Predicting how climate change will affect how and where terrestrial mammals will move

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1 Directed Acyclical Graphs

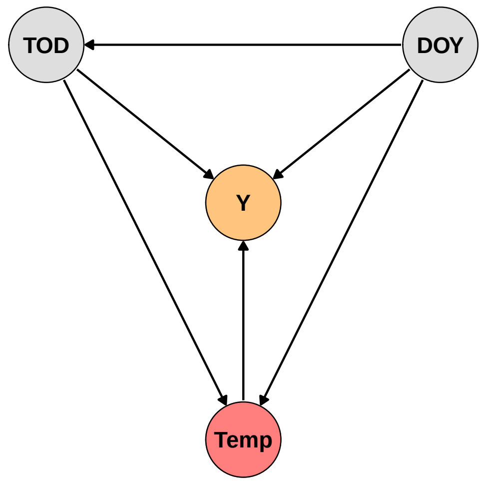

Figure B1: Directed Acyclical Graph assumed for inferring the causal effects of temperature (Temp) on probability of moving, speed when moving, or distance traveled (Y) while accounting for the effects of time of day (TOD), day of year (DOY), and their interaction effects. Temperature directly affects 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.

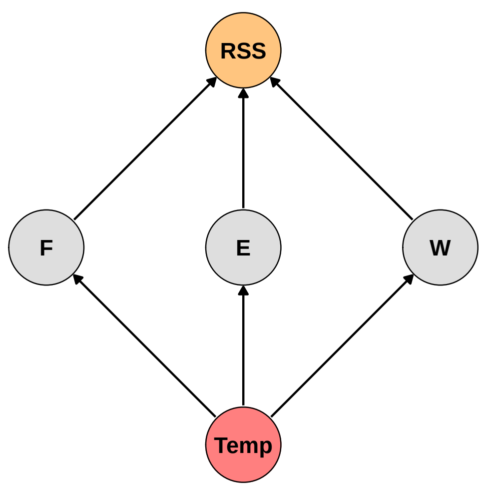

Figure B2: Directed Acyclical Graph assumed for inferring the causal effects of temperature (Temp) on Relative Selection Strength (RSS) for percent forest cover (F), elevation (E), and distance from water (W). The RSS for of a given habitat depends on all three resources, and the selection for each resource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

2 Effects of temperature on movement rates

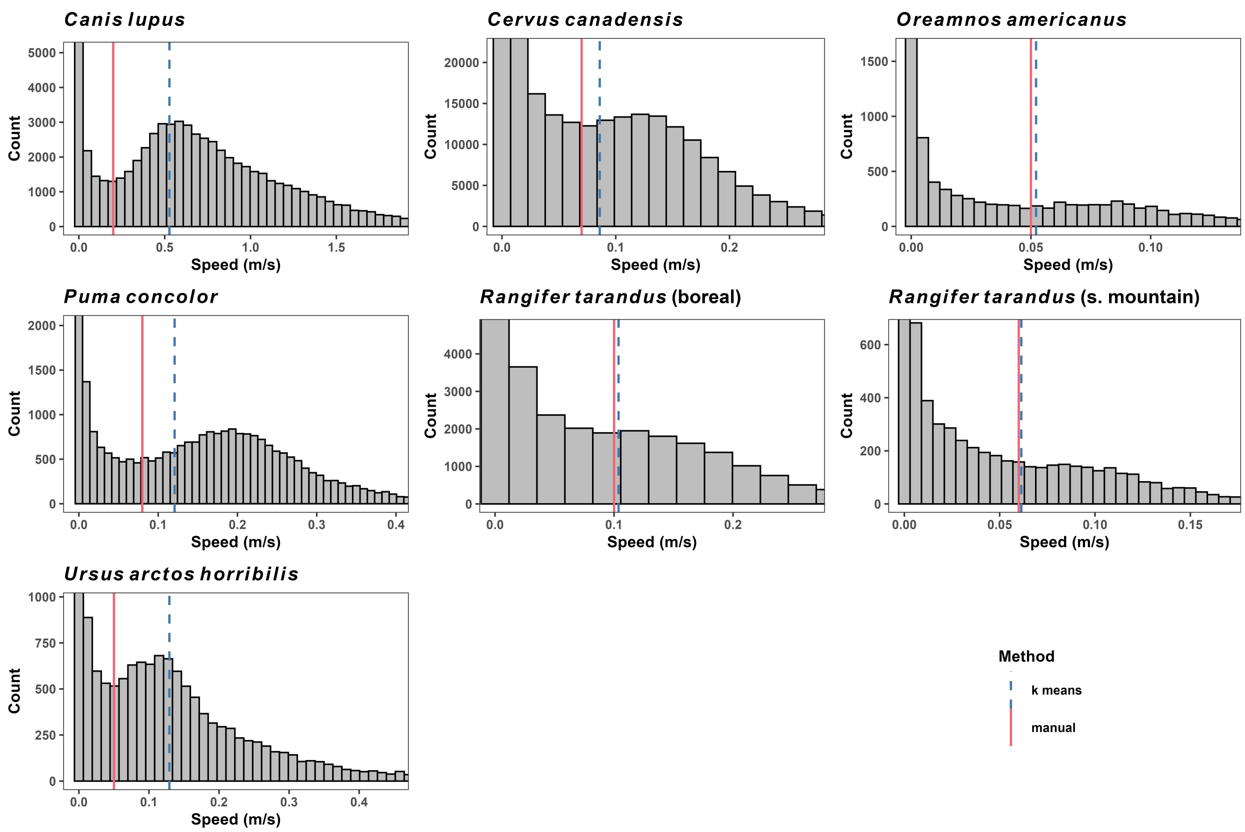

Figure B3: Histograms of each species' estimated speed. Continuous red lines indicate the values used to determine whether an animal was moving or not, which were determined visually using the inflection points of the histograms. Dashed blue lines indicate the minimum speed corresponding to a moving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

