

# Predicting how climate change will affect terrestrial mammals' movement and habitat selection in British Columbia, Canada

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## Abstract

Recent widespread warming has caused many terrestrial mammals to change when, how, and where they move. These changes in species' movement behavior have had cascading effects on individuals' fitness and habitat selection with consequences at the population, community, and ecosystem levels. Previous research has quantified changes in mammalian movement behavior, but we are lacking an estimate of the effects of climate change on fine-scale movement and habitat selection. We address this by using Continuous-Time Movement Models and Hierarchical Generalized Additive Models to quantify the effects of temperature on mammal's probability of movement, speed, and habitat selection. We then leverage the estimated effects to predict when, how, and where mammals will move in BC in the current century. We conclude with implications for energetics, encounter rates, habitat conservation, and human-wildlife conflicts.

## Useful references to add

- Hegel *et al.* (2010): weather affects caribou calf recruitment and interacts with predator (wolf) abundance
- Elmore *et al.* (2017): “thermal environments should be foundational in the understanding of the habitat concept”
- Pease (2024): the scale at which we measure variables affects their estumated effect
- Hetem *et al.* (2014):
  - rate of climate change is too fast for genetic adaptation to occur in mammals with longevities of decades
  - example of suitable habitat prediction to 2050
  - to read: <https://doi.org/10.1186/s40665-016-0024-1>

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## <sup>1</sup> 1 Introduction

<sup>2</sup> It is well understood that mammalian energetics depend on ambient temperature (Taylor,  
<sup>3</sup> Heglund & Maloiy, 1982; Brown *et al.*, 2004), but we have a limited understanding of how  
<sup>4</sup> mammals adapt their movement behavior in response to temperature (Elmore *et al.*, 2017;  
<sup>5</sup> but see: Milling *et al.*, 2017; Montgomery *et al.*, 2019). Previous work has focused on  
<sup>6</sup> energetic costs of movement (Taylor *et al.*, 1982; Dyer *et al.*, 2023), range shifts (Leclerc *et*  
<sup>7</sup> *al.*, 2021), thermoregulation (Mota-Rojas *et al.*, 2021; Melin *et al.*, 2023), and trait-based  
<sup>8</sup> responses (McCain, 2019), but there remains a need for a more comprehensive understanding  
<sup>9</sup> of how mammals will adapt their fine-scale movement and habitat selection to future changes  
<sup>10</sup> in temperature (Intergovernmental Panel On Climate Change, 2023). Movement plasticity  
<sup>11</sup> (Nathan *et al.*, 2008) allows mammals to react to changes in temperature on a shorter  
<sup>12</sup> timescale than evolutionary physiological adaptations (Levins, 1974). By changing when,  
<sup>13</sup> how, and where they move, mammals can conserve chemical and thermal energy as well  
<sup>14</sup> as reduce the risk of overheating (Attias *et al.*, 2018; Williams & Blois, 2018; Alston *et*  
<sup>15</sup> *al.*, 2020; Verzuh *et al.*, 2023; Dyer *et al.*, 2023; Giroux *et al.*, 2023). We present a multi-  
<sup>16</sup> species analysis of how mammals adapt their movement behavior in response to changes in  
<sup>17</sup> air temperature.

<sup>18</sup> Recent changes in climate have affected mammals' movement rates and habitat selection  
<sup>19</sup> (Deb, Forbes & MacLean, 2020), but it is still unclear how changes in the current century will  
<sup>20</sup> affect their fine-scale movement behavior and spatial distribution by the end of the century.  
<sup>21</sup> In the last 200 years, many ecosystems experienced widespread warming that resulted in  
<sup>22</sup> milder and shorter winters, hotter and longer summers, and a greater risk of extremely high  
<sup>23</sup> temperatures and severe forest fires (Zurowski, 2023; Intergovernmental Panel On Climate  
<sup>24</sup> Change, 2023). Over the next 100 years, these changes will continue to affect mammals'  
<sup>25</sup> fitness, movement behavior, and habitat selection as they cope with growing heat stress  
<sup>26</sup> (Deb *et al.*, 2020; Woo-Durand *et al.*, 2020) and frequency and intensity of extreme events

<sup>27</sup> (Bunnell, Kremsater & Wells, 2011) along with anthropogenic pressure (Sih, Ferrari & Harris,  
<sup>28</sup> 2011; Weststrate *et al.*, 2024).

<sup>29</sup> Understanding animals' responses to temperature is essential for anticipating their re-  
<sup>30</sup> sponse to climate change in the coming decades and the cascade of consequences such changes  
<sup>31</sup> will have. In light of the "30 by 30" conservation initiative, a global effort to conserve 30%  
<sup>32</sup> of the world's lands and oceans by 2030 ([ref?](#)), we must understand which areas are best  
<sup>33</sup> preserved to maximize the project's effectiveness. Predicting how climate change will affect  
<sup>34</sup> how, when, and where animals will move is necessary for choosing which 30% of the world  
<sup>35</sup> is most worth preserving. Changes in movement behavior impact several aspects of animals'  
<sup>36</sup> fitness, behavior, and odds of survival, including encounter rates (with food, competitors,  
<sup>37</sup> and predators: Martinez-Garcia *et al.*, 2020), energetic expenditure (Taylor *et al.*, 1982),  
<sup>38</sup> range shifts (Woo-Durand *et al.*, 2020). Thus, understanding the effects of temperature on  
<sup>39</sup> animals' movement behavior and their consequences is crucial for effective conservation.

