

Predicting how climate change will affect how and where terrestrial
mammals will move in British Columbia, Canada

Appendix B: Modeling the effects of temperature on movement behavior

Stefano Mezzini^{1,2} Chris H. Fleming^{3,4} Siobhan Darlington^{1,2}

Adam T. Ford^{1,2} Karen E. Hodges^{1,2} Kirk Safford⁵

Robert Serrouya^{1,2,6} Michael J. Noonan^{1,2,7}

¹ Okanagan Institute for Biodiversity, Resilience, and Ecosystem Services, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

² Department of Biology, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

³ Department of Biology, University of Central Florida, Orlando, Florida 32816, United States.

⁴ Smithsonian Conservation Biology Institute, National Zoological Park, 1500 Remount Rd., Front Royal, VA 22630, United States.

⁵ BC Parks

⁶ Wildlife Science Centre, Biodiversity Pathways, University of British Columbia Okanagan, Revelstoke, British Columbia, Canada.

⁷ Department of Computer Science, Math, Physics, and Statistics, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

1 Directed Acyclical Graphs

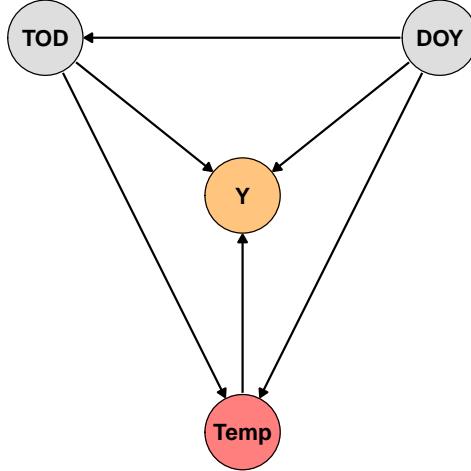


Figure B1: Directed Acyclical Graph assumed for inferring the causal effects of temperature (Temp) on probability of moving, speed when moving, or distance traveled (Y) while accounting for the effects of time of day (TOD), day of year (DOY), and their interaction effects. Temperature directly affects Y , but the effects of temperature depend on the time of day and season. Time of day and day of year also affect Y directly, but the effect of time of day changes throughout the year due to changes in day length and seasonality.

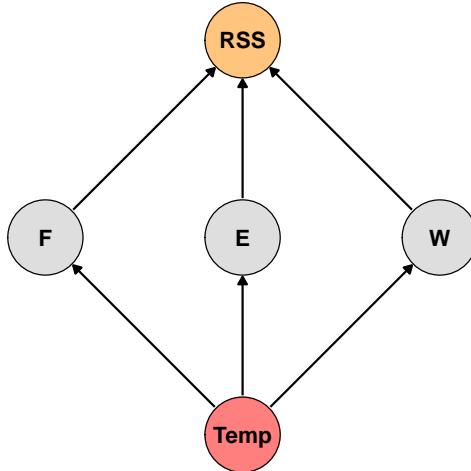


Figure B2: Directed Acyclical Graph assumed for inferring the causal effects of temperature (Temp) on Relative Selection Strength (RSS) for percent forest cover (F), elevation (E), and distance from water (W). The RSS for a given habitat depends on all three resources, and the selection for each resource is independent of the other two resources and dependent on temperature.

2 Effects of temperature on movement rates

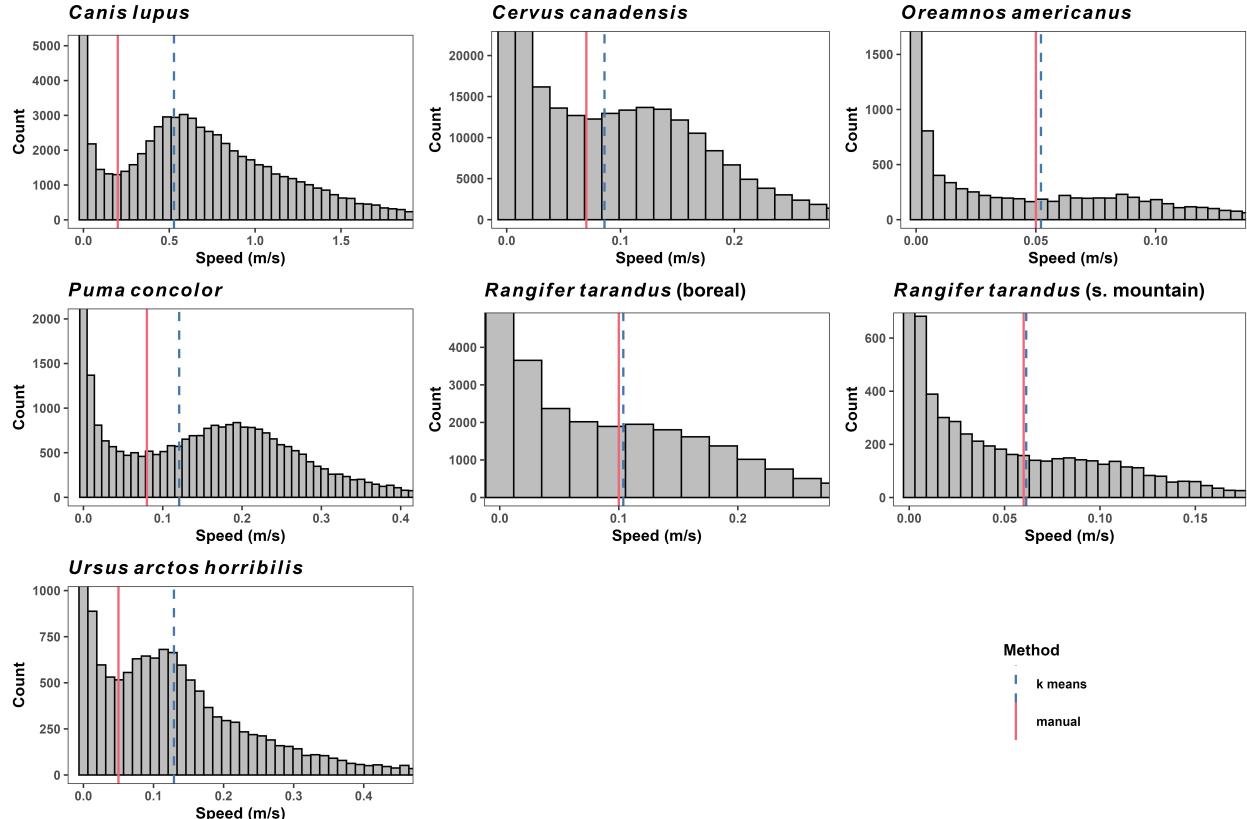


Figure B3: Histograms of each species' estimated speed. Continuous red lines indicate the values used to determine whether an animal was moving or not, which were determined visually using the inflection points of the histograms. Dashed blue lines indicate the minimum speed corresponding to a moving animal as determined by k -means algorithms with 2 clusters. For ease of readability, the x axes range from 0 to the 0.99 quantile, while the y axes range from 0 to one fortieth of the total number of estimates.