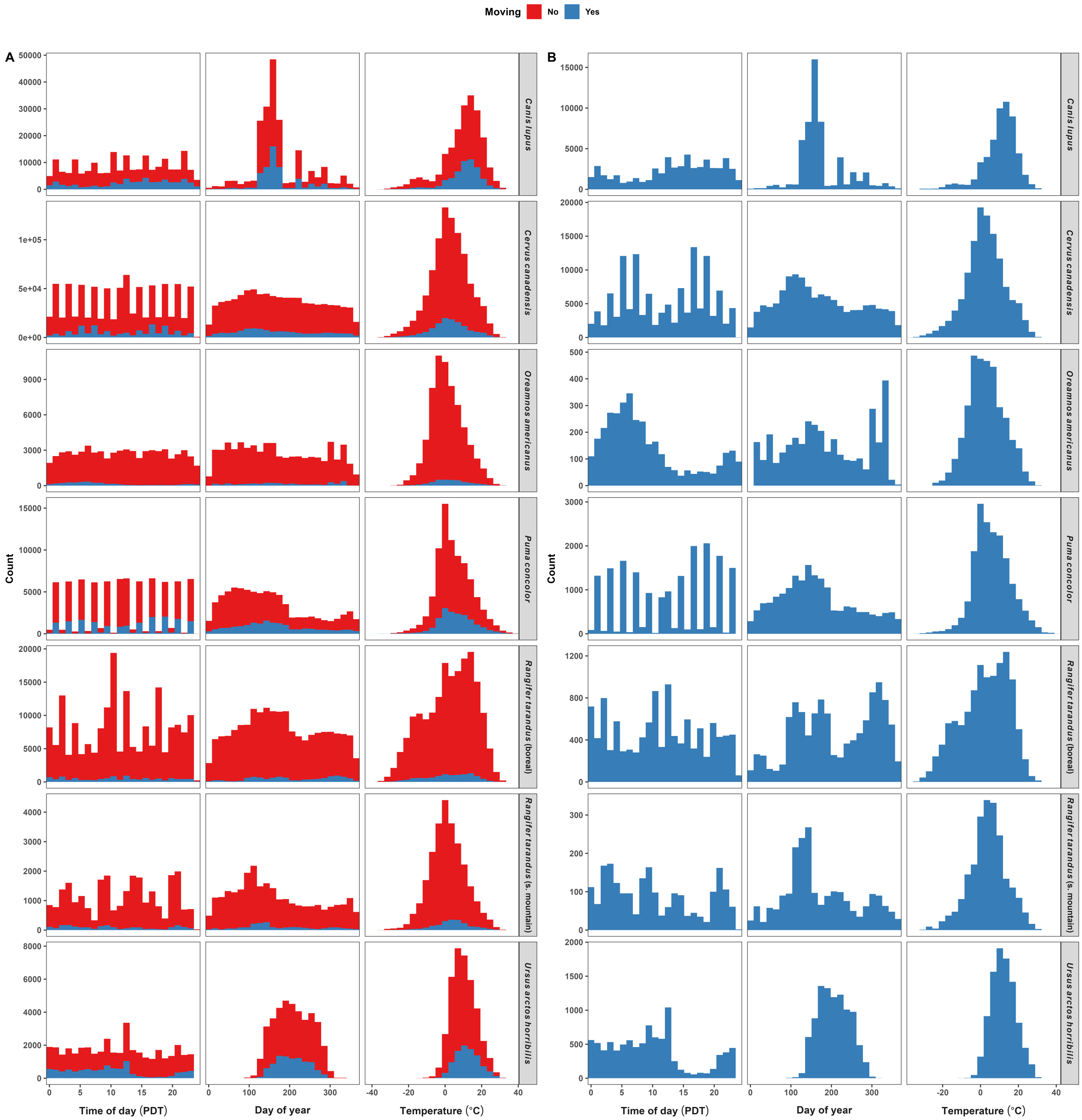

Figure B4: Histograms of the number of states (**A**) and speed estimates (**B**) over time of day (Pacific Daylight Time, PDT), day of year (Julian date), and air temperature.

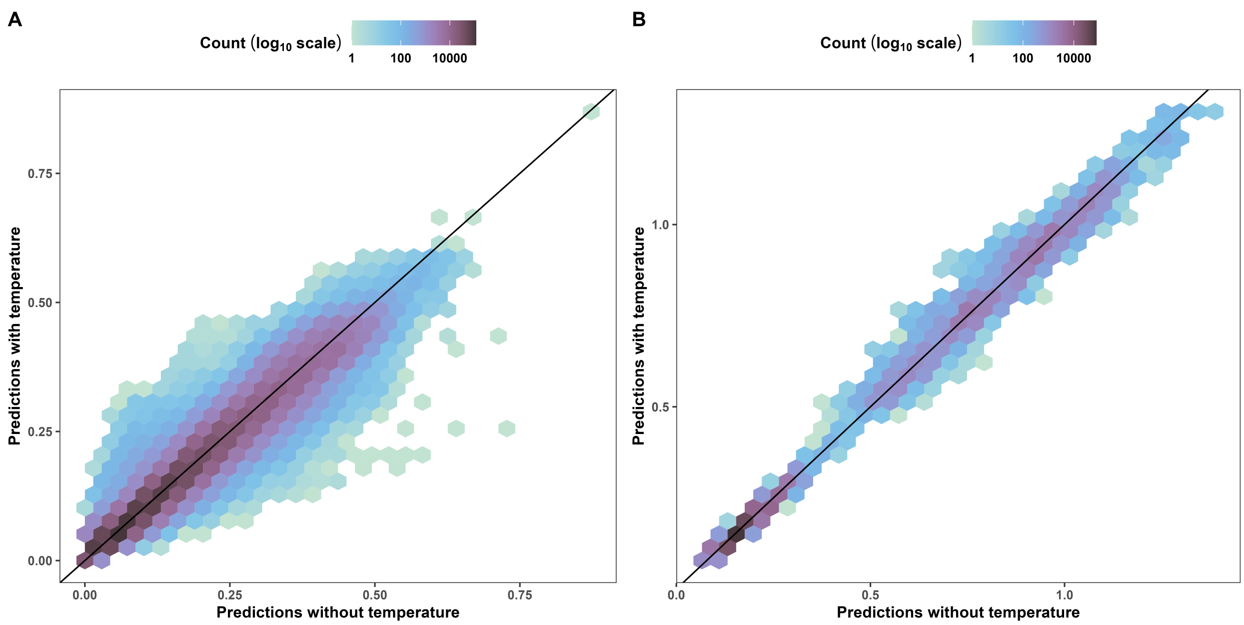

Figure B5: Hexplot of the fitted values from the HGAMs with and without including temperature for the probability of movement (**A**) and speed when moving (**B**).