<sup>40</sup> This paper provides an analysis of the effects of ambient temperature on the movement  
<sup>41</sup> of six terrestrial mammal species in British Columbia (BC), Canada (*Canis lupus*, *Cervus*  
<sup>42</sup> *canadensis*, *Oreamnos americanus*, *Puma concolor*, boreal and southern mountain *Rangifer*  
<sup>43</sup> *tarandus*, and *Ursus arctos horribilis*; Table 1). Using over two decades of telemetry data  
<sup>44</sup> over a large spatial range of British Columbia (Fig. 1) and hourly air temperature data,  
<sup>45</sup> we estimate how mammals altered their movement frequency, movement speed, and habi-  
<sup>46</sup> tat selection in response to air temperature. We then pair the estimated responses with  
<sup>47</sup> climate change projections to forecast changes in mammalian movement in 2100 under dif-  
<sup>48</sup> ferent climate-change scenarios (Shared Socioeconomic Pathways, see Riahi *et al.*, 2017). We  
<sup>49</sup> discuss the consequences of these changes in movement behavior with regards to energetics,  
<sup>50</sup> encounter rates, habitat conservation, and human-wildlife conflicts.

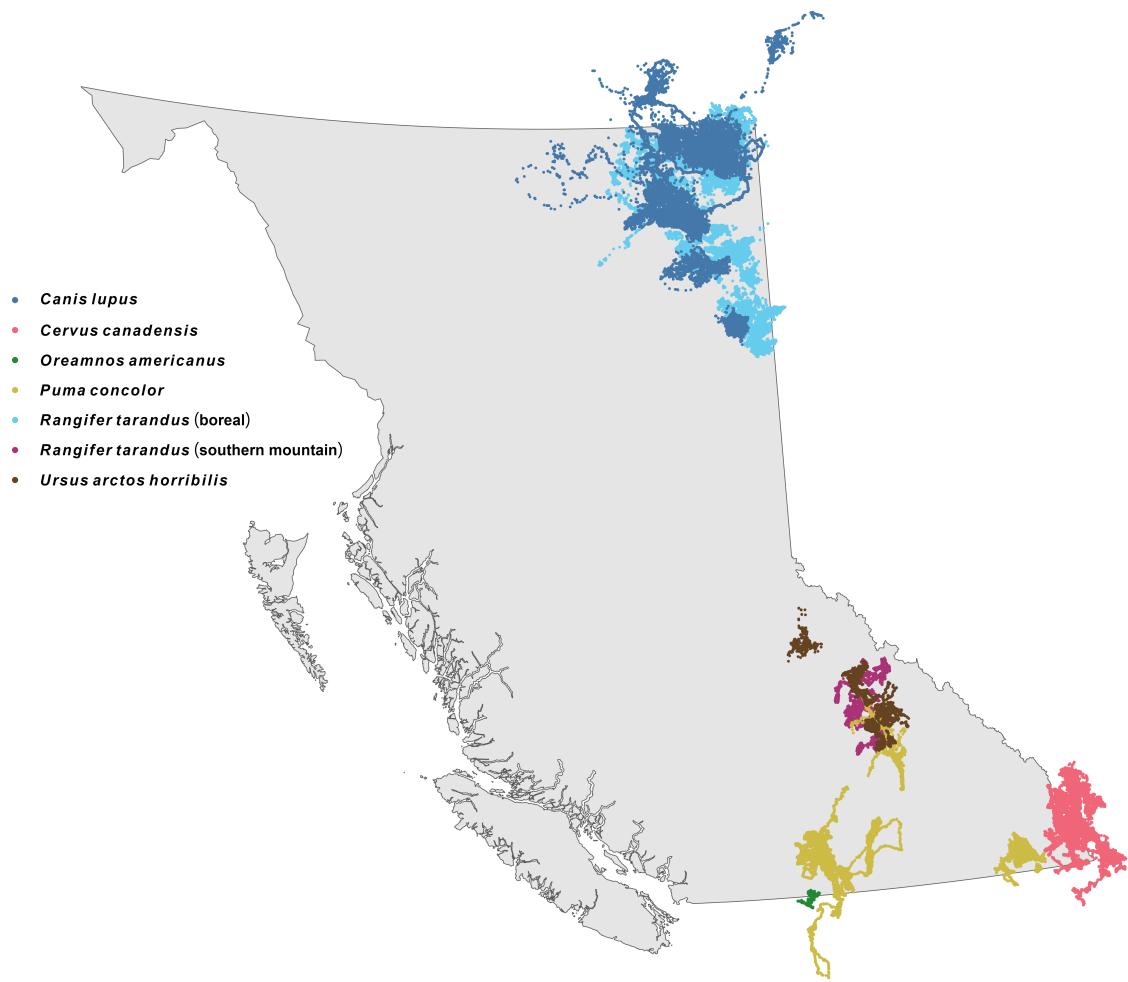


Figure 1: GPS telemetry data and 95% autocorrelated kernel density utilization distributions for the six species in this study.

