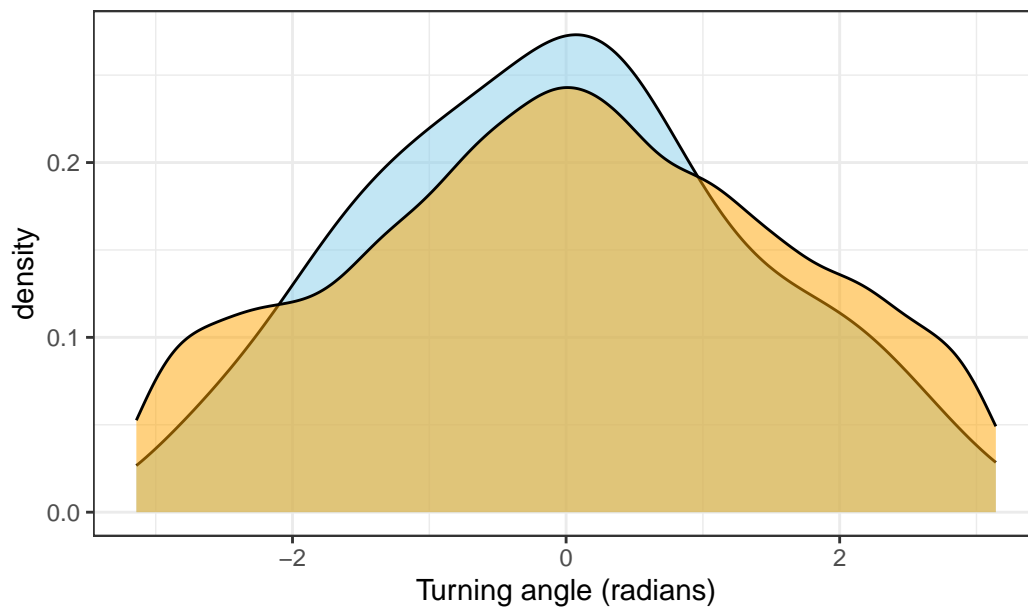
Hour: 16



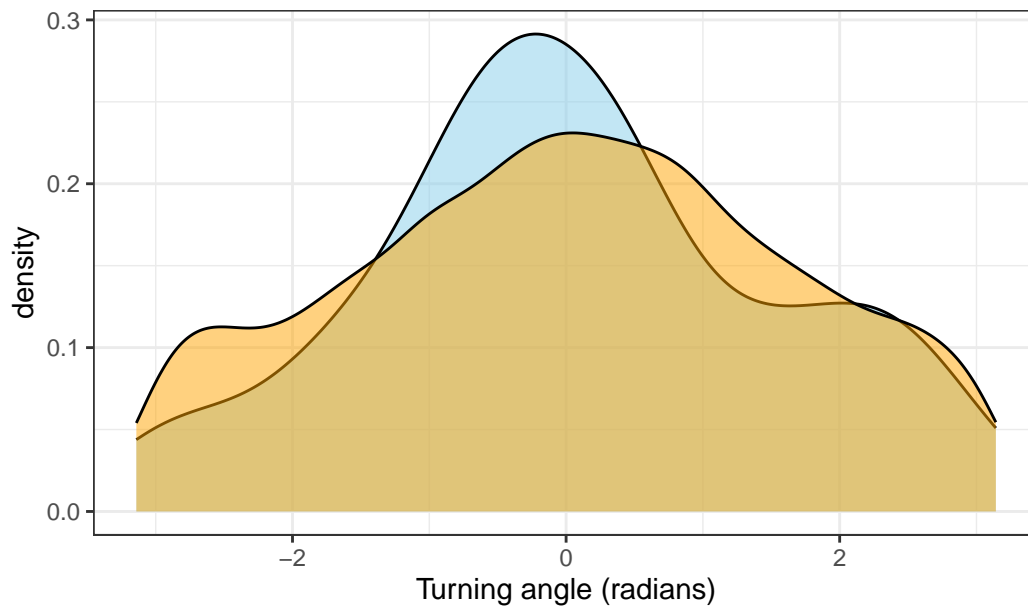
Hour: 17



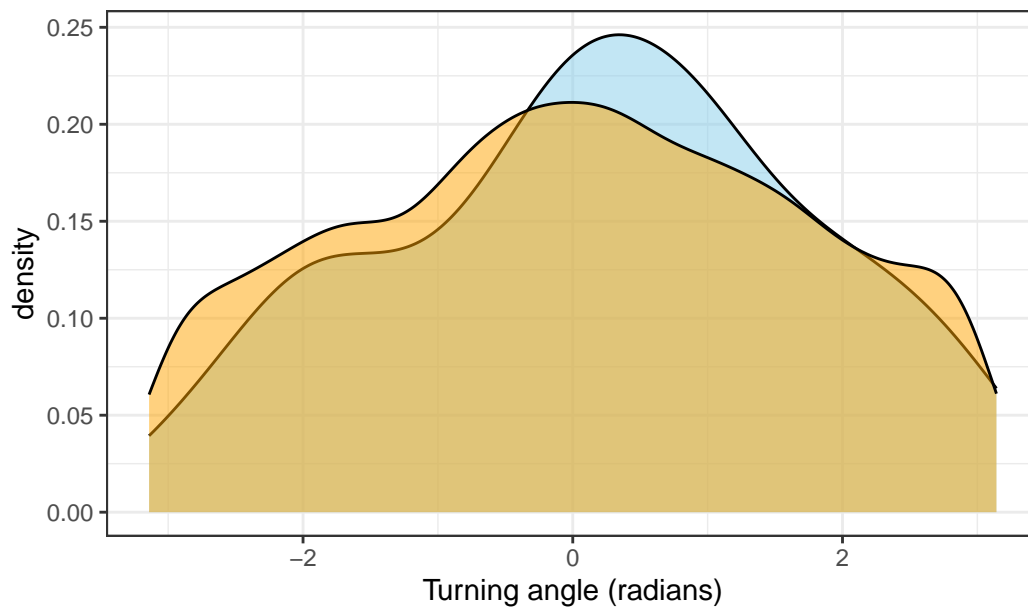
Hour: 18