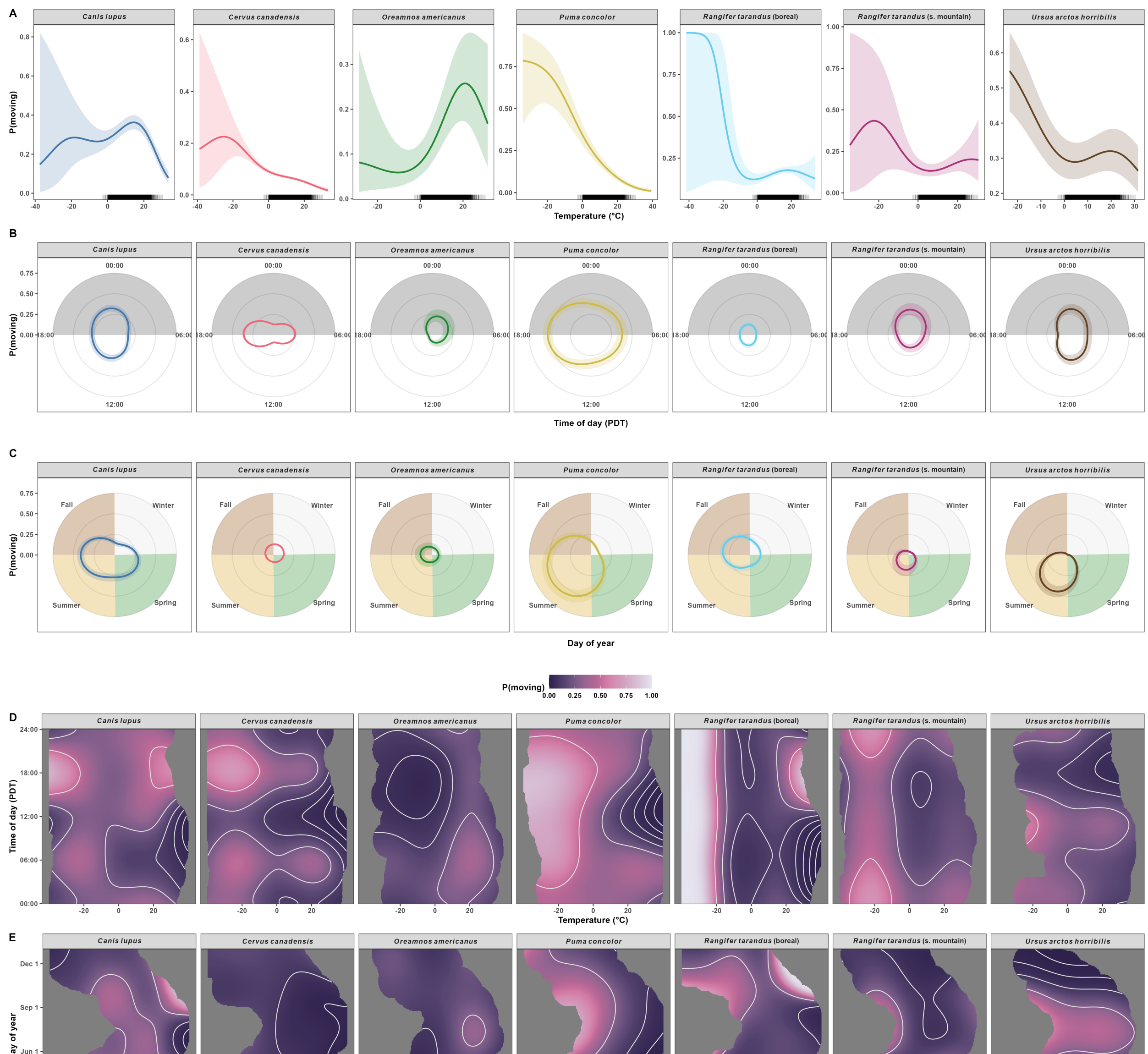

Figure B6: **A.** Estimated effects of temperature on each species' probability of moving on June 1^{st} at 12:00, Pacific Daylight Time (PDT). The rug plot indicates each species' data on June 1^{st}. **B.** Estimated effects of time of day on each species' probability of moving on June 1^{st} at 0°C. 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 1^{st} at 12:00 PDT. **E.** Effects of day of year and temperature on species' probability of moving at 12:00 PDT. Surfaces in panels D and E extend to 10% of the range away from each datum.

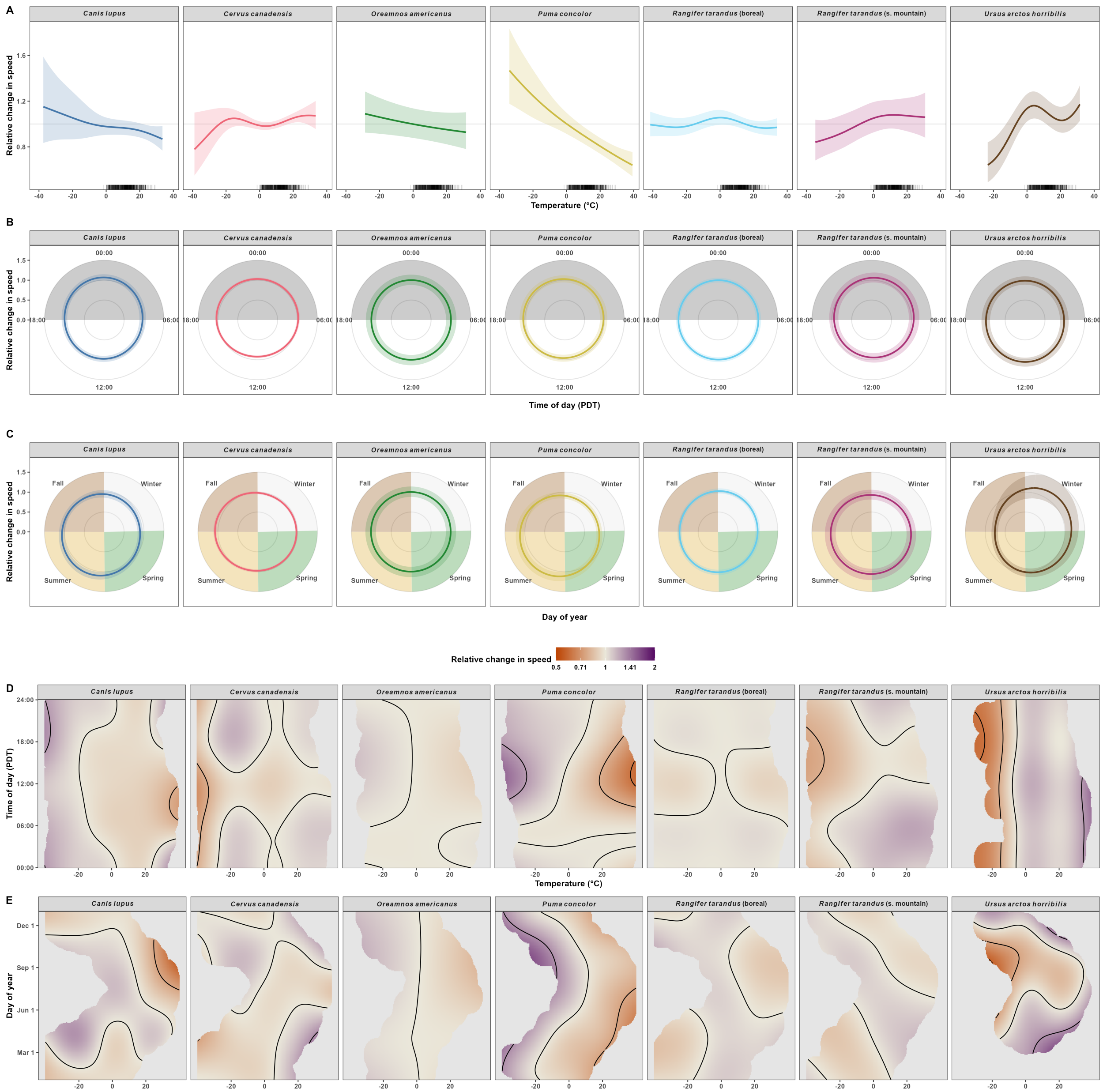

Figure B7: **A.** Estimated effects of temperature on each species' speed when moving on June 1st at 12:00, Pacific Daylight Time (PDT). The rug plot indicates each species' data points where an animal was moving on June 1st. **B.** Estimated effects of time of day on each species' speed when moving 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 $\log_2$ scale to help visualize patterns in doubling.