Table 1: Start and end of the GPS telemetries along with the median sampling interval ( $\Delta t$ ; stratified by individual) and number of animals with unresolved speed (NA speed) for each of the species in this study.

| Dataset                                | Start      | End        | Median $\Delta t$ (hours) | NA speed |
|--|------------|------------|---------------------------|----------|
| <i>Canis lupus</i>                     | 2013-01-27 | 2017-08-29 | 0.25                      | 0        |
| <i>Cervus canadensis</i>               | 2007-01-13 | 2013-11-20 | 2.00                      | 0        |
| <i>Oreamnos americanus</i>             | 2019-06-25 | 2023-10-05 | 6.25                      | 1        |
| <i>Puma concolor</i>                   | 2006-02-05 | 2021-07-13 | 2.00                      | 0        |
| <i>Rangifer tarandus</i> (boreal)      | 2011-03-02 | 2018-01-04 | 13.00                     | 15       |
| <i>Rangifer tarandus</i> (s. mountain) | 1998-03-21 | 2009-06-07 | 6.00                      | 2        |
| <i>Ursus arctos horribilis</i>         | 2004-09-30 | 2009-09-07 | 1.00                      | 0        |

## 51 2 Methods

### 52 2.1 GPS telemetry data

53 Elk (*Cervus canadensis*) data from Ciuti *et al.* (2012) were downloaded from Movebank  
 54 (study name: Elk in southwestern Alberta, see Kays *et al.*, 2022), while boreal caribou  
 55 (*Rangifer tarandus*) and wolf (*Canis lupus*) telemetries were acquired via a public BC Oil and  
 56 Gas Research and Innovation Society repository (<https://www.bcgoris.ca/projects/boreal->  
 57 caribou-telemetry-data), and the mountain goat (*Oreamnos americanus*) locations were pro-  
 58 vided by BC Parks. All other tracking data were obtained from private collaborators. Outlier  
 59 GPS locations were removed following diagnostic analyses of the distance from the median  
 60 location as well as straight-line displacement, turning angle, and time interval between con-  
 61 secutive points. Particular attention was paid to points with large turning angles ( $\gtrapprox 170^\circ$ )  
 62 and high straight-line displacement, especially if antecedent and subsequent points indicated  
 63 stationary behavior. The script used to clean the data and all associated custom func-  
 64 tions are available on GitHub (<https://github.com/QuantitativeEcologyLab/bc-mammals->  
 65 temperature).

66 **2.2 Historical temperature data**

67 Rasters of hourly reanalyzed air temperature data were downloaded from the ERA5 dataset  
68 (Hersbach *et al.*, 2023) from the European Center for Medium-range Weather Forecasting  
69 server (ECMWF; [www.ecmwf.int](http://www.ecmwf.int); <https://cds.climate.copernicus.eu>). Proximal tempera-  
70 ture was estimated for each location by extracting the values from the corresponding raster  
71 cell from the temporally nearest raster using the `extract()` function from the `terra` package  
72 (version 1.7-46, Hijmans, 2023) for `R` (R Core Team, 2024).

73 **2.3 Estimating mammals' instantaneous speeds**

74 We modeled each animal's movement using continuous-time movement models (Fleming *et*  
75 *al.*, 2014) via the `ctmm` package (version 1.2.0, Fleming & Calabrese, 2023) for `R`. We then  
76 estimated mammals' instantaneous speeds by applying the `ctmm::speeds()` function on all  
77 models with finite speed estimates (416 of 433, see Fleming *et al.*, 2014; Noonan *et al.*, 2019).  
78 The 18 telemtries with insufficiently fine sampling were for one mountain goat, 15 boreal  
79 caribou, and 2 southern mountain caribou (Table 1).

80 Since `ctmm`'s movement models assume stochastic but non-zero speeds (i.e., a single,  
81 stochastic moving state), data-informed speeds needed to be corrected so that the minimum  
82 instantaneous speed could be 0. We performed this correction by subtracting each model's  
83 mean speed while assuming speeds were  $\chi^2$ -distributed. The function we used is avail-  
84 able on GitHub at <https://github.com/QuantitativeEcologyLab/bc-mammals-temperature/>  
85 `blob/main/functions/detrend_speeds.R`. To avoid artifacts due to excessively small, non-  
86 zero speeds, we determined whether an animal was moving or not using the inflection point  
87 of each species' histogram of detrended speed estimates (Appendix A).

88 **2.4 Estimating the effects of temperature on mammals' movement**

89 The following two sections detail the modelling we used to estimate the effect on tem-  
90 perature on mammals' movement. To assess the importance of including temperature as an

91 explicit covariate (rather than including its effects with time of day and day of year **HERE**),  
92 we fit models with and without temperature and compared the fits and model predictions  
93 of the two sets of models.

#### 94 2.4.1 Movement frequency and speed

95 We estimated the effects of temperature on mammals' movement state (moving or not) and  
96 speed (when moving) using two Hierarchical Generalized Additive Models (HGAMs, see  
97 Pedersen *et al.*, 2019 and the code chunk below) with the `mgcv` package for R (version 1.9-1,  
98 Wood, 2017). The first HGAM estimated the probability that an animal was moving with a  
99 binomial family of distributions and logit link function. The second HGAM estimated an an-  
100 imal's speed (when moving) with a gamma family of distributions and log link function. The  
101 HGAMs included random intercepts for each animal (`s(..., bs = 're')`), fixed intercepts  
102 for each species, and species-level factor smooth interactions for time of day, day of year,  
103 and temperature (`s(..., bs = 'fs')`, see model S in Figure 4 of Pedersen *et al.*, 2019).  
104 Additionally, the models had three tensor product interaction terms (`ti()`) for each species:  
105 (1) day of year and time of day, (2) temperature and time of day, and (3) temperature and  
106 day of year. These three terms accounted for: (1) seasonal changes in day length, (2) hourly  
107 changes in the response to temperature (e.g., changes in nocturnality), and (3) seasonal  
108 changes in the response to temperature (e.g., changes in coats and migration timing). The  
109 HGAMs accounted for the cyclicity of time of day and day of year using cyclic cubic splines  
110 (`bs = 'cc'`, Wood, 2017). Together, the binomial HGAM and the gamma HGAM inform us  
111 on an animal's long-term average speed, since it is the product of the probability the animal  
112 is moving and its average speed when moving. We fit the models with fast REML ('fREML')  
113 and discretized covariates (`discrete = TRUE`) to optimize computational efficiency with no  
114 appreciable losses to model performance (Wood, Goude & Shaw, 2015; Wood *et al.*, 2017;  
115 Li & Wood, 2020). Additional details are provided in Appendix A.

```

m_moving <- bam(
  moving ~
  s(animal, bs = 're') +
  species + #' necessary since `by` terms do not include intercept terms
  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'),
  data = d,
  method = 'fREML', # fast REML
  discrete = TRUE, # discretize the covariates for faster computation
  knots = list(tod_pdt = c(0, 1), doy = c(0.5, 366.5))) # for bs = 'cc'

m_speed <- bam(
  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'),
  family = Gamma(link = 'log'),
  data = d_2, # data filtered for speed > 0
  method = 'fREML',
  discrete = TRUE,
  knots = list(tod_pdt = c(0, 1), doy = c(0.5, 366.5)))