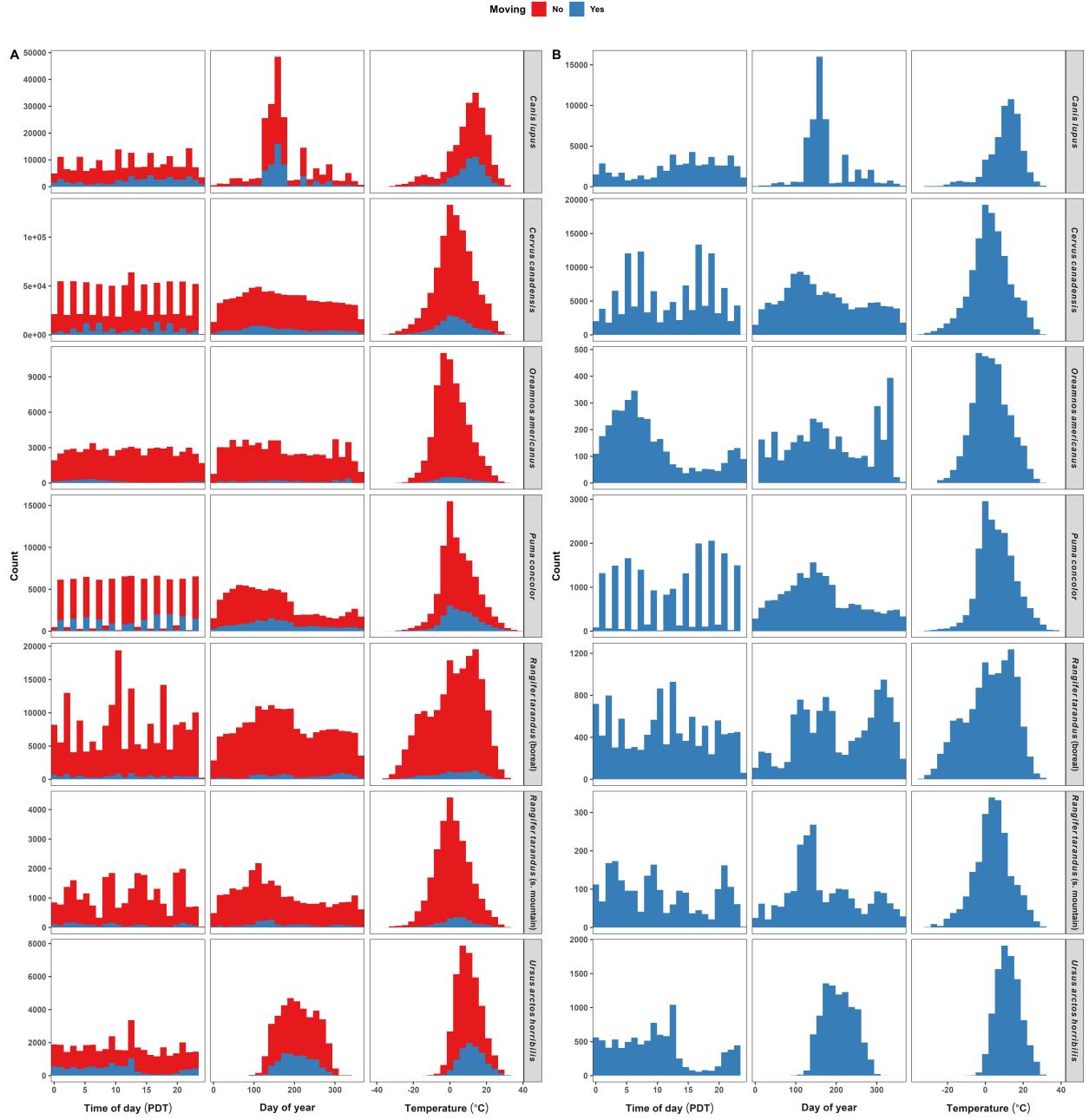


Figure B4: Histograms of the number of states (**A**) and speed estimates (**B**) over time of day (Pacific Daylight Time, PDT), day of year (Julian date), and air temperature.

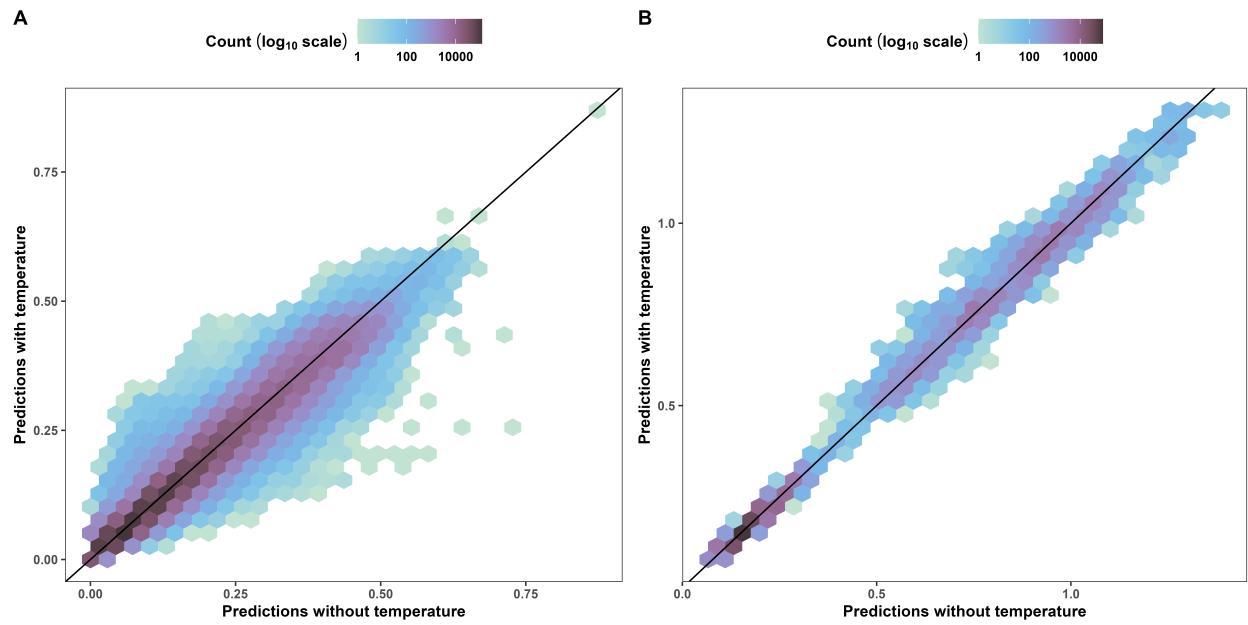


Figure B5: Hexplot of the fitted values from the HGAMs with and without including temperature for the probability of movement (**A**) and speed when moving (**B**).

