

Rising temperatures alter how and where mammals move

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Abstract

Widespread warming during the last century has caused many terrestrial mammals to change how and where they move, with cascading effects on fitness and community dynamics. Previous studies have estimated the effects of temperature on mammalian movement behaviour, but few disentangled them from seasonal behaviour cycles. Consequently, it is still uncertain how mammals will adapt their movement behaviour throughout the 21st century. We address this gap by quantifying the effects of temperature on the movement rates and habitat selection of six large-bodied mammalian species (boreal and southern mountain caribou, cougars, elk, grizzly bears, mountain goats, and wolves) throughout western Canada between 1998 and 2023. We show that temperature significantly affected how and where these mammals moved, and we predict that climate change will impact mammals' movement behaviour throughout the 21st century. Projected responses to climate change suggested that rising temperatures will drive southern mountain caribou and mountain goats to move more, while cougars, elk, and wolves will move less. Boreal caribou and grizzly bears showed little change in projected yearly movement rates but clear shifts in seasonal phenology. We also predict that rising temperatures will reduce median habitat selection strength for four of the species, although cougars and elk are expected to show increased selection strength for higher altitudes. As mammals increasingly alter their movement rates and select against portions of their current ranges, changes in individuals' movement behaviour will impact encounter rates, including predator-prey dynamics and human-wildlife interactions. Conservation efforts should therefore account for future changes in movement behaviour as well as the consequences such changes may have on communities. Anticipating changes in mammalian movement behaviour will become crucial for effectively and proactively understanding community-level responses and selecting high-quality habitat for long-term conservation.

¹ 1 Introduction

² For most animals, movement is a rapid and low-cost response to a variety of stimuli (Nathan
³ *et al.*, 2008). Animals move to optimize resource use (e.g., food, water, shelter; Charnov,
⁴ 1976; Kacelnik *et al.*, 1992; Merkle *et al.*, 2016; Mezzini *et al.*, 2025), optimize habitat use
⁵ (Winter *et al.*, 2024), and avoid predators and competitors (Tórrez-Herrera *et al.*, 2020; Pe-
⁶ terson *et al.*, 2021; Bartashevich *et al.*, 2024; Tan *et al.*, 2024). How and where animals move
⁷ thus also determines encounter rates with resources (Mezzini *et al.*, 2025), humans (Johnson
⁸ *et al.*, 2018; Weststrate *et al.*, 2024), predators, prey, and competitors (Martinez-Garcia *et*
⁹ *al.*, 2020; Glass *et al.*, 2021; Brivio *et al.*, 2024). However, ambient temperature affects
¹⁰ animals' movement rates by altering the energetic cost of movement and thermoregulation
¹¹ (McNab, 1970; Taylor *et al.*, 1982; Brown *et al.*, 2004; Fuller *et al.*, 2016; Jahn & Seebacher,
¹² 2022), and extreme temperatures can impact animals' movement rates (Dyer *et al.*, 2023),
¹³ phenology (McLellan & McLellan, 2015; Pigeon *et al.*, 2016; Johnson *et al.*, 2018; Carbeck
¹⁴ *et al.*, 2022), and life history (Newediuk *et al.*, 2024), and even cause physiological damage
¹⁵ and death (Hetem *et al.*, 2014; Powers *et al.*, 2017; Ratnayake *et al.*, 2019; Schmidt *et al.*,
¹⁶ 2020; Schwerdt *et al.*, 2024). Animals may search for a short-term buffer from extreme
¹⁷ temperatures by moving to thermal refugia (Hannah *et al.*, 2014; Elmore *et al.*, 2017; Attias
¹⁸ *et al.*, 2018; Arechavala-Lopez *et al.*, 2019; Gulland *et al.*, 2022), and shelter may even be
¹⁹ preferred over forage abundance (Hall *et al.*, 2016). However, climate change during the last
²⁰ century (IPCC, 2023) has caused animals to alter how and where they move as they respond
²¹ to hotter temperatures and increasingly severe and frequent extreme-heat events (Bunnell
²² *et al.*, 2011; Thompson *et al.*, 2022; IPCC, 2023).