```

116 **2.4.2 Habitat selection**

117 We estimated the effects of temperature on each species' selection for percent forest cover,  
118 elevation, and distance from fresh water (i.e., not sea water) by fitting a Hierarchical Resource  
119 Selection Function (Aarts *et al.*, 2008; **refs?**; [10.1111/ecog.07225](https://doi.org/10.1111/ecog.07225))  
120 an HGAM with a Poisson family of distributions and log link function for each species (Appendix B, also see  
121 Aarts *et al.*, 2008; Alston *et al.*, 2022). While we recognize there are other important drivers  
122 of habitat selection that we did not include in our models (e.g., forest age), we decided to  
123 only use these three proxies to produce results that are relatively comparable between species  
124 and to make province-wide predictions simpler. Each species' model had the same structure:

```
rsf <- bam(  
  detected ~ # 1 for GPS locations, 0 for quadrature data  
  # species-level average resource preference  
  s(forest_perc, k = 6, bs = 'tp') +  
  s(elevation_m, k = 6, bs = 'tp') +  
  s(dist_water_m, k = 6, bs = 'tp') +  
  # animal-level deviations from the species-level average  
  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')) +  
  # changes in preference with temperature  
  ti(forest_perc, temperature_C, k = 6, bs = 'cr') +  
  ti(elevation_m, temperature_C, k = 6, bs = 'cr') +  
  ti(dist_water_m, temperature_C, k = 6, bs = 'cr'),  
  family = poisson(link = 'log'),  
  data = d,  
  weights = weight, # based on AKDE  
  method = 'fREML',  
  discrete = TRUE)
```

125 Smooth effects of percent forest cover, elevation, and distance to fresh water accounted for  
126 the species-level average selection strength for each resource. A random effect for each indi-  
127 vidual animal corrected for uneven sampling across individuals, while factor smooth interac-  
128 tion terms (bs = 'fs') accounted for individual-level resource selection (i.e., individual-level  
129 deviations from the species-level average). Finally, tensor interaction product terms (ti())

130 of the three resources and temperature estimated the change in resource selection at different  
131 temperatures. Detections were weighted proportionally to their degree of independence from  
132 temporally proximate detections (see Appendix C and Alston *et al.*, 2022), while quadrature  
133 points had a weight of 1.

134 ***does elk HRSF use different k values?***

135 **2.5 Predicting changes in animal movement during the current century**

136 Rasters of projected monthly average temperature in BC from 2020 to 2100 were obtained  
137 via the `climatenetR` package (version 1.0, Burnett, 2023) for R. Since the climate projections  
138 only provided monthly means and ranges but no measures of variance or distributional  
139 assumptions, we used the hourly ERA5 data for BC from 1998 to 2023 (extremes included,  
140 see Hersbach *et al.*, 2023) to calculate within-month variance, which we defined as the  
141 variance within a given pixel, month, and year. We then modelled the estimated variance  
142 using a GAM for location and scale (GAMLS, see Rigby & Stasinopoulos, 2005; Stasinopoulos  
143 & Rigby, 2007; section 7.9 in Wood, 2017). The linear predictor for the location (i.e., the  
144 mean) included smooth terms of the within-pixel monthly mean temperature (for each year),  
145 month (as a cyclic smooth), a two-dimensional smooth of space, and a tensor interaction  
146 product term of space and month. The linear predictor for the scale term (which governs  
147 the mean-variance relationship) included smooth terms of the monthly mean, month, and  
148 space. Additional details are available in Appendix C.

149 We simulated for hourly variation in weather by assuming temperature followed a normal  
150 distribution with mean specified by the `climatenetR` climate projections and variance as  
151 specified by the Gamma GAMLS. We then predicted changes in movement behavior and  
152 habitat selection as a function of temperature using the HGAMs and HRSFs along with the  
153 temperature HGAM described above. For each month within each year from 2020 to 2100,  
154 we simulated hourly weather by including temperatures from the 0.1, 0.2, ..., 0.8, 0.9 quantiles  
155 and weighted each quantile proportionally to the (normalized) Gaussian probability density