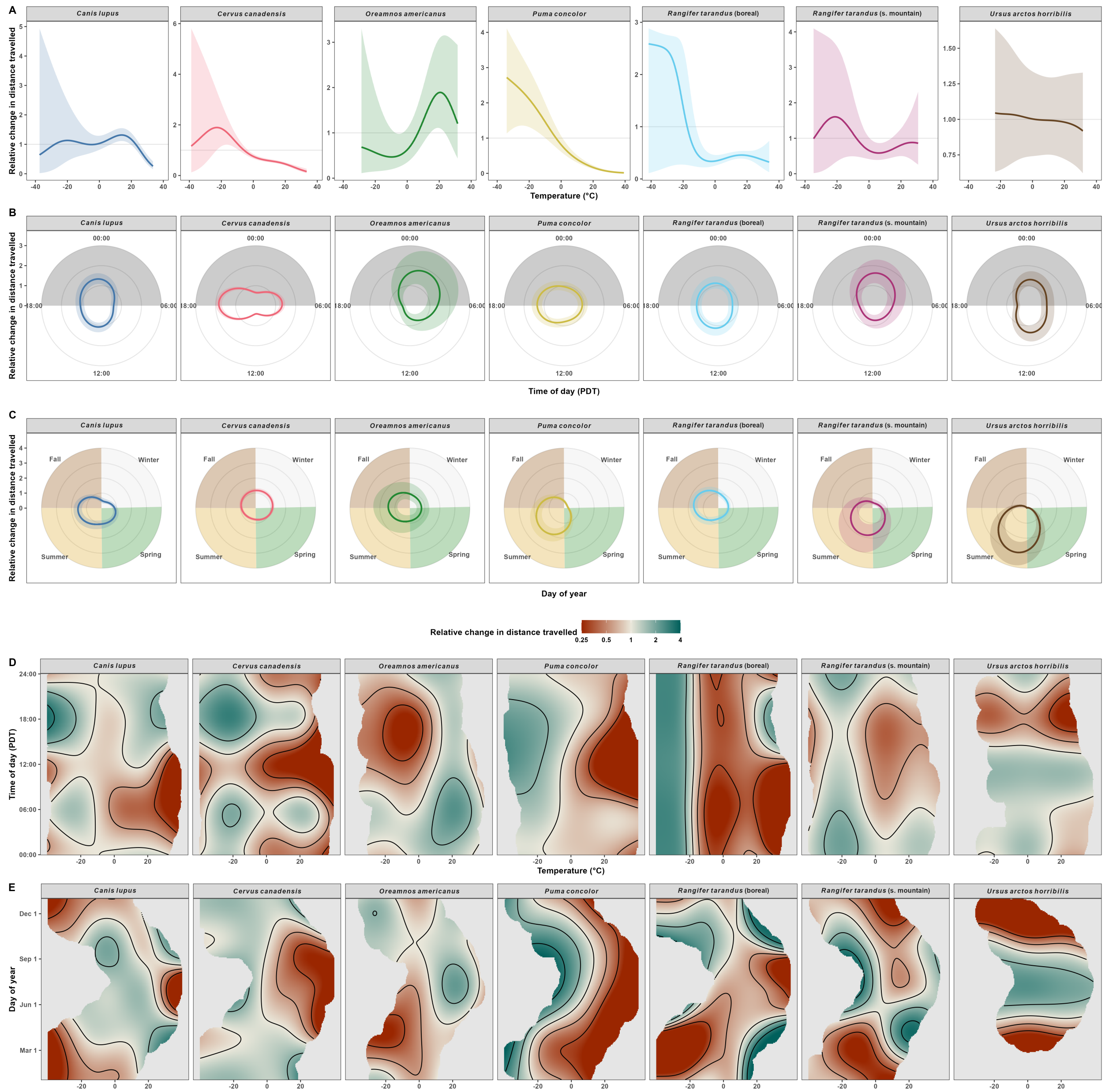

Figure B8: **A.** Estimated effects of temperature on each species' distance traveled on June 1st at 12:00, Pacific Daylight Time (PDT). The rug plot indicates each species' data points where an animal was moving on June 1st. **B.** Estimated effects of time of day on each species' distance traveled 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.