²³ Mammals are particularly susceptible to adverse effects from excessive heat (Sherwood
²⁴ & Huber, 2010). While extreme cold often leads to reduced movement, provided that in-
²⁵ dividuals can find refuge and take advantage of their body heat (Berger *et al.*, 2018; Hou
²⁶ *et al.*, 2020; Glass *et al.*, 2021), extreme heat can often result in more severe physiological

27 damage in a shorter span of time (Jessen, 2001; Sherwood & Huber, 2010; Mota-Rojas *et*
28 *al.*, 2021; Newediuk *et al.*, 2024). Mammals' homeothermy can cause them to have difficulty
29 dissipating heat, particularly when ambient temperatures are near or above body tempera-
30 ture. Larger-bodied mammals are more likely to alter their movement behaviour with rising
31 temperatures, since they tend to move long distances (Merkle *et al.*, 2016), are particularly
32 sensitive to overheating (Fuller *et al.*, 2016; Alston *et al.*, 2020; Verzuh *et al.*, 2023), and
33 their movement rates are thus strongly limited by excessive heat (Dyer *et al.*, 2023).

34 Global warming during the last century has resulted in milder and shorter winters, hotter
35 and longer summers, and a greater risk of extreme-heat events (IPCC, 2023), with widespread
36 changes in mammals' seasonal phenology, fitness, and life history (Botero *et al.*, 2015; McLel-
37 lan & McLellan, 2015; Pigeon *et al.*, 2016; Wells *et al.*, 2022; Newediuk *et al.*, 2024). How-
38 ever, behavioural responses to heat vary substantially across species depending on body size,
39 vagility, and activity times (McCain & King, 2014; Williams & Blois, 2018). For example,
40 warming temperatures have allowed deer (*Odocoileus* spp.) to shift northward, which has
41 led to increased density of wolves (*Canis lupus*) and higher predation on caribou (*Rangifer*
42 *tarandus caribou*) (Latham *et al.*, 2011; Barber *et al.*, 2018; Dickie *et al.*, 2024). Preparing
43 for and responding to future changes will require a detailed understanding of not only how
44 how and where mammals move throughout the thermal landscape but also the cascade of
45 effects that such changes will have at the population and community levels (Cunningham *et*
46 *al.*, 2021).

47 As heat stress intensifies throughout the 21st century, mammals will continue to suffer
48 impacts on their fitness, movement rates, and habitat selection (Deb *et al.*, 2020; Woo-
49 Durand *et al.*, 2020). It remains unclear how or whether species will be able to respond to
50 climate change in the current century (Deb *et al.*, 2020; Woo-Durand *et al.*, 2020; Verzuh
51 *et al.*, 2023), especially if populations fail to adapt (Botero *et al.*, 2015; Sawyer *et al.*, 2019)
52 or are physiologically incapable to do so (Sherwood & Huber, 2010; Botero *et al.*, 2015;
53 Williams & Blois, 2018). Recent work has documented the effects of climate change on

54 mammals' ranges (Leclerc *et al.*, 2021), thermoregulation (Mota-Rojas *et al.*, 2021), and
55 movement behaviour (McCain, 2019; Cunningham *et al.*, 2021; Melin *et al.*, 2023), but there
56 remains a need for fine-scale estimates of the effects of temperature on mammals' movement
57 behaviour and quantitative predictions of future changes in movement behaviour.

58 In this paper, we quantify the effects of proximal air temperature on mammalian move-
59 ment behaviour, namely movement rates and habitat selection of six large-bodied terrestrial
60 mammal species in western Canada (boreal and southern mountain caribou, cougars: *Puma*
61 *concolor*, elk: *Cervus canadensis*, grizzly bears: *Ursus arctos horribilis*, mountain goats:
62 *Oreamnos americanus*, and wolves; Table 1). Western Canada is currently experiencing
63 accelerating and widespread but spatially heterogeneous warming (Turner & Clifton, 2009;
64 Kienzle, 2018; Dierauer *et al.*, 2021), phenological shifts (plants: Post & Forchhammer,
65 2008; Tysor, 2025; ice: Basu *et al.*, 2024), and more frequent and intense extreme heat
66 events (Zhang *et al.*, 2023). Decision makers must understand which areas will best sustain
67 and protect biodiversity not only for current conditions but future decades, too. Failing to
68 understand how climate change will affect mammalian movement behaviour will hinder our
69 ability to respond to the current climate crisis and make decisions that are viable in the long
70 term. Furthermore, understanding how temperature affects individual species is the first
71 step towards understanding how temperature impacts the community dynamics (Hegel *et*
72 *al.*, 2010; Cunningham *et al.*, 2021; Carbeck *et al.*, 2022) and habitat phenology (Bunnell *et*
73 *al.*, 2011; Duncan *et al.*, 2012; Merkle *et al.*, 2016; Slatyer *et al.*, 2022; Gerlich *et al.*, 2025),
74 and how these changes will impact mammals in the coming decades (Sobie *et al.*, 2021; Eum
75 *et al.*, 2023; Weststrate *et al.*, 2024).