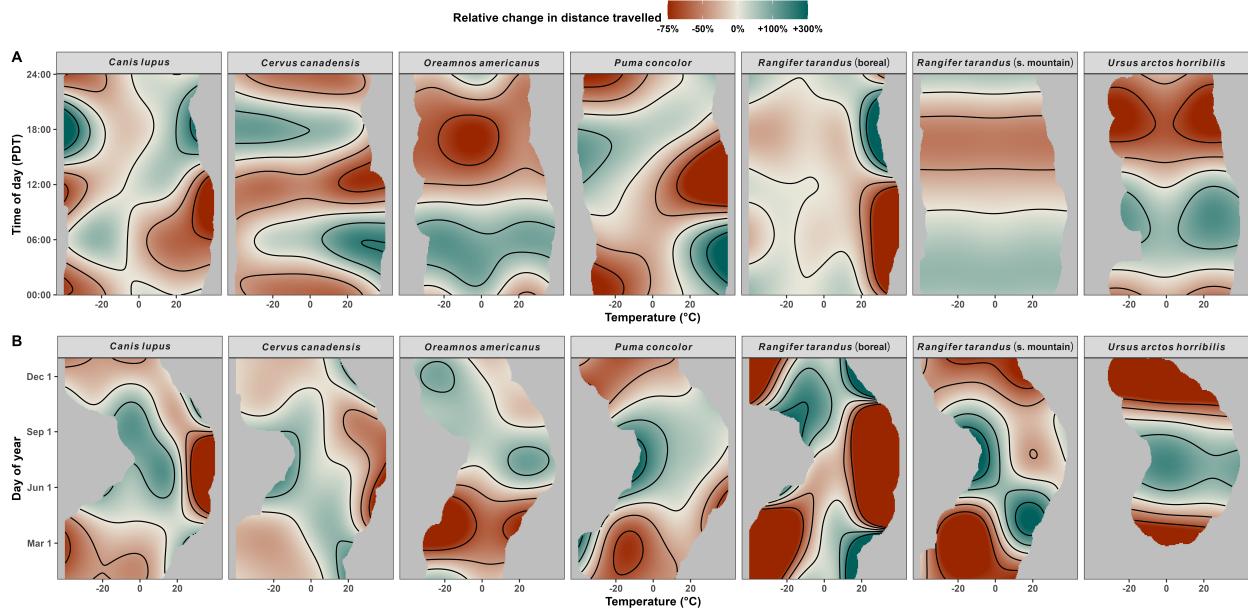
156 for each value (Appendix C).

157 **3 Results**

158 While adding temp did not improve model fit (add change in dev.expl), but it ... (delta  
159 BIC for both modelss) (Fig. ***SX*** pred vs pred)

160 **3.1 Effects of temperature on movement rates**

161 The partial effects of temperature varied in both direction and magnitude across species (Fig.  
162 ***AX***), even after accounting for differences in daily and seasonal activity (e.g., sleeping,  
163 migration, hibernation; see Fig. ***AX***). Smooth interaction terms were well-behaved and  
164 indicated clear shifts in daily activity for all species (Fig. ***AX***). The models explained  
165 reasonably high proportions of the deviance (11% for the binomial model and 79% for the  
166 Gamma model) and had good in-sample prediction (Fig. ***AX***). Both movement frequency  
167 and speed when moving decreased with increasing sampling interval, with a strong common  
168 effect (Fig. ***AX***). Most species adapted their daily and seasonal movement behavior to  
169 changes in temperature (Fig. 2), but the precision of the estimated change depends on the  
170 GPS sampling frequency. While **ctmm** models are scale independent (Noonan *et al.*, 2019), the  
171 accuracy, size, and stability of speed estimates still depends on the GPS sampling frequency.  
172 This is because coarser sampling contains information on large scale movements (e.g., range  
173 crossings, migrations) but not fine-scale movement (e.g., first-order habitat selection). Using  
174 the boreal caribou as an example, the 13-hour sampling interval allows us to reasonably  
175 estimate the caribou's movement path at a temporal scale of approximately 13 hours (or  
176 greater), but we cannot produce reasonable movement trajectories at a much finer (e.g.,  
177 hourly) scale. Consequently, the estimated movement behaviors should be compared across  
178 species carefully.



**Figure 2: Temperature is a strong determinant of how far and when mammals travel.** Estimated effects of temperature on relative change in distance travelled (probability of moving times speed when moving) over time of day (A) and day of year (B). Predictions in the surface plots 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, and values are capped to -75% and +300% for ease of readability.

### 179 3.1.1 Predicted changes in movement during the current century

180 The direction and degree of change in distance travelled varies greatly between species,  
 181 but worse climate-change scenarios consistently corresponded to greater absolute changes in  
 182 behavior as well as greater uncertainty in the estimated change (Fig. 3). Under the best-  
 183 case scenario, absolute projected changes by 2100 were small (0% to 2%, except for southern  
 184 mountain caribou, which had a change of ~5%). Under the worst-case scenario, absolute pro-  
 185 jected changes were by 2100 ranged from ~1% (boreal caribou) to ~25% (southern moutain  
 186 caribou) and had the greatest uncertainty in the estimates. Boreal caribou and elk showed  
 187 relatively little projected changes, especially relative to the degree of inter-annual variability  
 188 in displacement.