Hour: 19

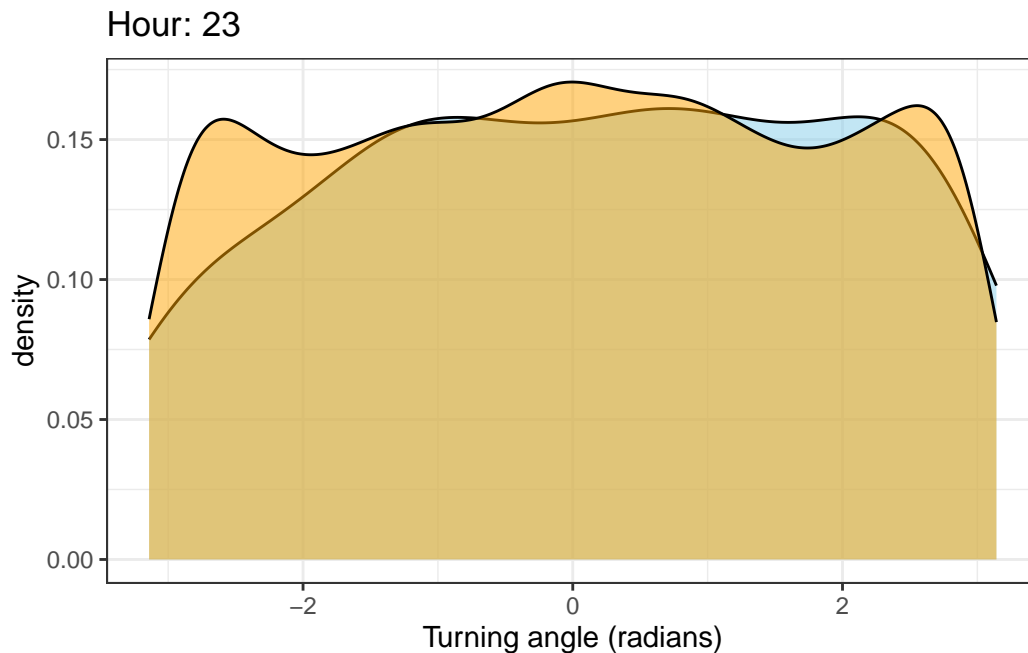


Hour: 20





Warning: Removed 51 rows containing non-finite outside the scale range
(`stat_density()`).