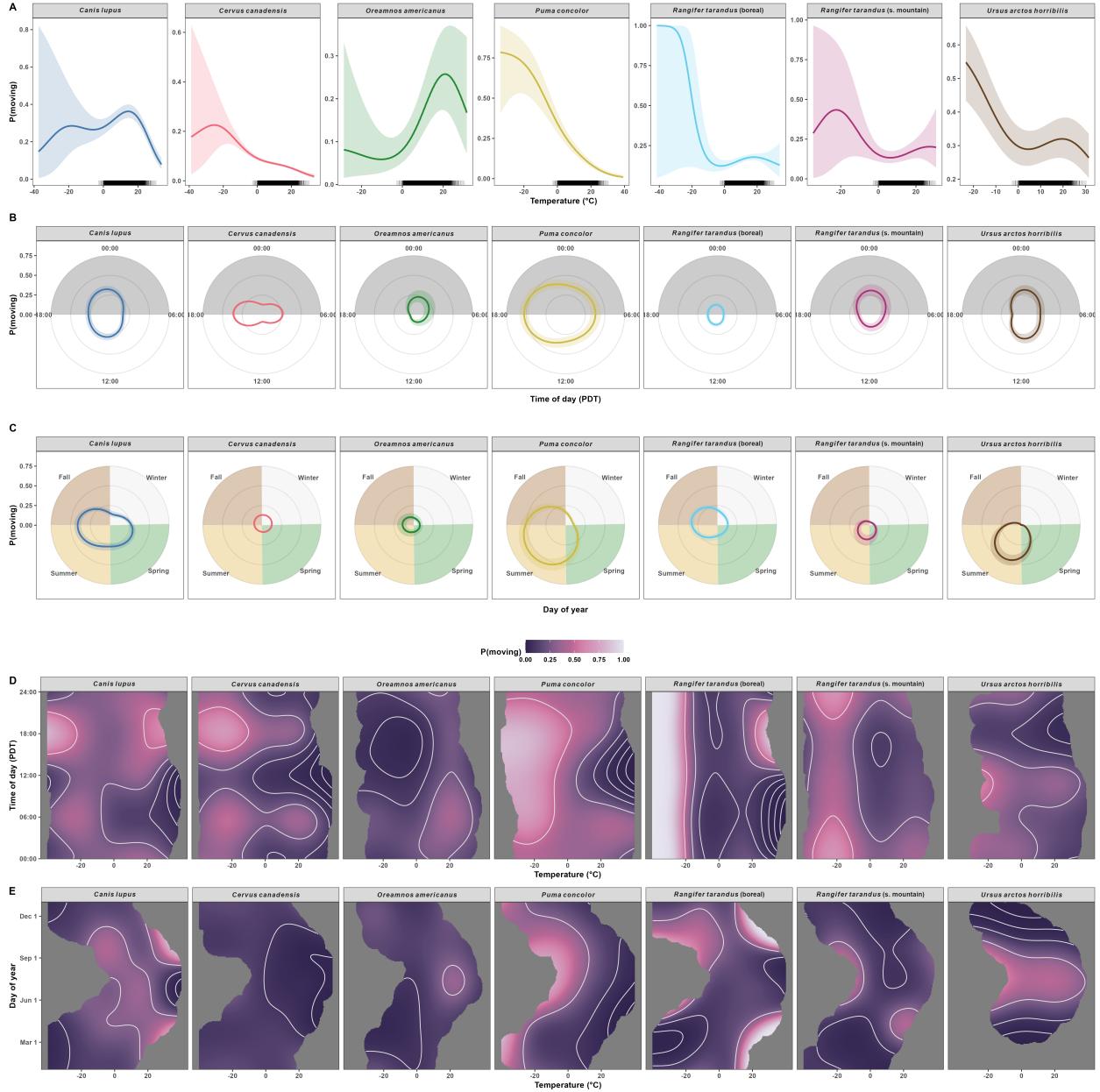


Figure B6: **A.** Estimated effects of temperature on each species' probability of moving on June 1st at 12:00, Pacific Daylight Time (PDT). The rug plot indicates each species' data on June 1st. **B.** Estimated effects of time of day on each species' probability of moving on June 1st at 0°C. The grey area indicates evening and night (hours between 18:00 and 6:00). **C.** Estimated effects of day of year on each species' probability of moving at 12:00 with a temperature of 0°C. The year is divided into the four seasons: winter (white), spring (green), summer (gold), and fall (brown). In panels A-C, ribbons indicate 95% Bayesian Credible Intervals, and the sampling rate was post-stratified to $\Delta t = 1$ hour for all species. **D.** Effects of time of day and temperature on species' probability of moving on June 1st at 12:00 PDT. Surfaces in panels D and E extend to 10% of the range away from each datum.

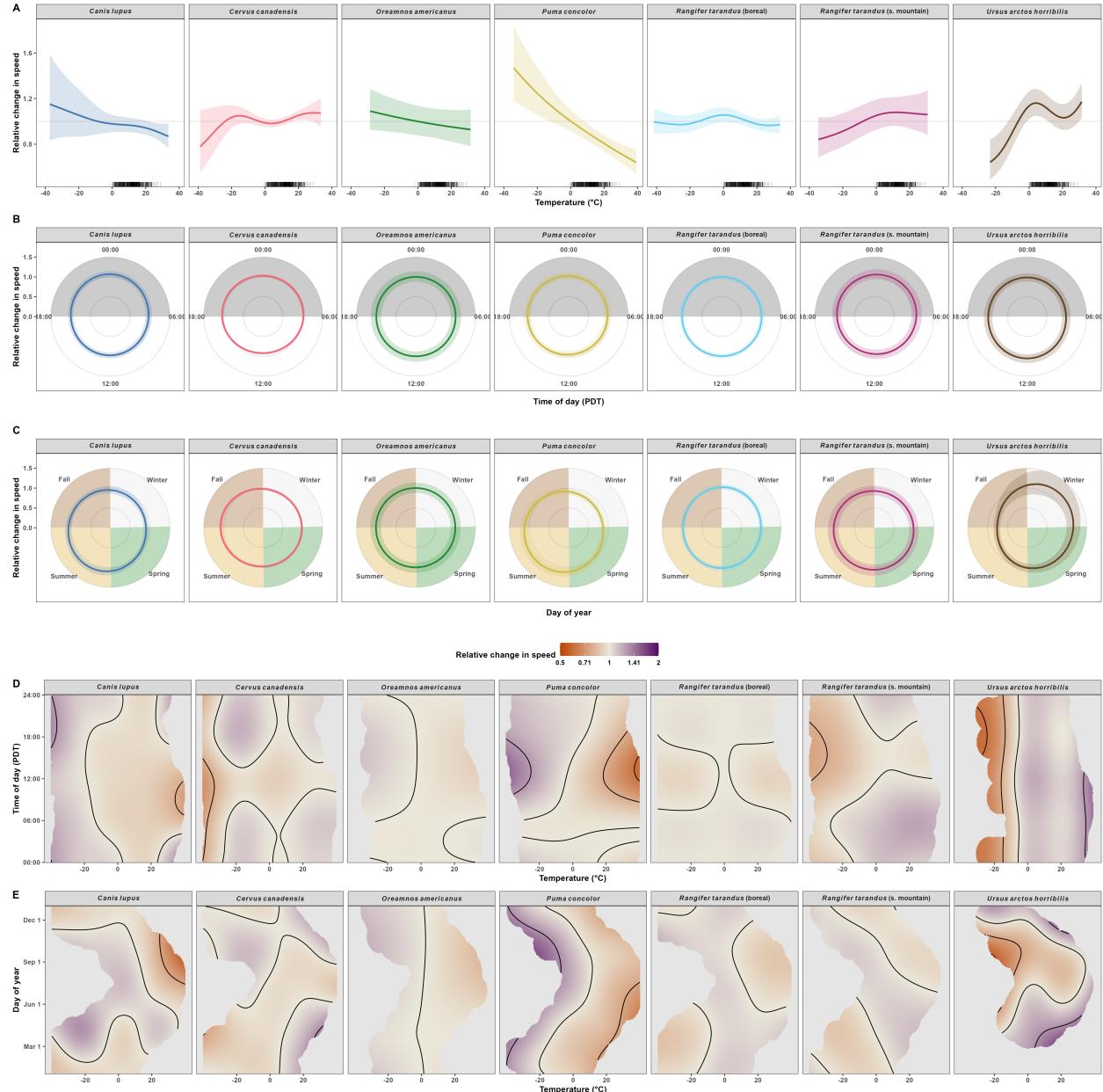


Figure B7: **A.** Estimated effects of temperature on each species' speed when moving on June 1st at 12:00, Pacific Daylight Time (PDT). The rug plot indicates each species' data points where an animal was moving on June 1st. **B.** Estimated effects of time of day on each species' speed when moving on June 1st at 0°C. The grey area indicates evening and night (hours between 18:00 and 6:00). **C.** Estimated effects of day of year on each species' speed when moving at 12:00 with a temperature of 0°C. The year is divided into the four seasons: winter (white), spring (green), summer (gold), and fall (brown). In panels A-C, ribbons indicate 95% Bayesian Credible Intervals, and the sampling rate was post-stratified to $\Delta t = 1$ hour for all species. **D.** Effects of time of day and temperature on species' speed when moving on June 1st. **E.** Effects of day of year and temperature on species' speed when moving, if the animal was moving at 12:00 PM PDT. Surfaces extend to 10% of the range away from each datum. The color bar is on the log₂ scale to help visualize patterns in doubling.