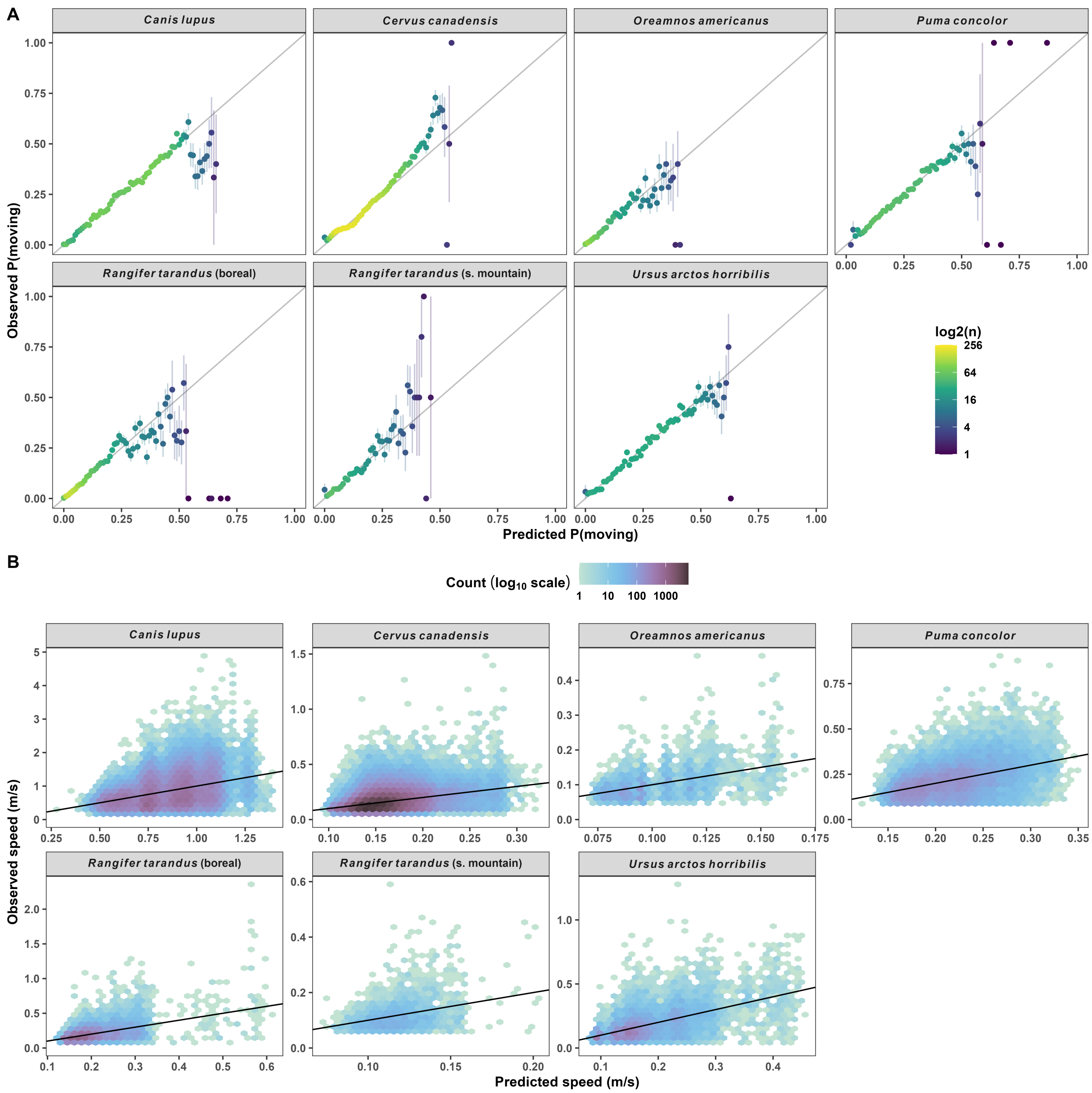

Figure B9: Relationsips between the observed and predicted values for probability of movement (**A**) and speed given that an animal was moving (**B**). The color in panel **A** indicates the number of points used to calculate the estimate (on the $\log_2$ scale), while the grey lines in both panels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

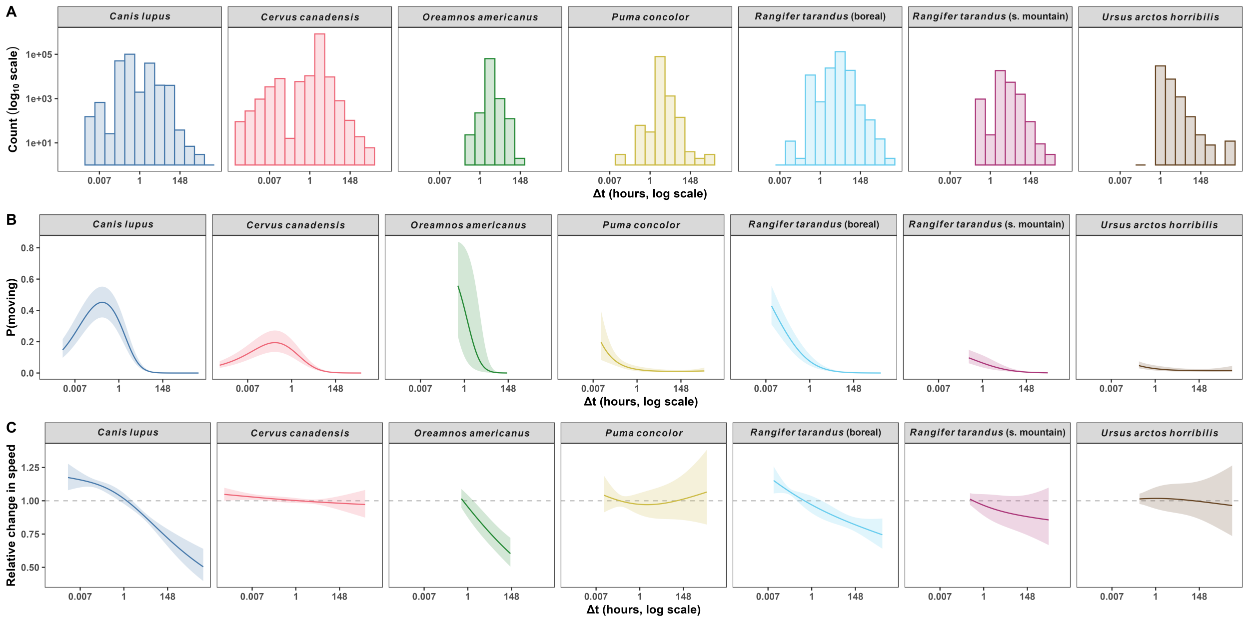

Figure B10: **A.** Histograms of sampling intervals between GPS locations, with counts on a $\log_{10}$ axis for ease of readability. **B.** Species-level smooth effects of sampling interval on the estimated probability of the animal moving. **C.** Species-level estimated smooth effects of sampling interval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