Extract covariate values

To check the distribution of environmental values, we can extract the values of the covariates at the locations of the observed and simulated data.

We also need to index the correct NDVI raster for each row of the data.

```
# for the simulated data
all_data_xy <- data.frame("x" = all_data$x1, "y" = all_data$y1)

# Calculate ndvi_index for all rows at once using vectorized operation
all_data <- all_data %>%
  mutate(
    ndvi_index = vapply(t1, function(t) which.min(abs(difftime(t, terra::time(ndvi)))), inte
  )

# Split row indices by the corresponding NDVI layer index
ndvi_groups <- split(seq_len(nrow(all_data_xy)), all_data$ndvi_index)

# Extract values per group in one call per layer
extracted_ndvi <- map2(ndvi_groups, names(ndvi_groups), function(rows, index_str) {
  # Convert the layer index from character to numeric if needed
  index <- as.numeric(index_str)
  terra::extract(ndvi[[index]], all_data_xy[rows, , drop = FALSE])[,2]
})
```

```
# Reassemble the extracted ndvi values into a single vector in original order
ndvi_values <- unsplit(extracted_ndvi, all_data$ndvi_index)

# Extract raster data based on calculated ndvi_index
all_data <- all_data %>%
  mutate(
    ndvi = ndvi_values,
    canopy_cover = terra::extract(canopy_cover, all_data_xy)[,2],
    veg_herby = terra::extract(veg_herby, all_data_xy)[,2],
    slope = terra::extract(slope, all_data_xy)[,2],
  )
```

Hourly movement behaviour and selection of covariates

Here we bin the trajectories into the hours of the day, and calculate the mean, median (where appropriate) and sd values for the step lengths and four habitat covariates.

We also save the results as a csv to compare between all of the models.

```
# there are some NA values in the hour_t2 column as well as the covariates
sum(is.na(all_data$hour_t2))
```

```
[1] 51
```

```
# drop NAs
all_data <- all_data %>% dplyr::select(-date) %>% drop_na()

hourly_habitat <-
  all_data %>%
  dplyr::group_by(hour_t2, id) %>%
  summarise(n = n(),
    step_length_mean = mean(sl, na.rm = TRUE),
    step_length_median = median(sl, na.rm = TRUE),
    step_length_sd = sd(sl, na.rm = TRUE),
    ndvi_mean = mean(ndvi, na.rm = TRUE),
    ndvi_median = median(ndvi, na.rm = TRUE),
    ndvi_sd = sd(ndvi, na.rm = TRUE),
    ndvi_min = min(ndvi, na.rm = TRUE),
    ndvi_max = max(ndvi, na.rm = TRUE),
    ndvi_mean = mean(ndvi, na.rm = TRUE),
    ndvi_median = median(ndvi, na.rm = TRUE),
    ndvi_sd = sd(ndvi, na.rm = TRUE),
```



```

    herby_mean = mean(veg_herby, na.rm = TRUE),
    herby_sd = sd(veg_herby, na.rm = TRUE),
    canopy_mean = mean(canopy_cover/100, na.rm = TRUE),
    canopy_sd = sd(canopy_cover/100, na.rm = TRUE),
    canopy_min = min(canopy_cover/100, na.rm = TRUE),
    canopy_max = max(canopy_cover/100, na.rm = TRUE),
    slope_mean = mean(slope, na.rm = TRUE),
    slope_median = median(slope, na.rm = TRUE),
    slope_sd = sd(slope, na.rm = TRUE),
    slope_min = min(slope, na.rm = TRUE),
    slope_max = max(slope, na.rm = TRUE)
  ) %>% ungroup() %>%
mutate(Data = ifelse(id == 2005, "Observed", "deepSSF"))

```

`summarise()` has grouped output by 'hour_t2'. You can override using the `.groups` argument.