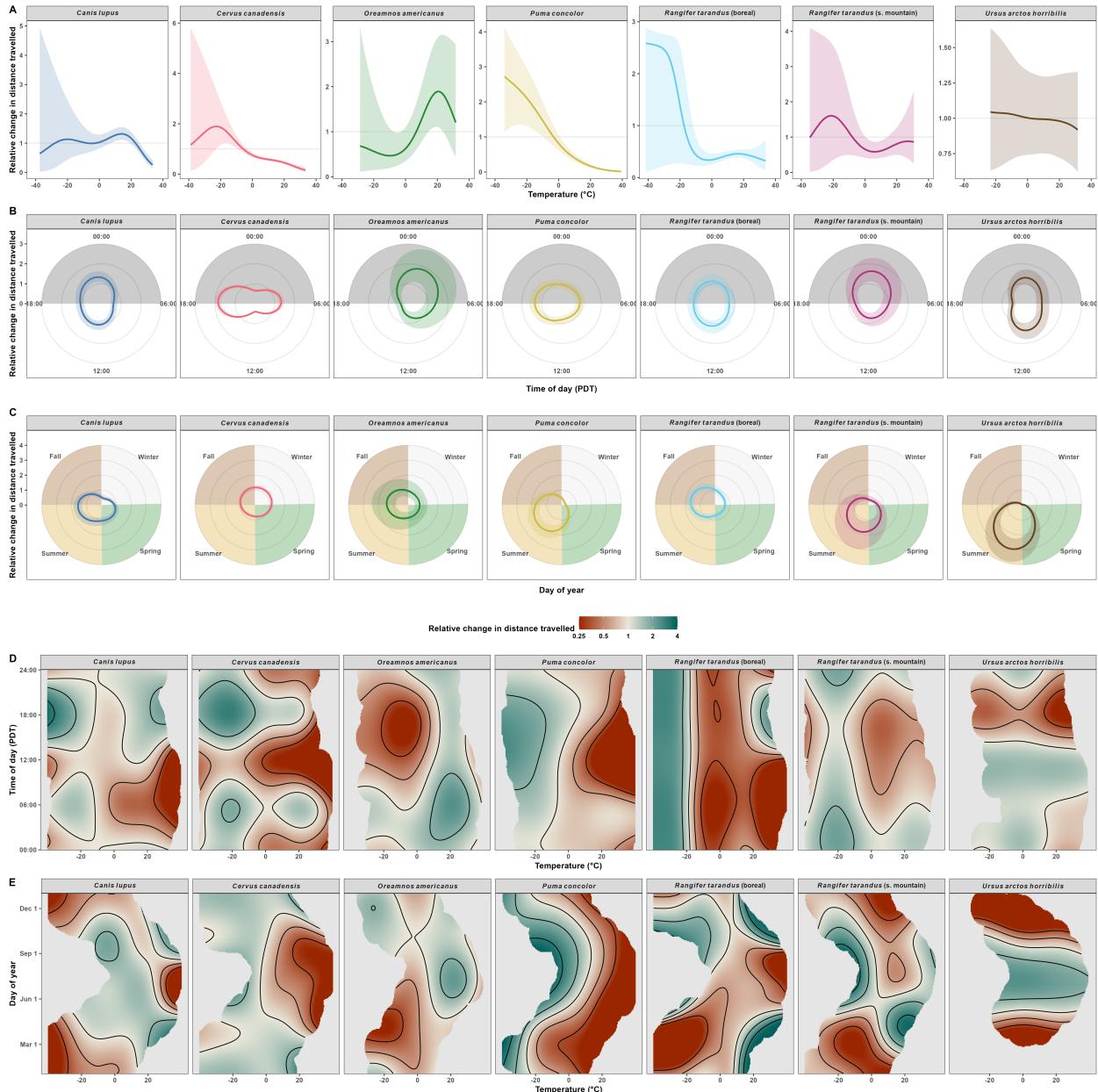


Figure B8: **A.** Estimated effects of temperature on each species' distance traveled on June 1st at 12:00, Pacific Daylight Time (PDT). The rug plot indicates each species' data points where an animal was moving on June 1st. **B.** Estimated effects of time of day on each species' distance traveled on June 1st at 0°C. The grey area indicates evening and night (hours between 18:00 and 6:00). **C.** Estimated effects of day of year on each species' distance traveled at 12:00 with a temperature of 0°C. The year is divided into the four seasons: winter (white), spring (green), summer (gold), and fall (brown). In panels A-C, ribbons indicate 95% Bayesian Credible Intervals, and the sampling rate was post-stratified to $\Delta t = 1$ hour for all species. **D.** Effects of time of day and temperature on species' distance traveled on June 1st at 12:00 PDT. **E.** Effects of day of year and temperature on species' distance traveled at 12:00 PDT. Surfaces extend to 10% of the range away from each datum. The color bar is on the \log_2 scale to help visualize patterns in doubling.

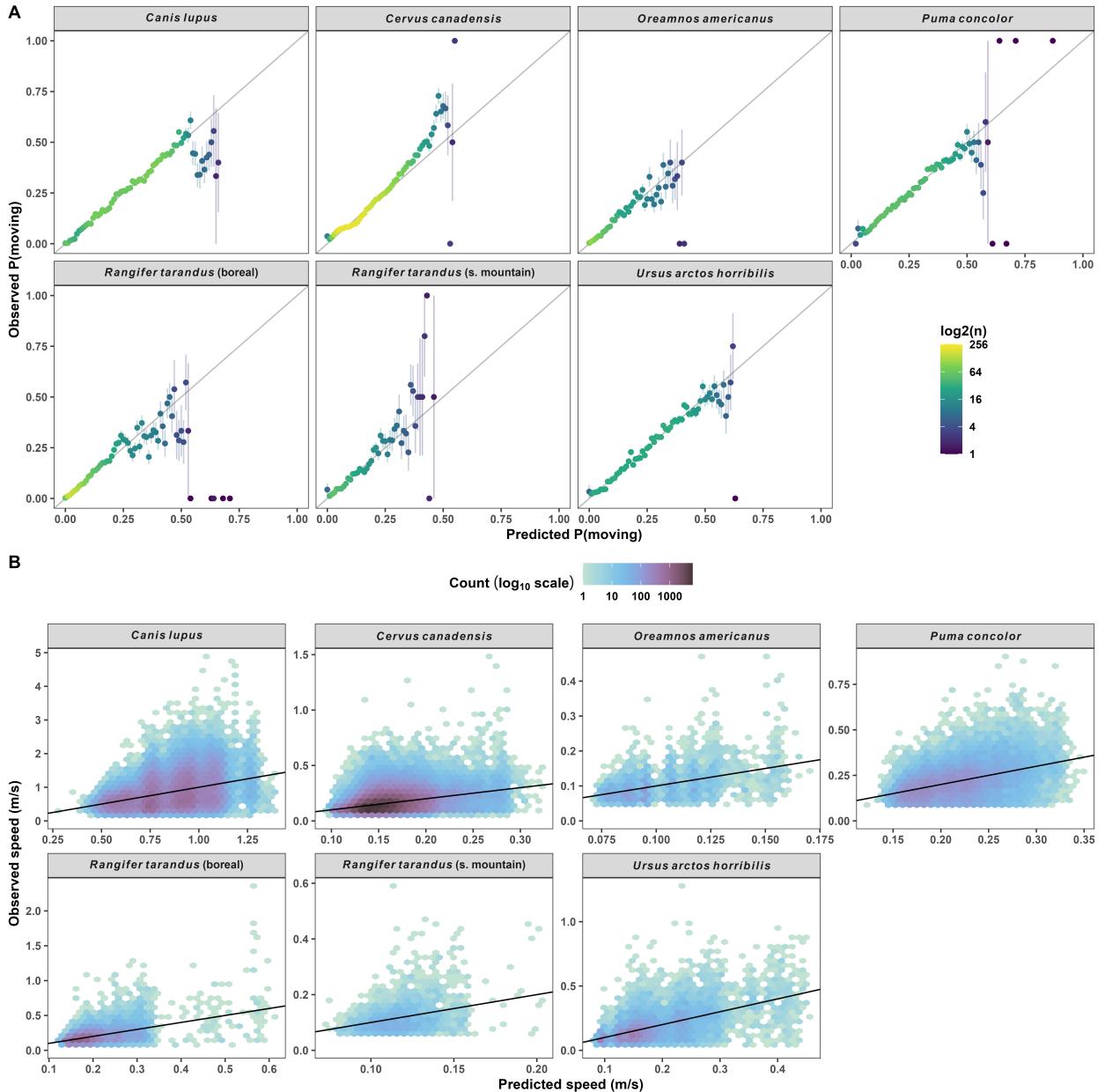


Figure B9: Relationships between the observed and predicted values for probability of movement (**A**) and speed given that an animal was moving (**B**). The color in panel **A** indicates the number of points used to calculate the estimate (on the \log_2 scale), while the grey lines in both panels indicate perfect prediction (i.e., the 1:1 line).