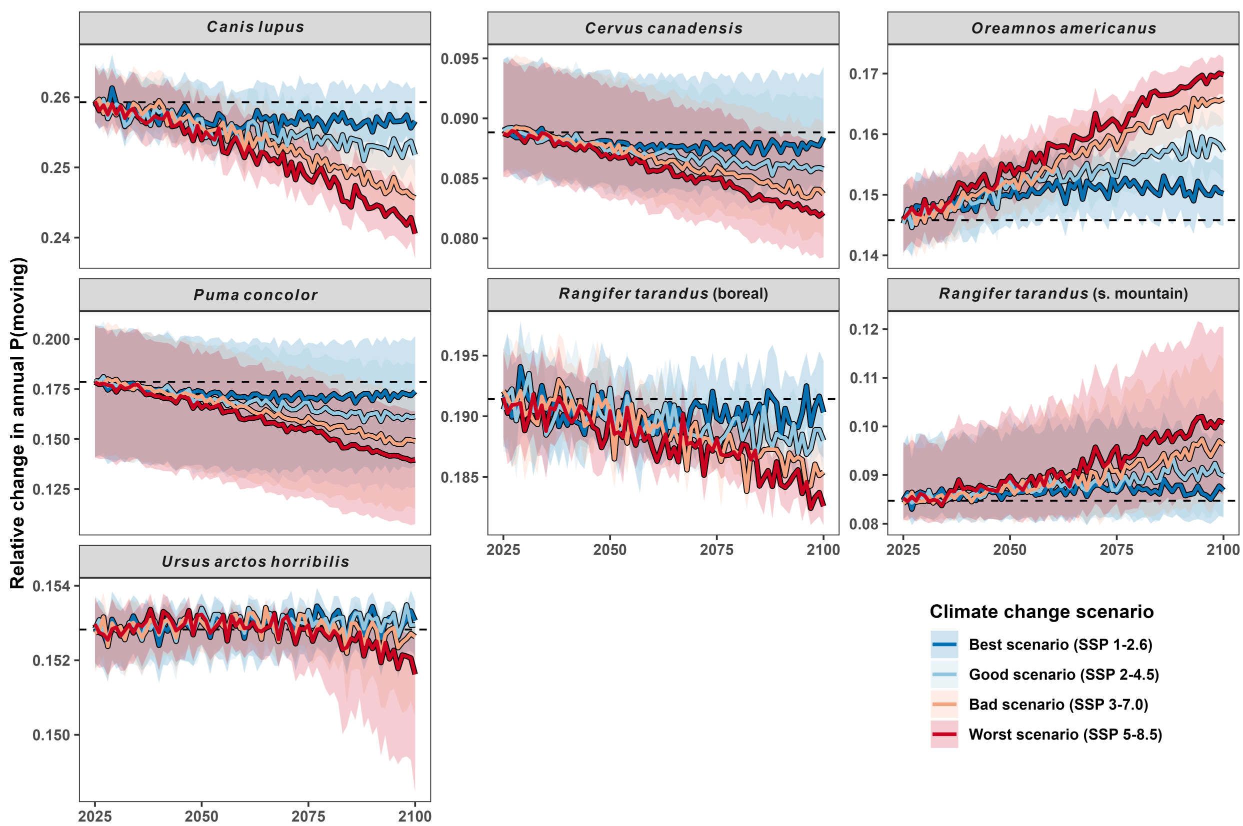

Figure B11: **The direction and magnitude of changes in probability of moving due to climate change varies among species, but worse climate-change scenarios result in the greatest change.** Lines indicate the median projected change in probability of moving due to changes in temperature within the species' 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 movement behavior (i.e., movement frequency and speed) and ignore changes in physiology or movement costs.

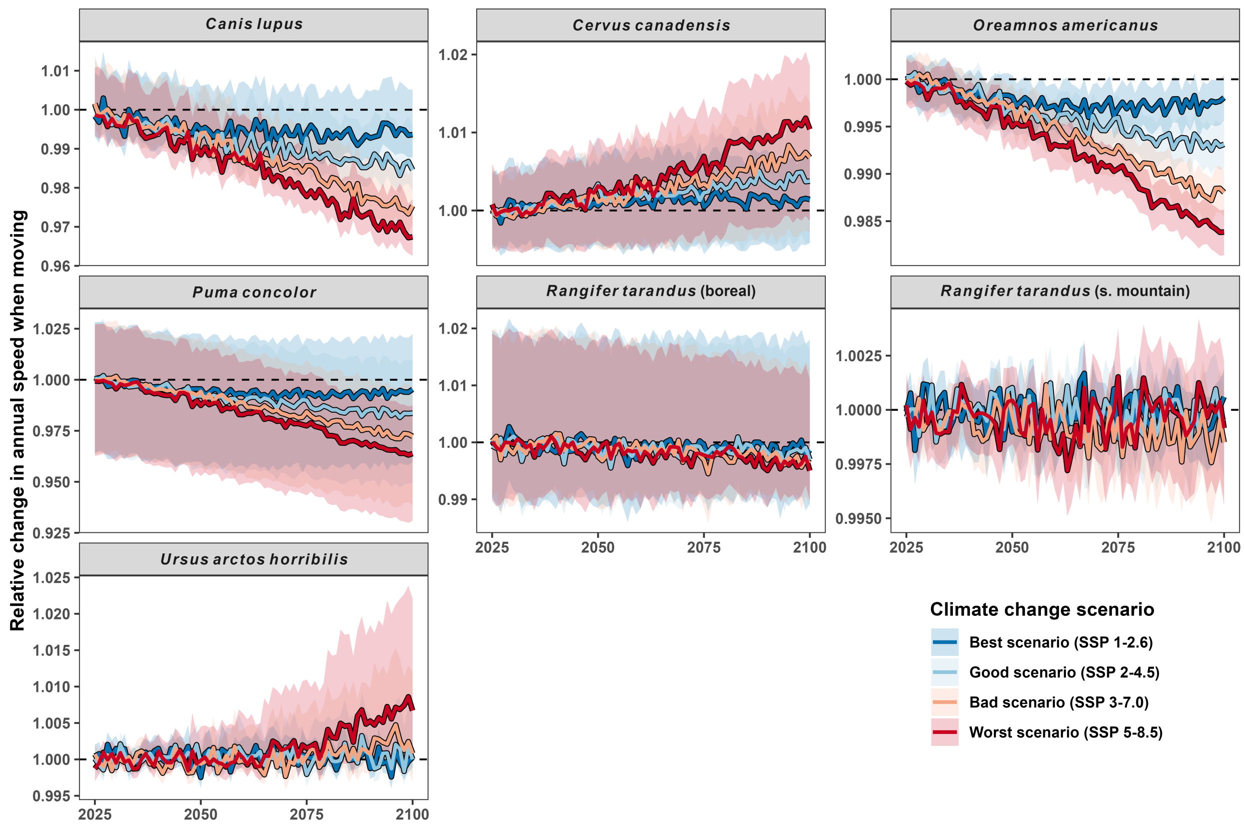

Figure B12: **The direction and magnitude of changes in speed due to climate change varies among species, but worse climate-change scenarios result in the greatest change.** Lines indicate the median projected change in speed due to changes in temperature within the species' current extent. Shaded areas 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