Table 1: Summary statistics of each species' set of GPS data, namely: the start and end of each set of GPS telemetry data, the number of GPS fixes (after data cleaning), the median sampling interval (Δt ; stratified by animal), the number of animals (Animals), and the number of animals with finite speed estimates (Has speed).

Species	Start	End	Fixes	Δt (hours)	Animals	Has speed
Caribou (boreal)	2011-03-02	2018-01-03	200,561	13.00	146	131

Species	Start	End	Fixes	Δt (hours)	Animals	Has speed
Caribou (southern mountain)	1998-03-20	2009-06-06	27,921	6.00	22	20
Cougars	2006-02-04	2021-07-12	80,650	2.00	29	29
Elk	2007-01-13	2013-11-19	875,853	2.00	169	169
Grizzly bears	2004-09-29	2009-09-07	39,021	1.00	18	18
Mountain goats	2019-06-24	2023-10-04	65,452	6.25	11	10
Wolves	2013-01-26	2017-08-29	202,433	0.25	39	39

76 2 Methods

77 2.1 Datasets used

78 In this study, we estimate how temperature affected mammals' probability of moving,
 79 speed when moving, and habitat selection by leveraging three datasets: (1) a multi-species
 80 collection of 25 years of GPS telemetry data throughout a large spatial range of western
 81 Canada (Fig. 1), (2) historical, hourly air temperature data from the ERA5 reanalyzed
 82 dataset (Hersbach *et al.*, 2023), and (3) temporally static rasters of percent forest cover,
 83 elevation, and distance from water. We then forecast each species' movement behaviour
 84 throughout the 21st century using monthly climate change projections under four Shared
 85 Socioeconomic Pathways (SSPs; Riahi *et al.*, 2017; Mahony *et al.*, 2022): SSP 1-2.6 ("Sus-
 86 tainability – Taking the Green Road"; low challenges to mitigation and adaptation), SSP
 87 2-4.5 ("Middle of the Road: medium challenges to mitigation and adaptation"), SSP 3-7.0
 88 ("Regional Rivalry – A Rocky Road"; high challenges to mitigation and adaptation), and
 89 SSP 5-8.5 ("Fossil-fueled Development – Taking the Highway"; high challenges to mitigation,
 90 low challenges to adaptation).

91 We acknowledge that our models of habitat selection ignore many important variables of
 92 habitat selection (e.g., forest type, structure, and age; terrain slope and aspect; prey avail-
 93 ability; population density). We limited our models to only use three simple and temporally
 94 static rasters to produce simple and easily interpretable estimates and forecasts under the
 95 assumption of temporally invariant landscapes.