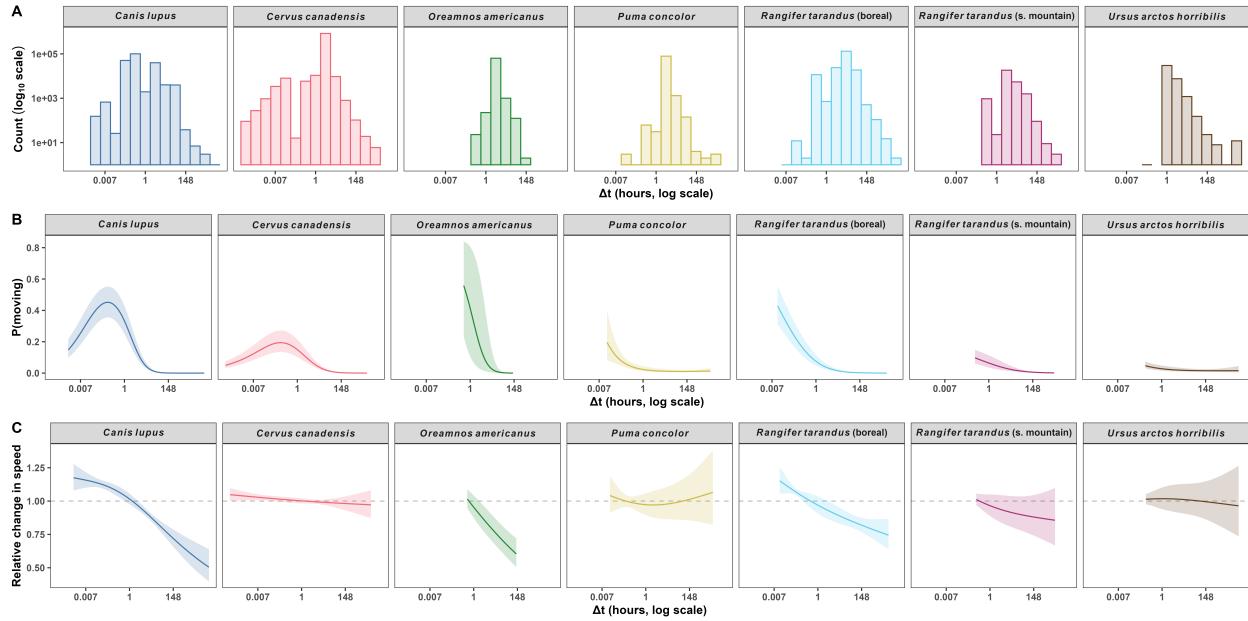


Figure B10: **A.** Histograms of sampling intervals between GPS locations, with counts on a \log_{10} axis for ease of readability. **B.** Species-level smooth effects of sampling interval on the estimated probability of the animal moving. **C.** Species-level estimated smooth effects of sampling interval on an animal's speed when moving. All x axes are on the natural logarithm scale.

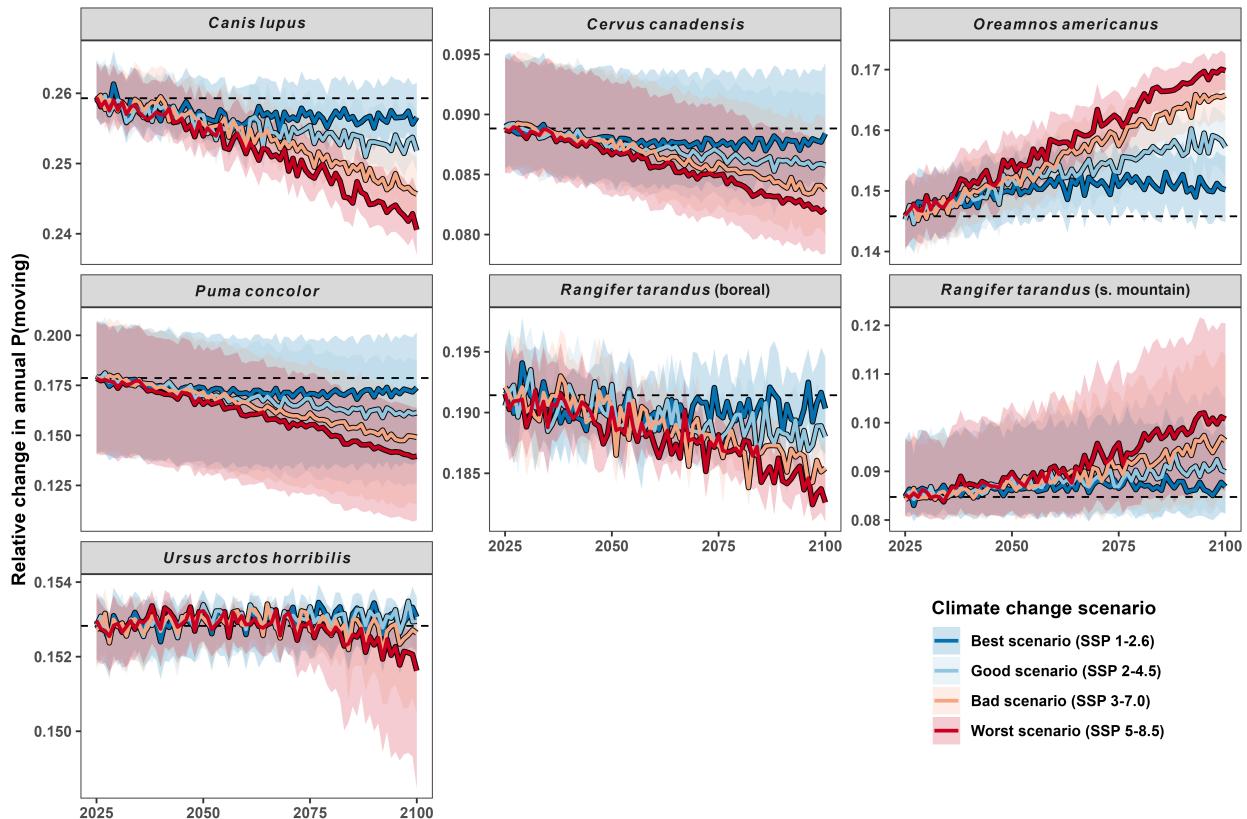


Figure B11: The direction and magnitude of changes in probability of moving due to climate change varies among species, but worse climate-change scenarios result in the greatest change. Lines indicate the median projected change in probability of moving due to changes in temperature within the species' current extent. Shaded areas indicate the 90% prediction interval within the range. The dashed black lines indicate the mean probability of movement in 2025 across the four scenarios. The projections only account for changes in movement behavior (i.e., movement frequency and speed) and ignore changes in physiology or movement costs.