### 189 COMMENTS ABOUT SPATIAL VARIATION IN DISPLACEMENT

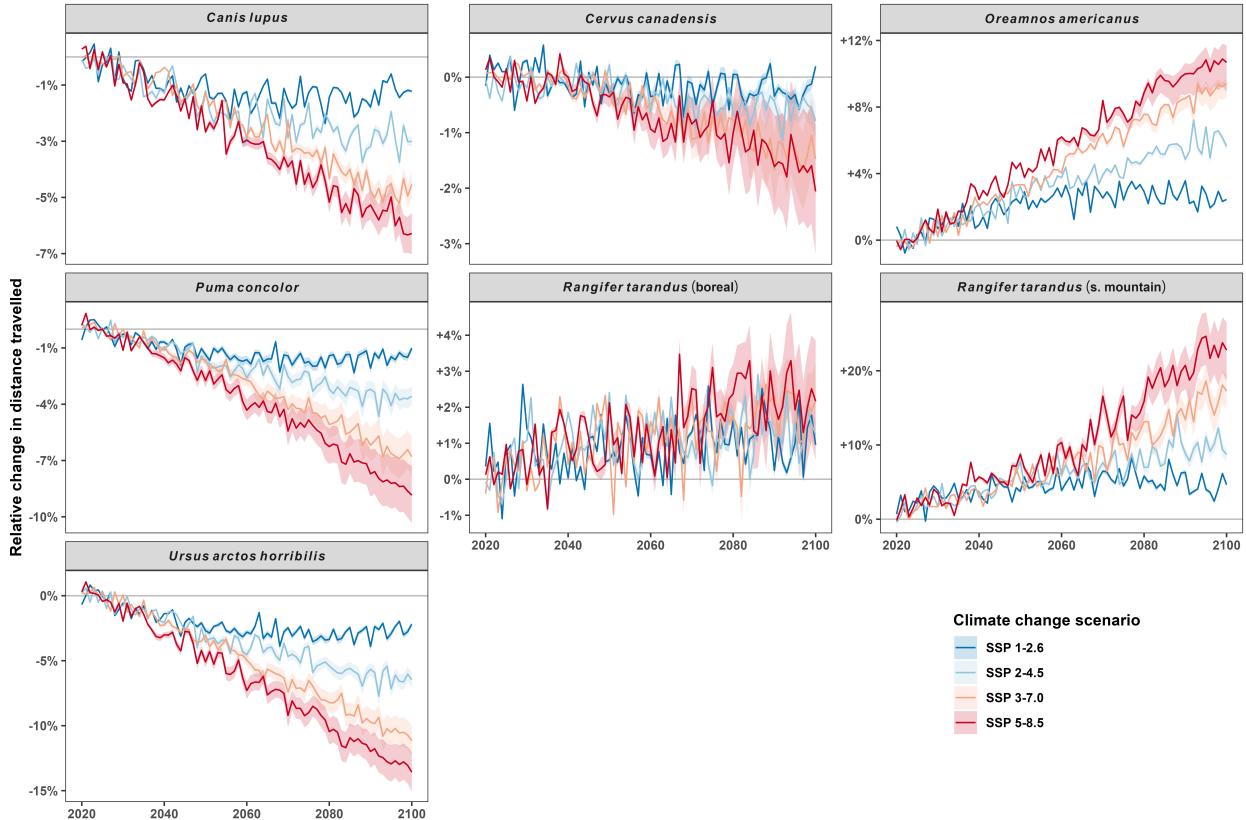
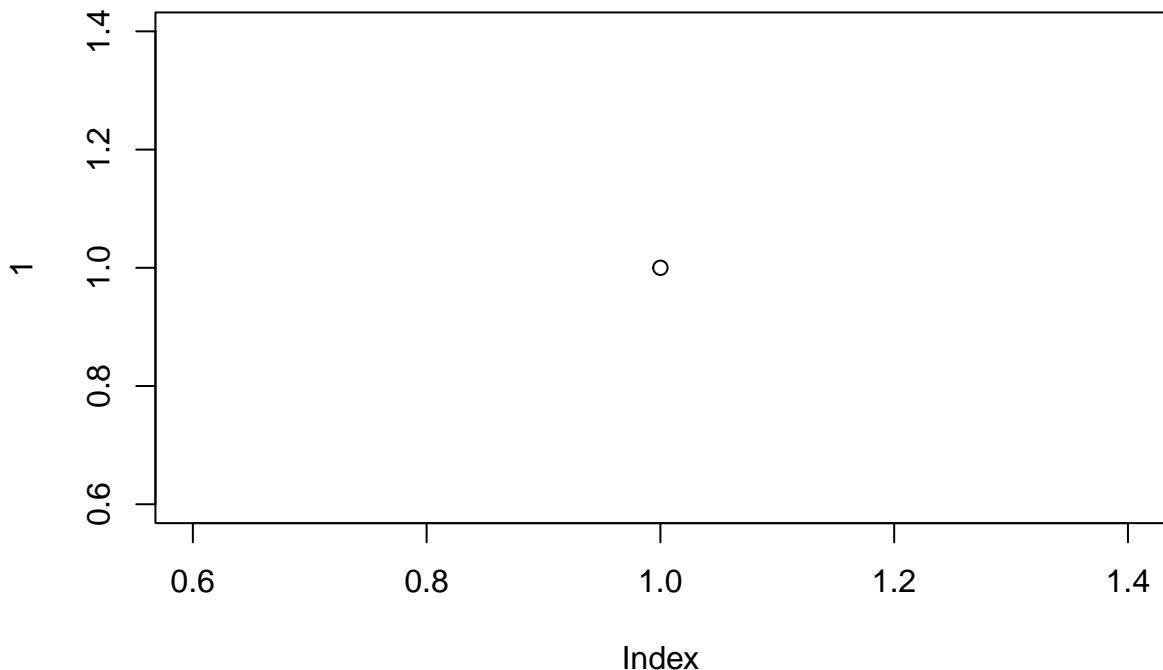


Figure 3: **The intensity and direction of changes in movement rates due to climate change vary among species, but worse climate-change scenarios consistently result in the greatest change and greatest uncertainty.** Lines indicate the projected relative change in mean distance travelled (probability of moving times speed when moving) due to changes in temperature within the species' current extent. Shaded areas indicate the mean 95% Bayesian credible intervals. Changes are relative to the mean distances travelled in 2020 across the four Shared Socioeconomic Pathways (SSPs). The SSPs are listed in order of similarity to current conditions, from SSP 1-2.6 (sustainability, best-case scenario) to 5-8.5 (fossil-fueled development, worst-case scenario). The projections only account for changes movement behavior (i.e., movement frequency and speed) and ignore changes in physiology or movement costs.