Plotting the hourly habitat selection

```

hourly_habitat_long <- hourly_habitat %>%
  pivot_longer(cols = !c(Data, hour_t2, id), names_to = "variable", values_to = "value")

```

To show the stochasticity of the simulations, here we show the 25th to 50th quantiles and the 2.5th to 97.5th quantiles of the data. Remember that the 'data' are the means for each hour for each trajectory, so the quantiles are calculated across the means for each hour. We use a dashed-line ribbon for the 95% interval and a solid-line ribbon for the 50% interval. We show the mean as a solid line.

This is the plotting approach that we used in the paper.

Calculate the quantiles

```

hourly_summary_quantiles <- hourly_habitat_long %>%
  dplyr::group_by(Data, hour_t2, variable) %>%
  summarise(n = n(),
    mean = mean(value, na.rm = TRUE),
    sd = sd(value, na.rm = TRUE),
    q025 = quantile(value, probs = 0.025, na.rm = TRUE),
    q25 = quantile(value, probs = 0.25, na.rm = TRUE),
    q50 = quantile(value, probs = 0.5, na.rm = TRUE),
    q75 = quantile(value, probs = 0.75, na.rm = TRUE),
    q975 = quantile(value, probs = 0.975, na.rm = TRUE))

```

`summarise()` has grouped output by 'Data', 'hour_t2'. You can override using the `.groups` argument.

Set up the plotting parameters

```
# set plotting parameters here that will change in each plot
buff_path_alpha <- 0.1
ribbon_95_alpha <- 0.5
ribbon_50_alpha <- 0.25
path_95_alpha <- 1

# set path alpha
buff_path_alpha <- 0.25

# linewidth
buff_path_linewidth <- 0.5

# Create color mapping
unique_groups <- unique(hourly_habitat_long$Data)
colors <- viridis(length(unique_groups))
names(colors) <- unique_groups
colors["Observed"] <- "skyblue"
colors["deepSSF"] <- "orange"
```

Hourly covariate selection

Note the tabs for the step lengths and each of the covariates

Mean step lengths

```
hourly_path_sl_plot <- ggplot() +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(Data == "Buffalo" & variable == "step_length_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "step_length_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
```

```

    alpha = ribbon_50_alpha) +

geom_path(data = hourly_habitat_long %>%
  filter(Data == "Buffalo" & variable == "step_length_mean"),
  aes(x = hour_t2, y = value, colour = Data, group = interaction(id, Data)),
  alpha = buff_path_alpha,
  linewidth = buff_path_linewidth) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "step_length_mean"),
  aes(x = hour_t2, y = q025, colour = Data),
  linetype = "dashed",
  alpha = path_95_alpha) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "step_length_mean"),
  aes(x = hour_t2, y = q975, colour = Data),
  linetype = "dashed",
  alpha = path_95_alpha) +

geom_path(data = hourly_summary_quantiles %>%
  filter(Data == "Buffalo" & variable == "step_length_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "step_length_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

scale_fill_manual(values = colors) +
scale_colour_manual(values = colors) +
scale_y_continuous("Mean value") +
scale_x_continuous("hour_t2", breaks = seq(0,24,3)) +
ggtitle("Step length (m)") +
theme_bw() +
theme(legend.position = "bottom")

hourly_path_sl_plot

```



NDVI

```
hourly_path_ndvi_plot <- ggplot() +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(Data == "Buffalo" & variable == "ndvi_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "ndvi_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_path(data = hourly_habitat_long %>%
    filter(Data == "Buffalo" & variable == "ndvi_mean"),
    aes(x = hour_t2, y = value, colour = Data, group = interaction(id, Data)),
    alpha = buff_path_alpha,
    linewidth = buff_path_linewidth) +

  geom_path(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "ndvi_mean"),
    aes(x = hour_t2, y = q025, colour = Data),
    linetype = "dashed",
    alpha = path_95_alpha) +
```

```

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "ndvi_mean"),
  aes(x = hour_t2, y = q975, colour = Data),
  linetype = "dashed",
  alpha = path_95_alpha) +

geom_path(data = hourly_summary_quantiles %>%
  filter(Data == "Buffalo" & variable == "ndvi_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "ndvi_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

scale_fill_manual(values = colors) +
scale_colour_manual(values = colors) +
scale_y_continuous("Mean value") +
scale_x_continuous("hour_t2", breaks = seq(0,24,3)) +
ggtitle("NDVI") +
theme_bw()

hourly_path_ndvi_plot