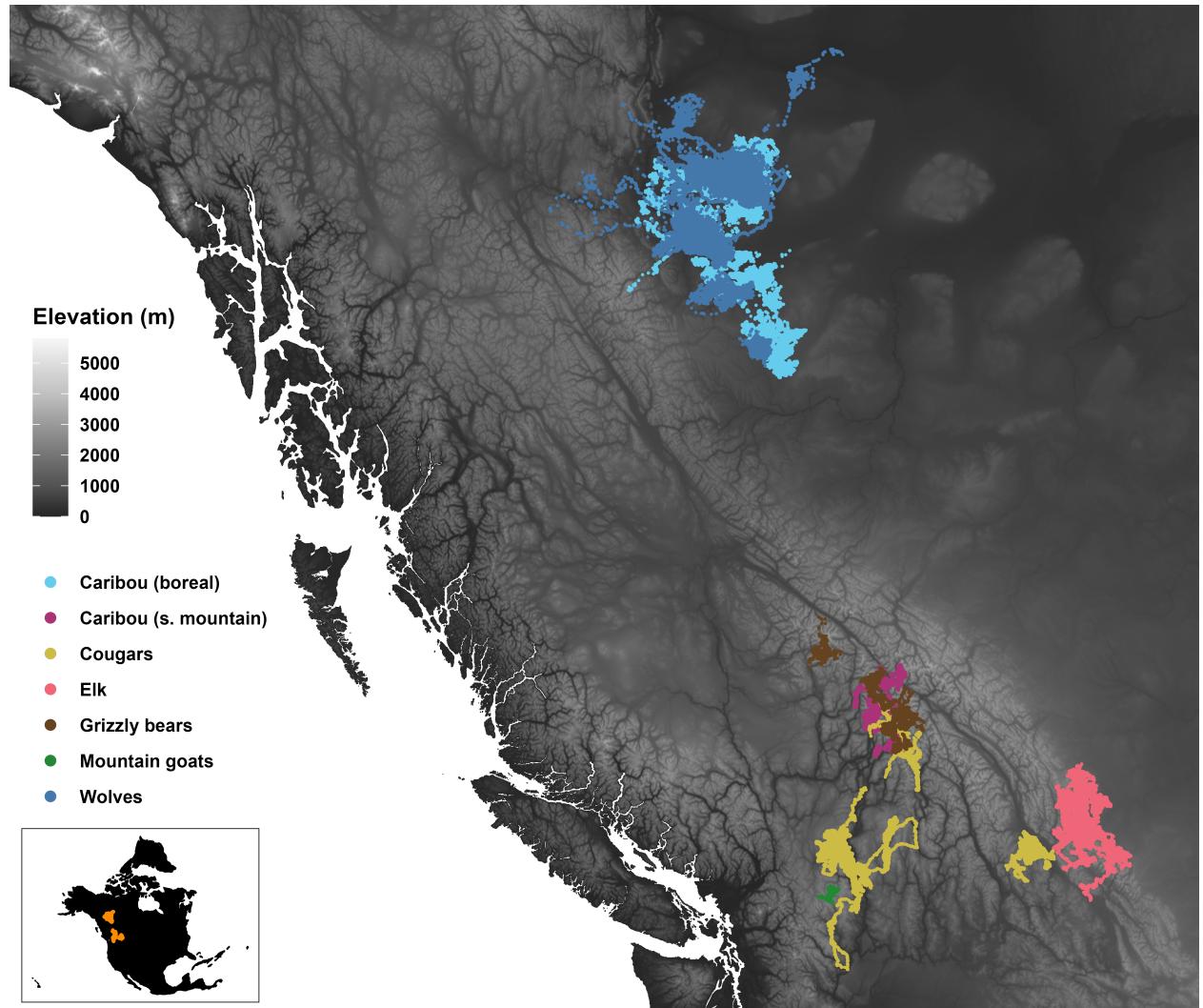


Figure 1: GPS telemetry data for the six species in this study (dots) over a digital elevation model for the study area. The inset in the bottom left shows the telemetry data within the north american continent. Both maps use the BC Albers Equal Area Conic projection (EPSG:3005).

96 **2.1.1 GPS telemetry data**

97 Boreal caribou and wolf telemetry data were acquired from a data repository of the British
98 Columbia Oil and Gas Research and Innovation Society (BC ORGIS) that was collected as
99 part of the boreal caribou radio-collaring program of the BC OGRIS Research and Effec-
100 tiveness Monitoring Board (REMB; BC OGRIS, 2018). Southern mountain caribou data
101 were obtained from Ford *et al.* (2023). Cougar data are from Darlington *et al.* (2025) and
102 (**serrouya_ref?**). Elk data from the work of Ciuti *et al.* (2012) were downloaded from
103 Movebank (Kays *et al.*, 2022). Finally, grizzly bear telemetry data are from (**ref?**), while
104 mountain goat data are from (**ref?**).

105 From the full set of telemetry data, we removed 2,396 problematic GPS locations (0.16%,
106 including collar calibration data) after inspecting diagnostic plots of (1) distance from the
107 median location, (2) straight-line displacement between locations, (3) turning angle, and
108 (4) time interval between consecutive points. Particular attention was paid to points with
109 large turning angles ($\gtrapprox 170^\circ$) and excessively high straight-line displacement, especially if
110 antecedent and subsequent points indicated relatively stationary behaviour (Appendix A).