## 4. spatial projections of distance in 2020 and 2100



190

### 191 3.2 Effects of temperature on habitat selection

192 to do: \* check  $t_i$  terms of RSFs

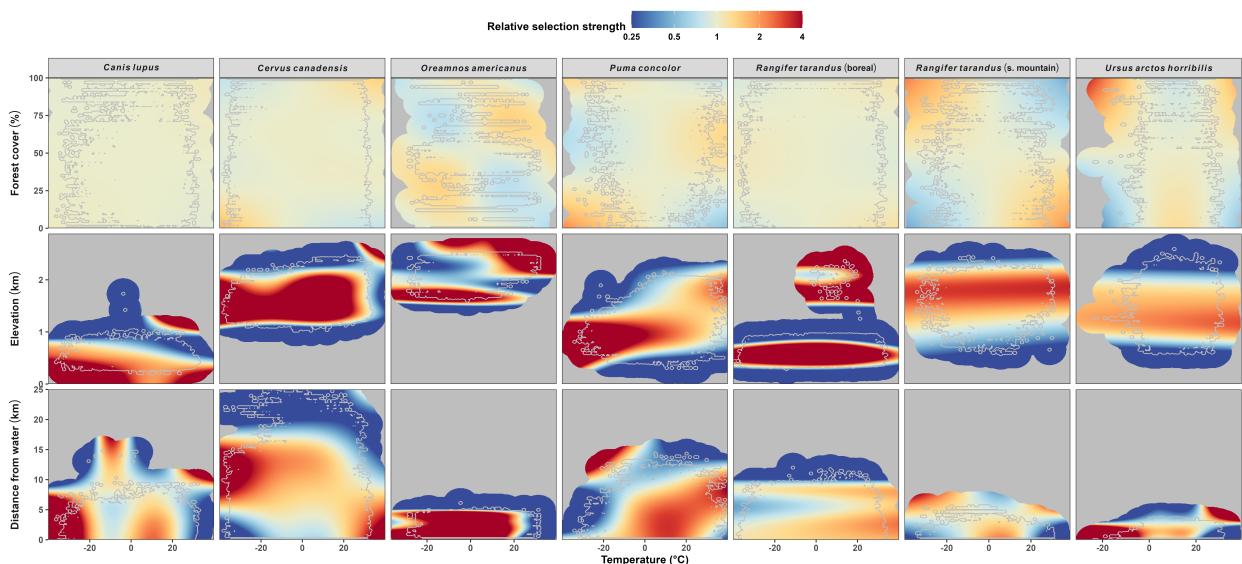


Figure 4: **Temeperature strongly affects mammals' habitat selection.** Estimated resource selection strength for forest cover (%), elevation (km), and distance from fresh water (km) as a function of temperature. The grey contours indicate the extent of each species' observed locations.