```



Canopy cover

```
hourly_path_canopy_plot <- ggplot() +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_path(data = hourly_habitat_long %>%
    filter(Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, y = value, colour = Data, group = interaction(id, Data)),
    alpha = buff_path_alpha,
    linewidth = buff_path_linewidth) +

  geom_path(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, y = q025, colour = Data),
    linetype = "dashed",
    alpha = path_95_alpha) +

  geom_path(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, y = q975, colour = Data),
    linetype = "dashed",
    alpha = path_95_alpha) +

  geom_path(data = hourly_summary_quantiles %>%
    filter(Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, y = mean, colour = Data),
    linewidth = 1) +

  geom_path(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "canopy_mean"),
    aes(x = hour_t2, y = mean, colour = Data),
    linewidth = 1) +

  scale_fill_manual(values = colors) +
  scale_colour_manual(values = colors) +
```

```
scale_y_continuous("Mean value") +
scale_x_continuous("hour_t2", breaks = seq(0,24,3)) +
ggtitle("Canopy cover") +
theme_bw()
```

hourly_path_canopy_plot



Herbaceous vegetation

```
hourly_path_herby_plot <- ggplot() +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(Data == "Buffalo" & variable == "herby_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "herby_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_path(data = hourly_habitat_long %>%
    filter(Data == "Buffalo" & variable == "herby_mean"),
    aes(x = hour_t2, y = value, colour = Data, group = interaction(id, Data)),
```

```

        alpha = buff_path_alpha,
        linewidth = buff_path_linewidth) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "herby_mean"),
  aes(x = hour_t2, y = q025, colour = Data),
  linetype = "dashed",
  alpha = path_95_alpha) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "herby_mean"),
  aes(x = hour_t2, y = q975, colour = Data),
  linetype = "dashed",
  alpha = path_95_alpha) +

geom_path(data = hourly_summary_quantiles %>%
  filter(Data == "Buffalo" & variable == "herby_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "herby_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

scale_fill_manual(values = colors) +
scale_colour_manual(values = colors) +
scale_y_continuous("Mean value") +
scale_x_continuous("hour_t2", breaks = seq(0,24,3)) +
ggtitle("Herbaceous vegetation") +
theme_bw()

hourly_path_herby_plot