111 **2.1.2 Historical temperature data and climate change projections**

112 Rasters of hourly air temperature data were downloaded from the ERA5 database (Hers-
113 bach *et al.*, 2023) from the European Center for Medium-range Weather Forecasting server
114 (ECMWF; www.ecmwf.int; <https://cds.climate.copernicus.eu>). Proximal air temperature
115 was estimated for each location by extracting the value from the corresponding raster cell
116 from the temporally nearest raster using the `extract()` function from the `terra` package
117 (v. 1.7-46, Hijmans, 2023) for `R` (R Core Team, 2024).

118 To obtain projected average monthly temperatures from 2025 to 2100 at a 0.08° spatial
119 resolution, we used the `climatenetR` package (v. 1.0, Burnett, 2023) for `R` and ClimateNA
120 v. 7.4.2 (Wang *et al.*, 2016; Mahony *et al.*, 2022). However, the climate projections only
121 included estimates of future monthly averages, a scale substantially coarser than that of our

tracking data (Table 1). To estimate the distribution of temperatures at an hourly scale within a month, we assumed values to be approximately normally distributed with mean μ_T and variance σ_T^2 . We estimated μ_T using the ClimateNA projections, while we estimated σ_T^2 by modeling the observed variance in historical weather data for western Canada from 1998 to 2023 (inclusive). For each location $\langle x, y \rangle$ and month m of each year (e.g., the observed variance at coordinates $\langle -119.40, 49.94 \rangle$ in April 2005), we calculated the variance in historical temperature data, for a total of $(2024 - 1998) \times 12 = 312$ observations per location. We then modeled σ_T^2 a Generalized Additive Model (GAM) for Location and Scale (GAMLS, Rigby & Stasinopoulos, 2005; Stasinopoulos & Rigby, 2007; section 7.9 in Wood, 2017) fitted with the `mgcv` package for R (v. 1.9-1, Wood, 2017). The linear predictor for the location (i.e., the mean) included smooth terms of: each year's estimated within-pixel monthly mean temperature ($\hat{\mu}_T$), month (m), a two-dimensional smooth of spatial coordinates $\langle x, y \rangle$, and a tensor product interaction term of month and space to allow for seasonal terms to vary smoothly over space. The linear predictor for the scale term, which governs the mean-variance relationship (table 3.1 on p. 104 of Wood, 2017), included smooth terms of the monthly mean temperature, month, and space. We did not include smooth terms of year to avoid unrealistic projections when extrapolating beyond past 2023. The complete model for the distribution of projected temperature was thus

$$\left\{ \begin{array}{l} T \sim \text{Normal}(\mu_T, \sigma_T^2) \\ \mu_T \approx \hat{\mu}_T \text{ as projected by ClimateNA} \\ \sigma_T^2 \sim \text{Gamma}(\mu_{\sigma_T^2}, \nu_{\sigma_T^2}) \\ \mathbb{E}(\sigma_T^2) = \mu_{\sigma_T^2} \\ \mathbb{V}(\sigma_T^2) = (\mu_{\sigma_T^2})^2 / \nu_{\sigma_T^2} \\ \log(\mu_{\sigma^2}) = \beta_{L,0} + f_{L,1}(\mu_T) + f_{L,2}(m) + f_{L,3}(x, y) + f_{L,4}(x, y, m) \\ \log(\nu_{\sigma^2}) = \beta_{S,0} + f_{S,1}(\mu_T) + f_{S,2}(m) + f_{S,3}(x, y) \end{array} \right. , \quad (1)$$

where $\mu_{\sigma_T^2}$ and $\nu_{\sigma_T^2}$ indicate the location and scale parameters of the gamma distribution of σ_T^2 , and together they determine the variance of σ_T^2 , indicated as $\mathbb{V}(\sigma_T^2)$. Functions $f_{L,j}$ and $f_{S,j}$ indicate the j^{th} smooth functions for the location and scale parameters, respectively. To ensure the smooth functions of month, $f_{L,2}(m)$ and $f_{S,2}(m)$, joined smoothly between December and January, the terms use cyclic cubic spline bases. The spatial terms used two-dimensional Duchon splines, a generalization of thin-plate regression splines (p. 221 of Wood (2017)). The smoothness parameters were estimated via REstricted Maximum Likelihood (REML; p. 83 of Wood, 2017). See the Data Availability Statement for additional information on the code used to fit the model.