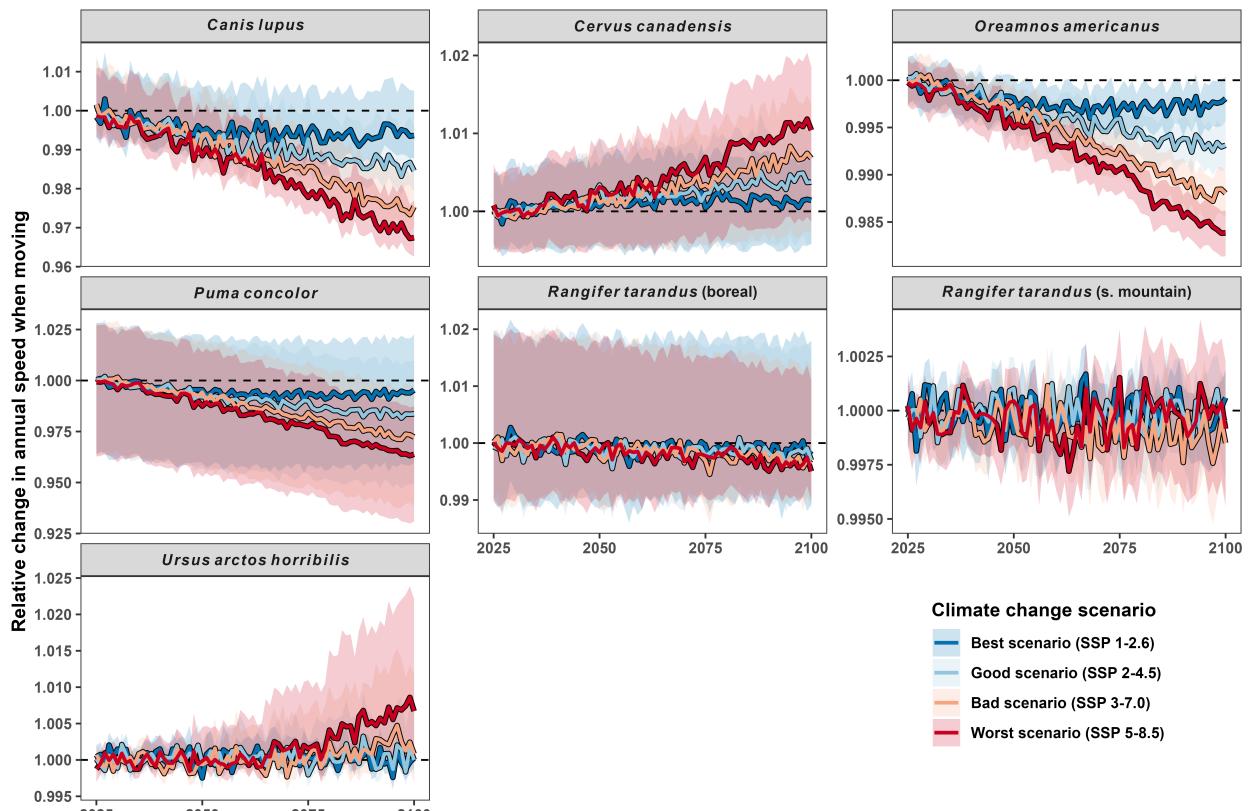


Figure B12: **The direction and magnitude of changes in speed due to climate change varies among species, but worse climate-change scenarios result in the greatest change.** Lines indicate the median projected change in speed due to changes in temperature within the species' current extent. Shaded areas indicate the 90% prediction interval within the range. The dashed black lines indicate the mean speed in 2025 across the four scenarios. The projections only account for changes movement behavior (i.e., movement frequency and speed) and ignore changes in physiology or movement costs.

3 Effects of temperature on habitat selection

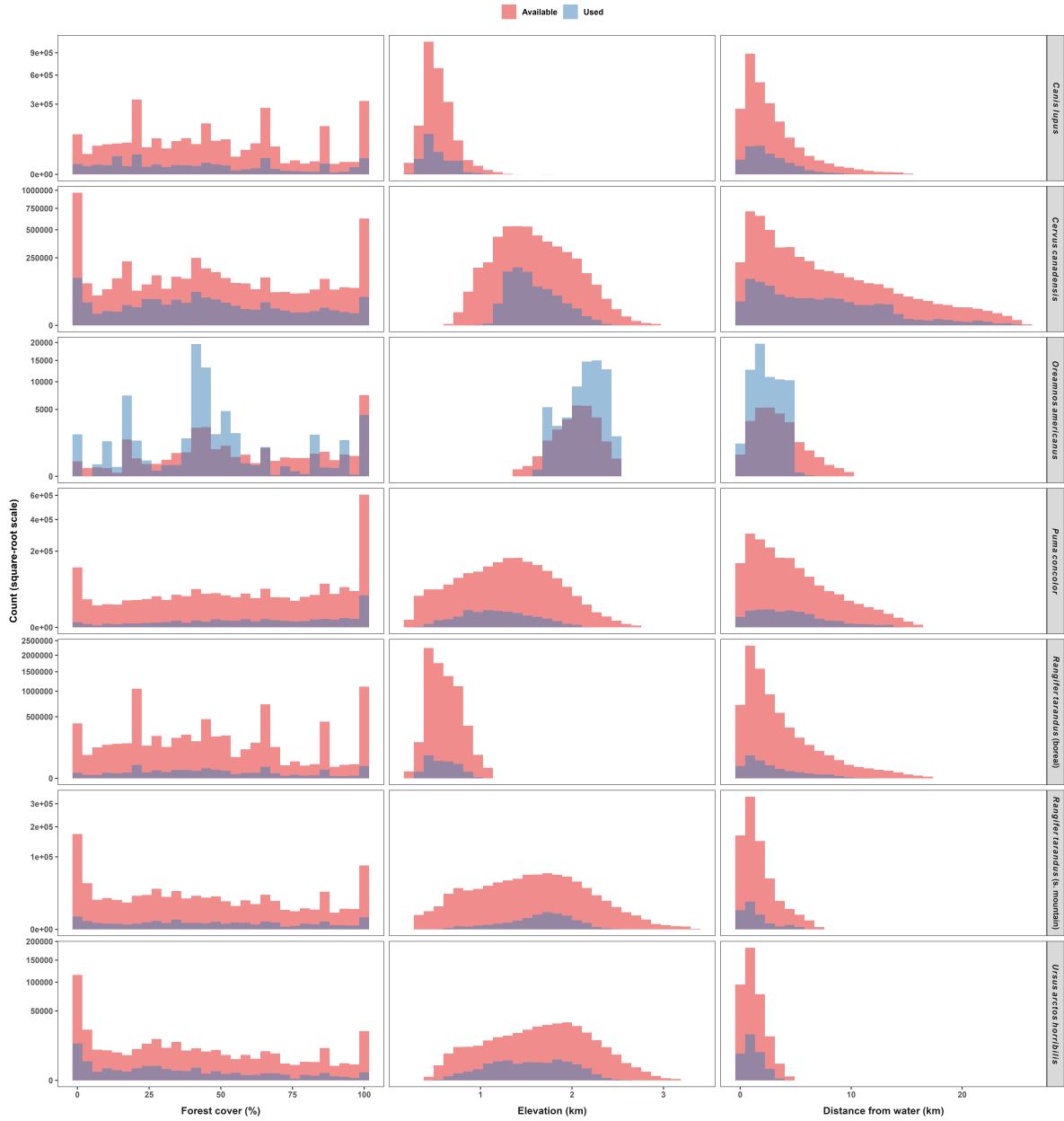


Figure B13: Histograms of available (red) and used (blue) resources. All GPS fixes counts as one observation. The y axis is on the square-root scale to help visualize values with low counts.