<sup>193</sup> 3.2.1 Predicted changes in movement during the current century

## 6. temporal projections of RSFs within current area

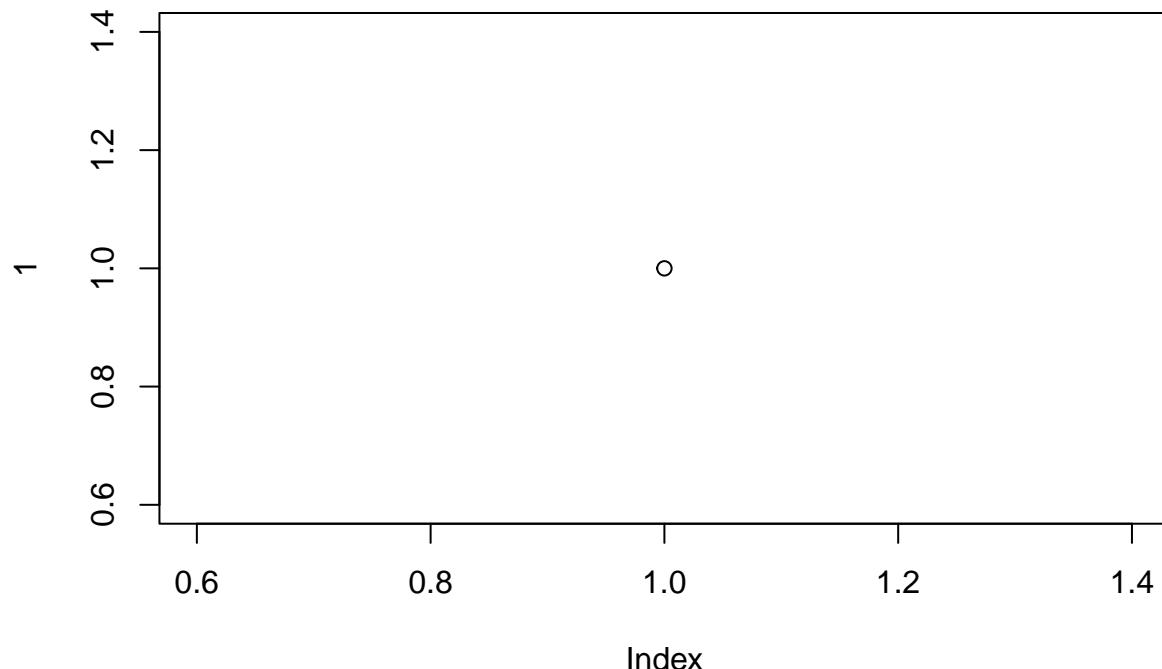
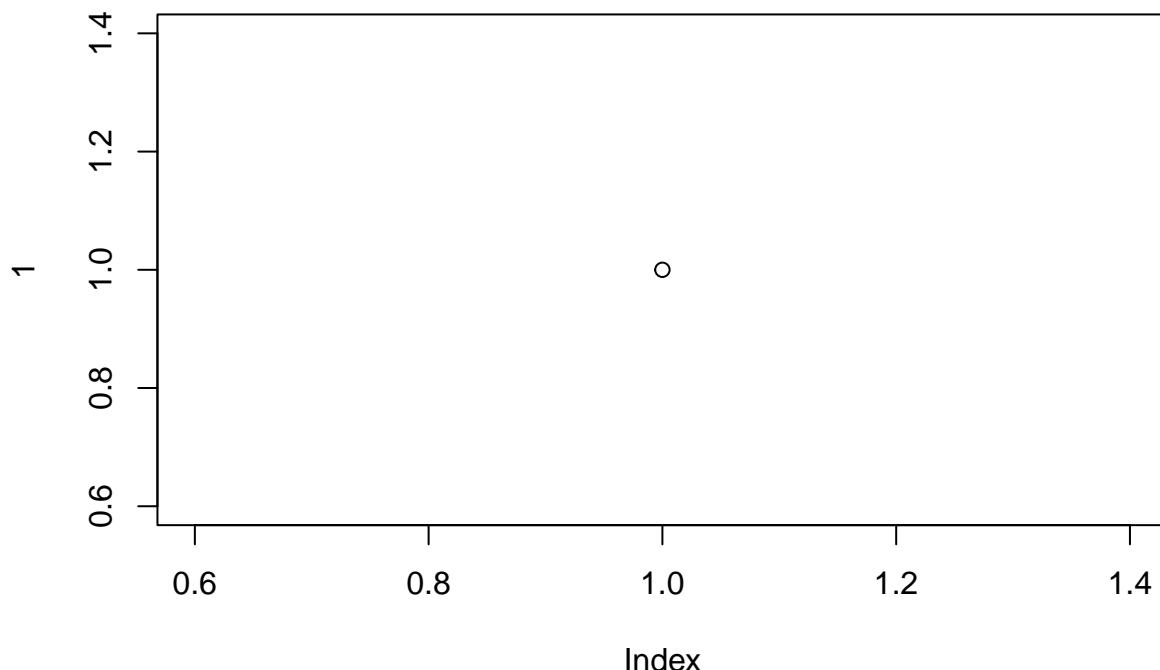


Figure 5: The intensity and direction of changes in habitat selection due to climate change vary among species, but worse climate-change scenarios consistently result in the greatest change and greatest uncertainty. Lines indicate the projected change in relative selection strength for forest cover (%), elevation (km), and distance from fresh water (km) due to changes in temperature within the species' current extent. Shaded areas indicate the mean 95% Bayesian credible intervals. Changes are relative to the relative selection strength in 2020 across the four Shared Socioeconomic Pathways (SSPs). The SSPs are listed in order of similarity to current conditions, from SSP 1-2.6 (sustainability, best-case scenario) to 5-8.5 (fossil-fueled development, worst-case scenario).

## 7. spatial projections of RSFs in 2020 and 2100



194

## 195 4 Discussion

- 196 • We discuss the consequences of these changes in movement behavior with regards to  
197 energetics, encounter rates, habitat conservation, and human-wildlife conflicts.
- 198 • as temperatures get warmer, we will be pushing into the unknown portion of the surface  
199 plots
- 200 • our models don't include any physiological responses to temperature that may impact  
201 movement (e.g., hibernation)
- 202 • our models also assume the behaviour we modeled now will persist into the future  
203 (e.g., hibernation, migration)
- 204 • based on the model, temperature doesn't affect grizzlies' hibernation much, and their  
205 displacement in winter is very low due to  $P(\text{moving})$  being so low:
- 206 • if the RSS decreases a lot, individuals may disperse, populations may relocate, or stay

207 where they are and suffer

208 **4.1 Effects of temperature on mammals' movement**

209 **4.2 Effects of temperature on mammals' habitat selection**

210 **4.3 Consequences for conservation**

- 211 • improve projections at the edges of the HRSFs with local and Traditional Knowledge  
212 (**two-eyed\_seeing\_ref?**)
- 213 • changes in temperatures are pushing to areas in the surface plots that have little  
214 data and may be poorly estimated. We will need to extrapolate to prepare for future  
215 changes, which implies some degree of inevitable risk. The best way to avoid this is by  
216 designing models that are statistically sound and interpretable. The models we present  
217 provide an estimate of the changes in behavior, but they are not tailored specifically  
218 to any of the species in the dataset. Species-specific models should account for more  
219 particular variables (e.g., forest age for caribou) and use dynamic resource rasters (i.e.,  
220 not use a static estimate of forest cover). Nonetheless, we present important results for  
221 understanding how mammals will respond to changes in climate and weather during  
222 the next ~75 years.
- 223 • energetics
- 224 • GPS sampling intervals were large: need more work on fine-scale movement, including  
225 accounting for multiple movement states (e.g., traveling, grazing, resting, hunting, etc.).  
226 this would help deal with over-dispersion
- 227 • encounter rates (lower encounter rates with food (Hou *et al.*, 2020))
- 228 • HWI

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