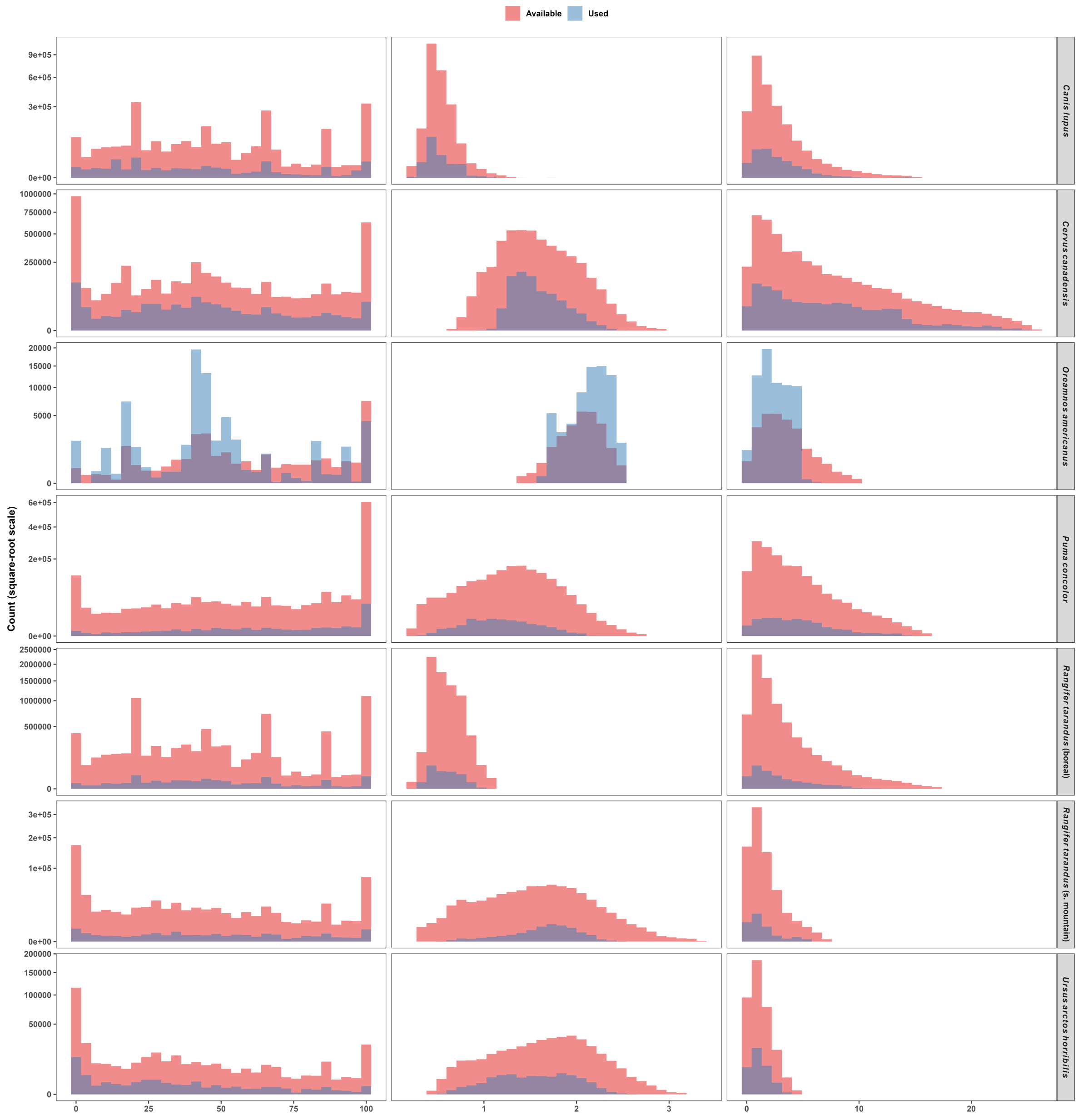

Figure B13: Histograms of available (red) and used (blue) resources. All GPS fixes counts as one observation. The y axis is on the square-root scale to help visualize values with low counts.

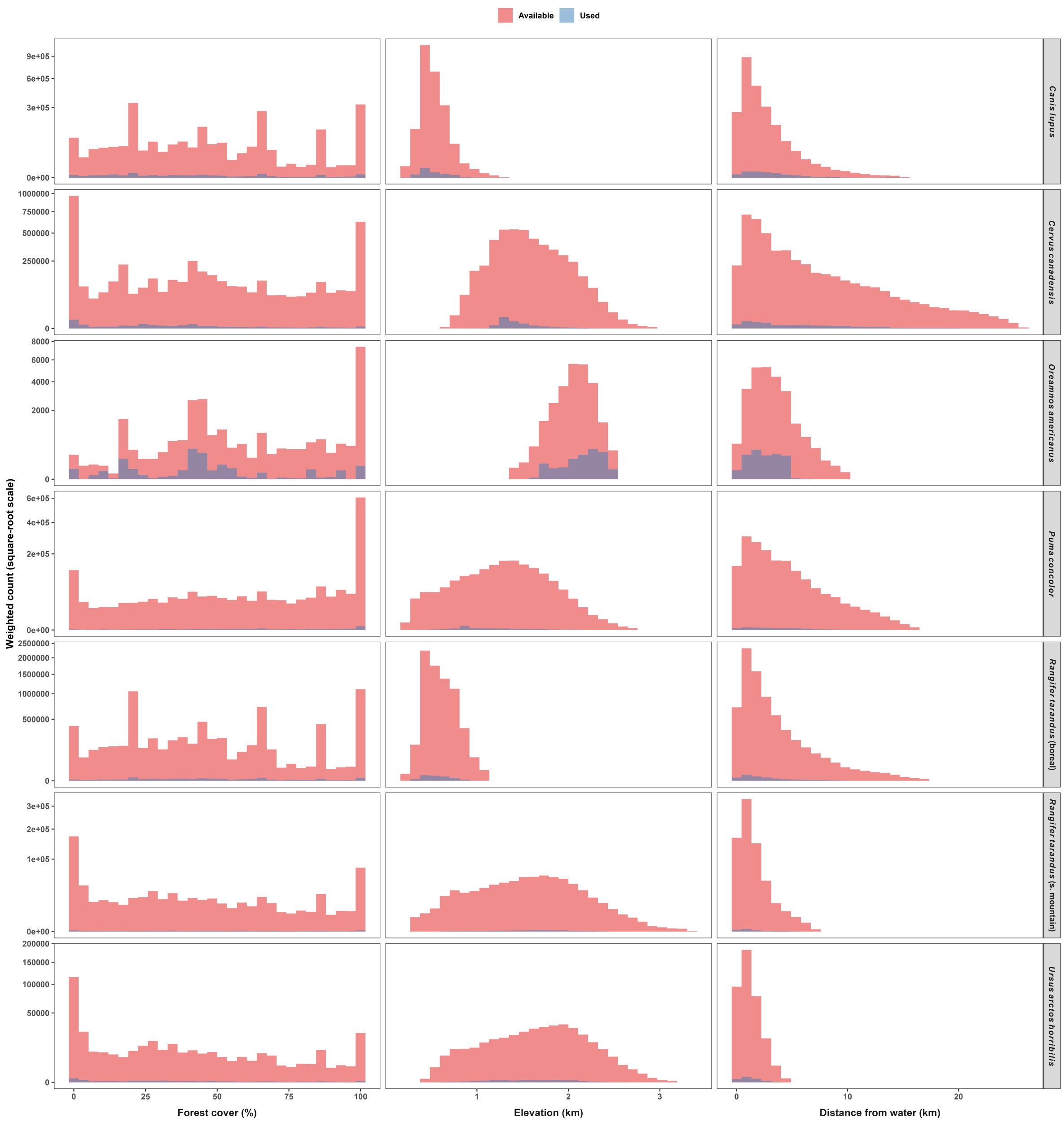

Figure B14: Histograms of available (red) and used (blue) resources. All GPS fixes are weighted according to their independence relative to the respective animals' range crossing time and Autocorrelated Kernel Density Estimate (i.e., the weights returned by AKDE weights multiplied by the number of home-range-crossing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