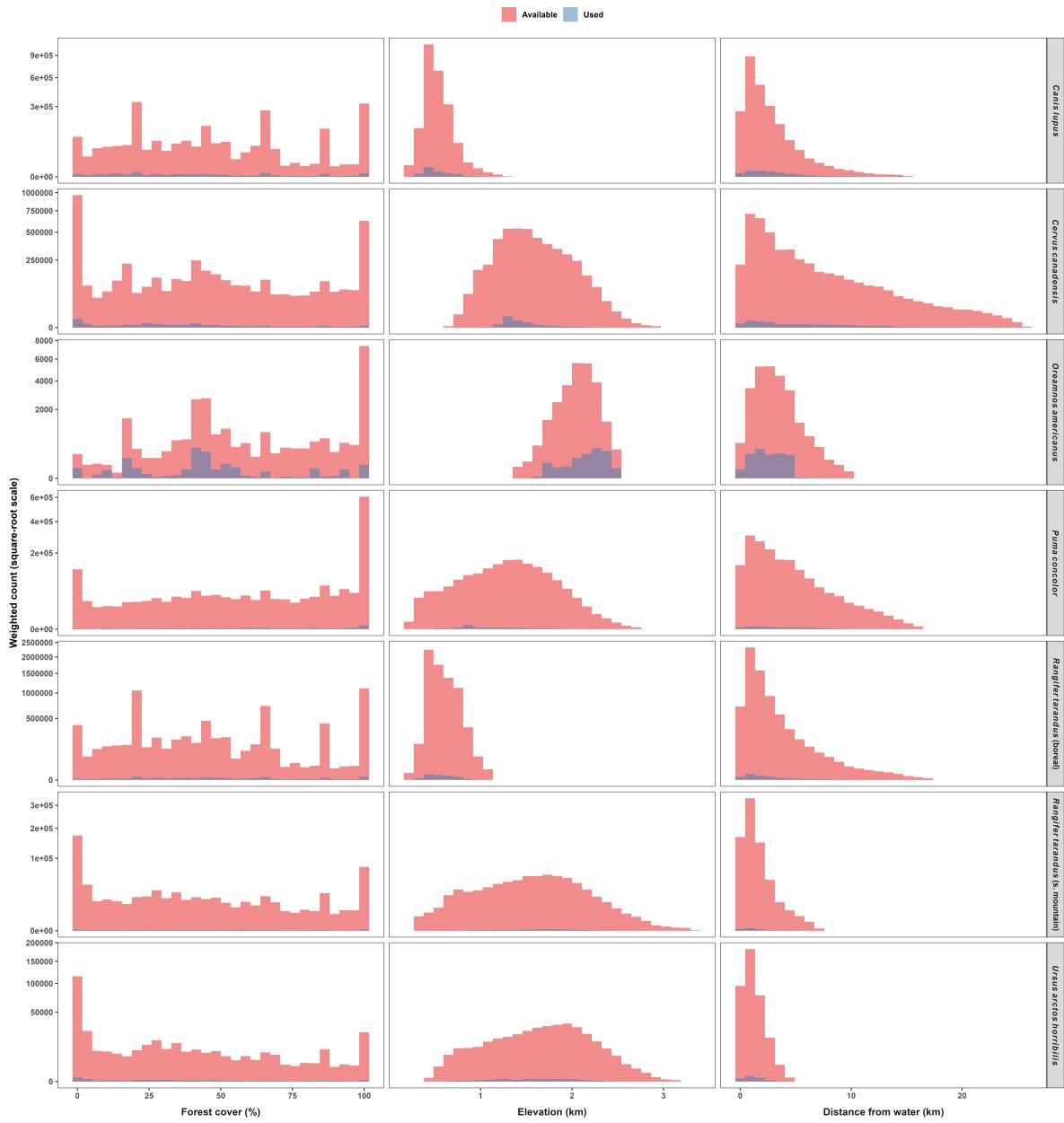


Figure B14: Histograms of available (red) and used (blue) resources. All GPS fixes are weighted according to their independence relative to the respective animals' range crossing time and Autocorrelated Kernel Density Estimate (i.e., the weights returned by AKDE weights multiplied by the number of home-range-crossing degrees of freedom). The y axis is on the square-root scale to help visualize values with low counts.

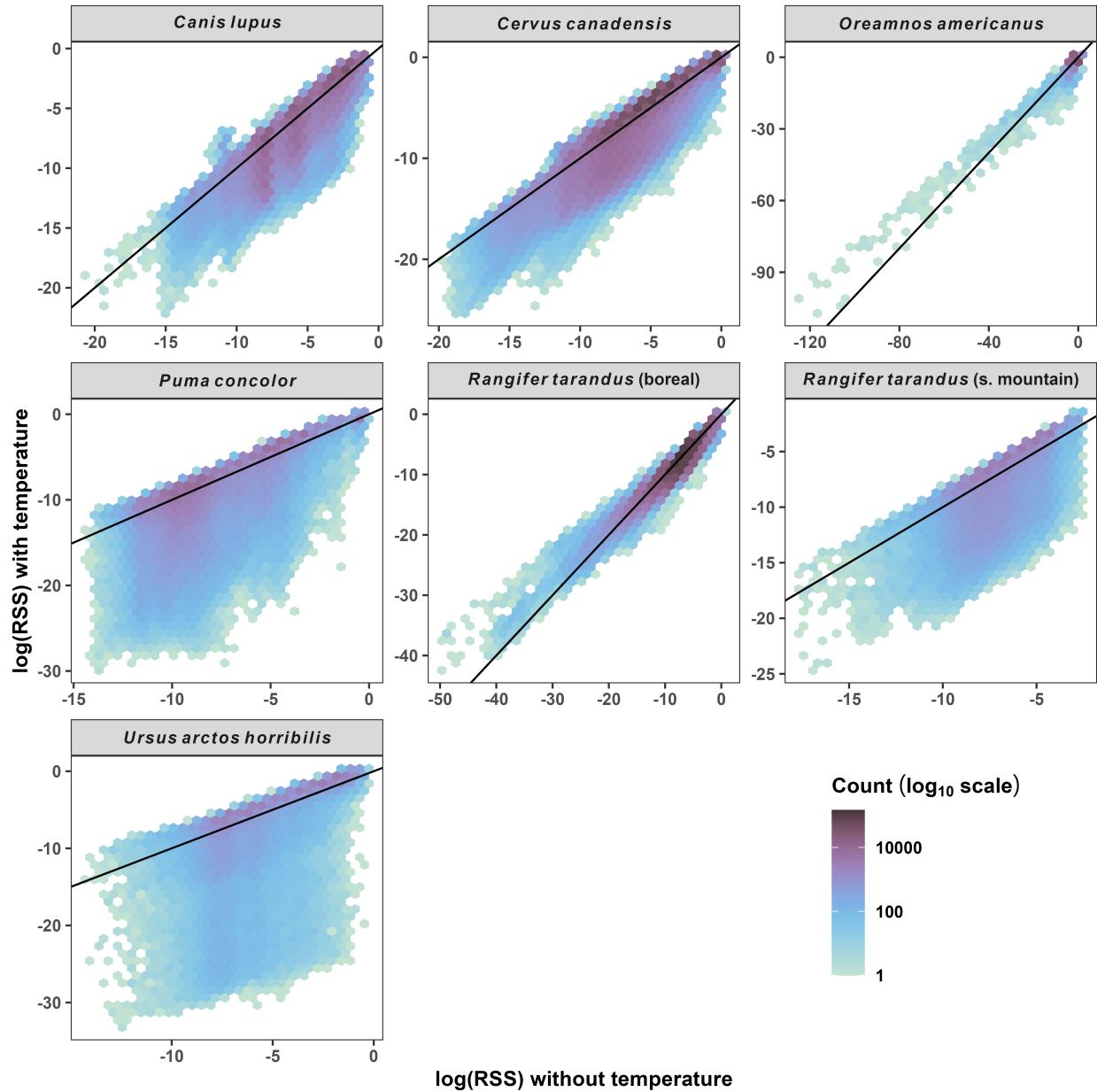


Figure B15: Hexplot of the fitted values from the HRSFs with and without including temperature.

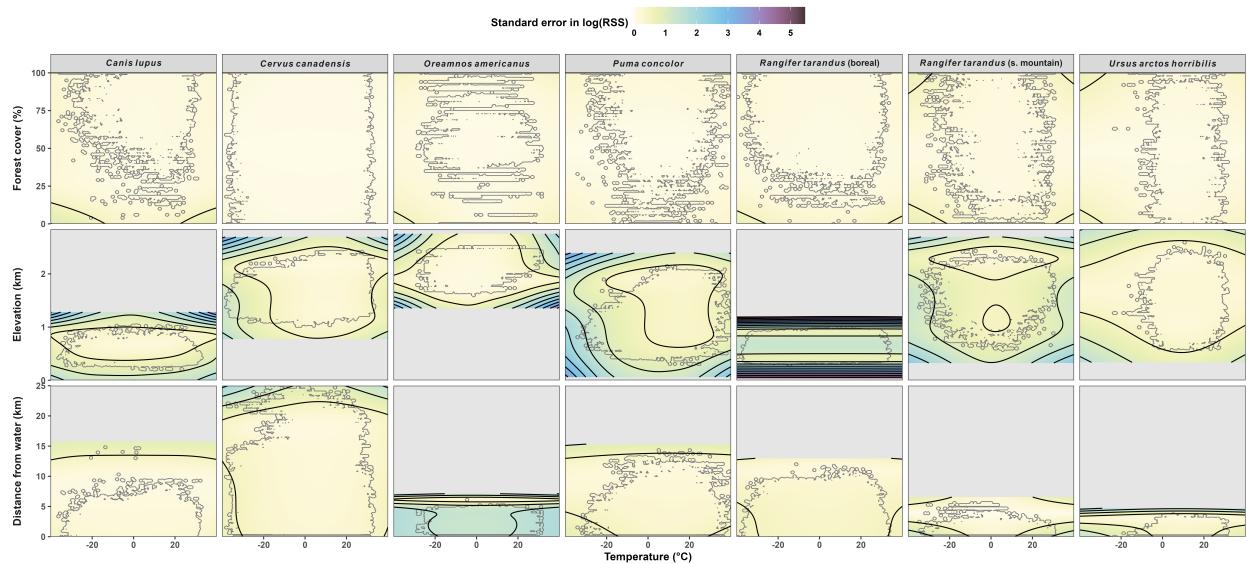


Figure B16: Estimated standard error in the relative selection strength (RSS) for forest cover (%), elevation (km), and distance from water (km) as a function of temperature (see Fig. 3 in the main text). The grey contours indicate the extent of each species' observed locations.