```




Slope

```
hourly_path_slope_plot <- ggplot() +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(Data == "Buffalo" & variable == "slope_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_ribbon(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "slope_mean"),
    aes(x = hour_t2, ymin = q25, ymax = q75, fill = Data),
    alpha = ribbon_50_alpha) +

  geom_path(data = hourly_habitat_long %>%
    filter(Data == "Buffalo" & variable == "slope_mean"),
    aes(x = hour_t2, y = value, colour = Data, group = interaction(id, Data)),
    alpha = buff_path_alpha,
    linewidth = buff_path_linewidth) +

  geom_path(data = hourly_summary_quantiles %>%
    filter(!Data == "Buffalo" & variable == "slope_mean"),
    aes(x = hour_t2, y = q025, colour = Data),
    linetype = "dashed",
    alpha = path_95_alpha) +
```

```

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "slope_mean"),
  aes(x = hour_t2, y = q975, colour = Data),
  linetype = "dashed",
  alpha = path_95_alpha) +

geom_path(data = hourly_summary_quantiles %>%
  filter(Data == "Buffalo" & variable == "slope_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

geom_path(data = hourly_summary_quantiles %>%
  filter(!Data == "Buffalo" & variable == "slope_mean"),
  aes(x = hour_t2, y = mean, colour = Data),
  linewidth = 1) +

scale_fill_manual(values = colors) +
scale_colour_manual(values = colors) +
scale_y_continuous("Mean value") +
scale_x_continuous("hour_t2", breaks = seq(0,24,3)) +
ggtitle("Slope") +
theme_bw()

hourly_path_slope_plot

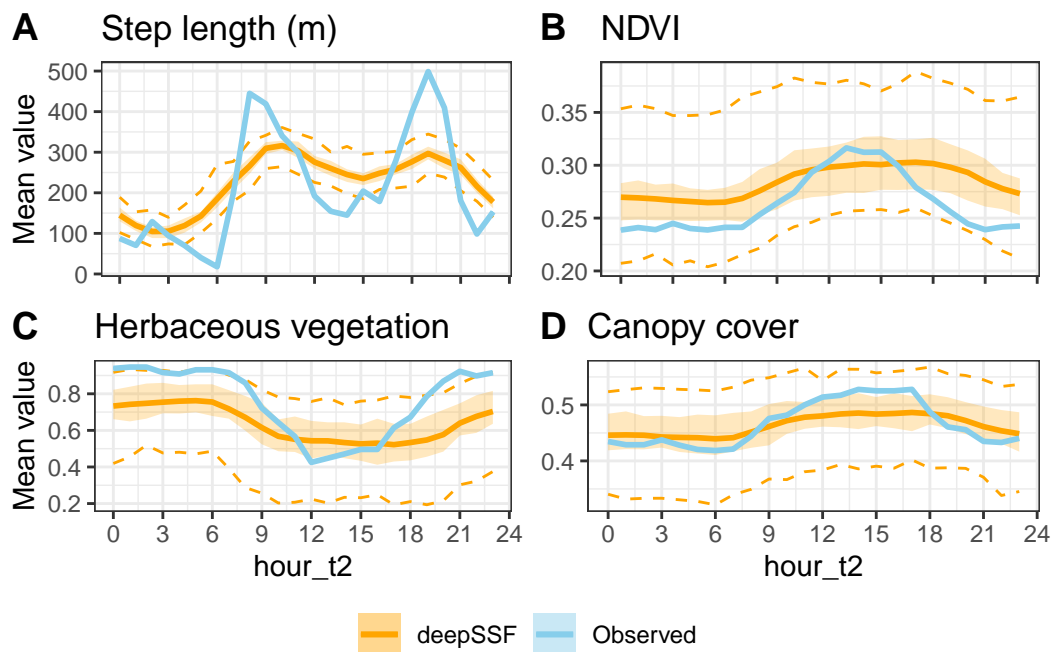
```



Combining the hourly plots

Step lengths instead of slope

```
ggarrange(hourly_path_sl_plot +  
  theme(axis.title.x = element_blank(),  
        axis.text.x = element_blank(),  
        legend.title = element_blank()),  
  
  hourly_path_ndvi_plot +  
  theme(axis.title.x = element_blank(),  
        axis.text.x = element_blank(),  
        axis.title.y = element_blank()),  
  
  hourly_path_herby_plot,  
  
  hourly_path_canopy_plot +  
  theme(axis.title.y = element_blank()),  
  
  labels = c("A", "B", "C", "D"),  
  ncol = 2, nrow = 2,  
  legend = "bottom",  
  common.legend = TRUE)
```



Slope instead of step lengths

```
ggarrange(hourly_path_ndvi_plot +
  theme(axis.title.x = element_blank(),
        axis.text.x = element_blank(),
        legend.title = element_blank()),

  hourly_path_canopy_plot +
  theme(axis.title.x = element_blank(),
        axis.text.x = element_blank(),
        axis.title.y = element_blank()),

  hourly_path_herby_plot,

  hourly_path_slope_plot +
  theme(axis.title.y = element_blank()),

  labels = c("A", "B", "C", "D"),
  ncol = 2, nrow = 2,
  legend = "bottom",
  common.legend = TRUE)
```



```
ggsave(paste0("outputs/hourly_summaries.png"), width=180, height=150, units="mm", dpi = 1000)
```