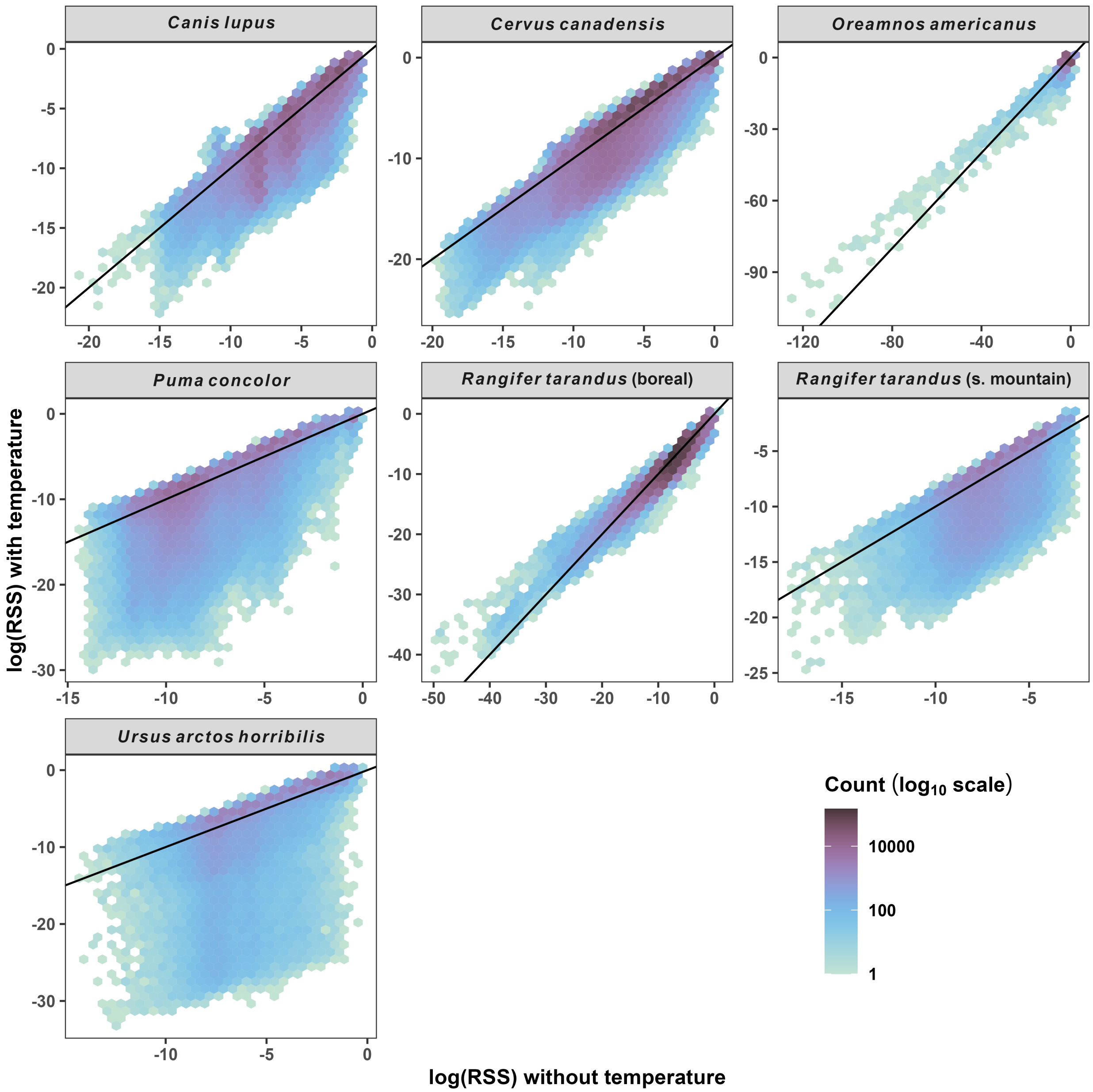

Figure B15: Hexplot of the fitted values from the HRSFs with and without including temperature.

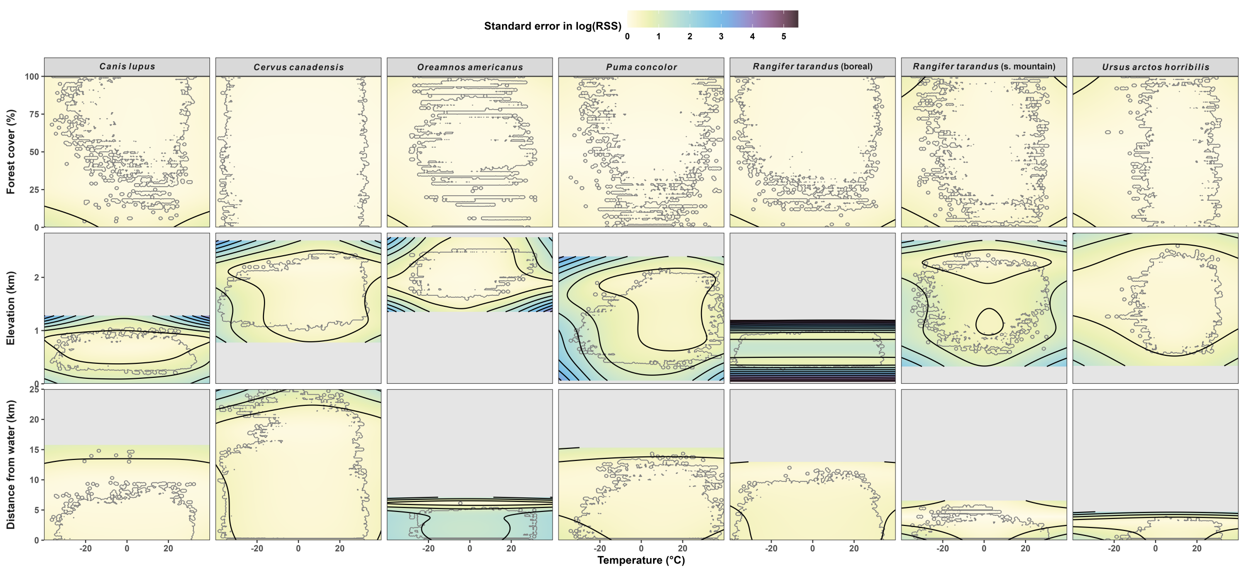

Figure B16: Estimated standard error in the relative selection strength (RSS) for forest cover (%), elevation (km), and distance from water (km) as a function of temperature (see Fig. 3 in the main text). The grey contours indicate the extent of each speices' observed locations.

4 Model selection

Table B1: Changes in deviance expained (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 (Akaike, 1974), 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	Canis lupus	9.2%	6566
HRSF	Cervus canadensis	4.6%	4448
HRSF	Oreamnos americanus	18.6%	813
HRSF	Puma concolor	8%	966
HRSF	Rangifer tarandus (boreal)	5.3%	5637
HRSF	Rangifer tarandus (s. mountain)	12%	342
HRSF	Ursus arctos horribilis	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 Wood (2017). 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 Wood, 2017).

```
# 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
```

```r
# 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
```

```r
# 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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

```r
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
```

Refences

Akaike H (1974) A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, **19**, 716–723.

Wood SN (2017) Generalized additive models: An introduction with R, Second edition edn. CRC Press/Taylor & Francis Group, Boca Raton.