4 Model selection

Table B1: Changes in deviance explained (ΔDE) and Akaike Information Criterion (ΔAIC) from including temperature in the models estimating probability of movement ($P(M)$) and speed when moving (Speed) as well as in species-level Hierarchical Resource Selection Functions (HRSF). Unlike conventional marginal AIC [1], The AIC values provided by the `mgcv` package for R are calculated using the models' estimated effective degrees of freedom and the Bayesian variance-covariance matrices, which avoids issues related to random effects or Restricted Maximum Likelihood (REML).

Model	Species	ΔDE	ΔAIC
$P(M)$	All	0.5%	5927
Speed	All	0.2%	1682
HRSF	<i>Canis lupus</i>	9.2%	6566
HRSF	<i>Cervus canadensis</i>	4.6%	4448
HRSF	<i>Oreamnos americanus</i>	18.6%	813
HRSF	<i>Puma concolor</i>	8%	966
HRSF	<i>Rangifer tarandus</i> (boreal)	5.3%	5637
HRSF	<i>Rangifer tarandus</i> (s. mountain)	12%	342
HRSF	<i>Ursus arctos horribilis</i>	17.7%	914

4.1 Analyses of Deviance

Here we produce approximate p-values for analyses of deviance (a form of generalized likelihood ratio tests) following the methods of Section 3.3 in [2]. We use an F test rather than a χ^2 test for the Gamma models because the scale parameter for the Gamma distribution is estimated rather than known or fixed [as in the case of binomial or Poisson distributions – see table 3.1 on page 104 of 2].

```
# P(moving)
anova(readRDS('../models/binomial-gam-without-temperature.rds'),
      readRDS('../models/binomial-gam.rds'),
      test = 'Chisq')

## Analysis of Deviance Table
##
## Model 1: moving ~ s(animal, bs = "re") + species + s(tod_pdt, by = species,
##           k = 5, bs = "cc") + s(doy, by = species, k = 5, bs = "cc") +
##           ti(doy, tod_pdt, by = species, k = 5, bs = c("cc", "cc")) +
##           s(log(dt), k = 3) + s(log(dt), species, k = 3, bs = "fs")
## Model 2: moving ~ s(animal, bs = "re") + species + s(tod_pdt, by = species,
##           k = 5, bs = "cc") + s(doy, by = species, k = 5, bs = "cc") +
##           s(temp_c, by = species, k = 5, bs = "tp") + ti(doy, tod_pdt,
##           by = species, k = 5, bs = c("cc", "cc")) + ti(temp_c, tod_pdt,
##           by = species, k = 5, bs = c("tp", "cc")) + ti(temp_c, doy,
##           by = species, k = 5, bs = c("tp", "cc")) + s(log(dt), k = 3) +
##           s(log(dt), species, k = 3, bs = "fs")
##   Resid. Df Resid. Dev      Df Deviance Pr(>Chi)
## 1    1476577     1129510
## 2    1476436     1123326 141.59      6184 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```

# speed when moving
anova(readRDS('../models/gamma-gam-without-temperature.rds'),
      readRDS('../models/gamma-gam.rds'),
      test = 'F')

## Analysis of Deviance Table
##
## Model 1: speed_est ~ s(animal, bs = "re") + species + s(tod_pdt, by = species,
##                 k = 5, bs = "cc") + s(doy, by = species, k = 5, bs = "cc") +
##                 ti(doy, tod_pdt, by = species, k = 5, bs = c("cc", "cc")) +
##                 s(log(dt), k = 3) + s(log(dt), species, k = 3, bs = "fs")
## Model 2: speed_est ~ s(animal, bs = "re") + species + s(tod_pdt, by = species,
##                 k = 5, bs = "cc") + s(doy, by = species, k = 5, bs = "cc") +
##                 s(temp_c, by = species, k = 5, bs = "tp") + ti(doy, tod_pdt,
##                 by = species, k = 5, bs = c("cc", "cc")) + ti(temp_c, tod_pdt,
##                 by = species, k = 5, bs = c("tp", "cc")) + ti(temp_c, doy,
##                 by = species, k = 5, bs = c("tp", "cc")) + s(log(dt), k = 3) +
##                 s(log(dt), species, k = 3, bs = "fs")
##   Resid. Df Resid. Dev      Df Deviance      F      Pr(>F)
## 1     223798    37934
## 2     223710    37649  87.751   285.11 17.456 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

# HRSFs
anova(readRDS('../models/rsf-Canis_lupus-2025-01-20.rds'),
      readRDS('../models/rsf-Canis_lupus-no-temperature-2025-01-20.rds'),
      test = 'Chisq')

```

```

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##                 k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##                 bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##                 s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##                 s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##                 ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
##                 temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
##                 k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
##                 s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##                 k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##                 bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##                 s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##                 s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance  Pr(>Chi)
## 1     639545    39183
## 2     639643    45920 -97.944  -6736.8 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

anova(readRDS('../models/rsf-Cervus canadensis-2025-01-20.rds'),
      readRDS('../models/rsf-Cervus canadensis-no-temperature-2025-01-20.rds'),
      test = 'Chisq')

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
##   temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
##   k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
##   s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance Pr(>Chi)
## 1    1436458     19199
## 2    1436594    23816 -136.27   -4617.1 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(readRDS('../models/rsf-Oreamnos americanus-2025-01-20.rds'),
      readRDS('../models/rsf-Oreamnos americanus-no-temperature-2025-01-20.rds'),
      test = 'Chisq')

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
##   temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
##   k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
##   s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance Pr(>Chi)
## 1    70696     1576.8
## 2    70694    2387.3 2.1921   -810.56

```

```

anova(readRDS('../models/rsf-Puma concolor-2025-01-20.rds'),
      readRDS('../models/rsf-Puma concolor-no-temperature-2025-01-20.rds'),
      test = 'Chisq')

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
## k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
## bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
## temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
## k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
## s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
## k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
## bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance Pr(>Chi)
## 1     324734    4076.5
## 2     324772    5099.7 -38.033   -1023.3 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(
  readRDS('../models/rsf-Rangifer tarandus boreal-2025-01-21.rds'),
  readRDS('../models/rsf-Rangifer tarandus boreal-no-temperature-2025-01-20.rds'),
  test = 'Chisq')

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
## k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
## bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
## temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
## k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
## s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
## k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
## bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
## s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance Pr(>Chi)
## 1     1452896    48216
## 2     1452959    53927 -62.606   -5711.3 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

anova(readRDS('../models/rsf-Rangifer tarandus southern mountain-2025-01-20.rds'),
      readRDS('../models/rsf-Rangifer tarandus southern mountain-no-temperature-2025-01-20.rds'),
      test = 'Chisq')

```

```

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
##   temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
##   k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
##   s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance  Pr(>Chi)
## 1     132580    2026.1
## 2     132589  2384.5 -8.8792  -358.34 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

anova(readRDS('../models/rsf-Ursus arctos horribilis-2025-01-20.rds'),
      readRDS('../models/rsf-Ursus arctos horribilis-no-temperature-2025-01-20.rds'),
      test = 'Chisq')

```

```

## Analysis of Deviance Table
##
## Model 1: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   ti(forest_perc, temperature_C, k = 4, bs = "cr") + ti(elevation_m,
##   temperature_C, k = 4, bs = "cr") + ti(dist_water_m, temperature_C,
##   k = 4, bs = "cr") + s(temperature_C, k = 4, bs = "cr") +
##   s(temperature_C, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
## Model 2: detected ~ s(forest_perc, k = 4, bs = "cr") + s(elevation_m,
##   k = 4, bs = "cr") + s(dist_water_m, k = 4, bs = "cr") + s(animal,
##   bs = "re") + s(forest_perc, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(elevation_m, animal, k = 4, bs = "fs", xt = list(bc = "cr")) +
##   s(dist_water_m, animal, k = 4, bs = "fs", xt = list(bc = "cr"))
##   Resid. Df Resid. Dev      Df Deviance  Pr(>Chi)
## 1     99164    2356.7
## 2     99165  3275.0 -1.1525  -918.26 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

References

1. Akaike H. A new look at the statistical model identification. *IEEE Transactions on Automatic Control* [Internet]. 1974 [cited 2022 Dec 28];19:716–23. Available from: <http://ieeexplore.ieee.org/document/1100705/>
2. Wood SN. Generalized additive models: An introduction with R. Second edition. Boca Raton: CRC Press/Taylor & Francis Group; 2017.