We simulated hourly variation in future years by assuming hourly temperature followed a normal distribution with mean specified by the monthly `climatenar` climate projections and variance as specified by the gamma GMLS. For each month within each year from 2025 to 2100, we simulated hourly weather by including temperatures from the 0.1 to the 0.9 quantiles by increments of 0.1, and we weighted each quantile proportionally to the normalized Gaussian probability density for each quantile.

2.1.3 Habitat rasters

We estimated percent forest cover and distance from water using the temporally static rasters created by Tuanmu & Jetz (2014). We calculated total forest cover by summing the four rasters of evergreen/deciduous needle-leaf trees, evergreen broadleaf trees, deciduous broadleaf trees, and mixed/other trees (raster classes 1-4, respectively). We converted the raster of percent cover of open water (class 12) to a binary raster of pixels with water (cover > 0%) or without water (cover = 0%) and then calculated each pixel's distance from the nearest pixel with water using the `distance()` function from the `terra` package. Finally, we obtained two digital elevation models using the `get_elev_raster()` function from the `elevatr` package (v. 0.99.0, Hollister *et al.*, 2023). We used a raster with a zoom of 6 (a resolution of 0.009°) for model fitting and one with a zoom of 3 (a resolution of 0.08°)

166 for downloading climate change projections via `climatenetR`. All final rasters and code are
167 available on GitHub (see the Data Availability Statement). For ease of interpretability and
168 comparison with current conditions, we assumed resources would remain constant through
169 to 2100, although we recognize that the spatial distribution of forest cover and open water
170 will change throughout the 21st century.

171 **2.2 Estimating mammals' instantaneous speeds**

172 We modeled each animal's movement using continuous-time movement models (Fleming
173 *et al.*, 2014) via the `ctmm` package (v. 1.2.0, Fleming & Calabrese, 2023) for R. We then
174 estimated each mammal's instantaneous speed at each observed location by applying the
175 `ctmm::speeds()` function on all models with finite speed estimates (415 of 433; Fleming *et*
176 *al.*, 2014; Noonan *et al.*, 2019a). The remaining 18 movement models had sampling rates that
177 were too coarse, relative to the animals' directional persistence, to reconstruct the animals'
178 movement trajectories (Noonan *et al.*, 2019a; Nathan *et al.*, 2022; DeNicola *et al.*, 2025).
179 The models were for one mountain goat, 15 boreal caribou, and two southern mountain
180 caribou (Table 1).

181 Since `ctmm`'s movement models assume a single moving state with stochastic but non-zero
182 speed (Calabrese *et al.*, 2016; Noonan *et al.*, 2019a), we corrected data-informed speeds so
183 that the minimum instantaneous speed could be 0. We performed this correction by sub-
184 tracting each model's mean speed while assuming speeds were χ^2 -distributed. The function
185 we used is available on GitHub (see the Data Availability Statement). To avoid artifacts
186 due to excessively small, non-zero speeds, we determined whether an animal was moving or
187 not using a *k*-means algorithm with 2 clusters for each species' distribution of detrended
188 speeds. When the algorithm clearly failed to discriminate between states, we estimated the
189 split point using the inflection points in histograms of the detrended speeds (Fig. B1).

190 **2.3 Estimating the effects of temperature on mammals' movement behaviour**

191 Ambient temperature is only one of the many drivers of mammalian movement behaviour
192 (Fig. 2). Many species alter their movement rates (e.g., movement frequency and speed)
193 daily or seasonally in response to factors such as solar time, photoperiod, forage availability,
194 reproductive cycles, and predator avoidance. Similarly, ambient temperature also fluctuates
195 throughout the day and across seasons. Therefore, estimating the effects of temperature
196 on movement rates requires accounting for how mammals' response to temperature changes
197 with time of day and day of year (Fig. 2A; Péron *et al.*, 2017; Buderman *et al.*, 2018; Leclerc
198 *et al.*, 2021; Xu *et al.*, 2021). Similarly, mammals' selection strength for resources depends
199 on ambient temperature, since higher temperatures can promote a selection for refuge from
200 heat (e.g., thicker forest cover, higher elevation, proximity to water; Attias *et al.*, 2018;
201 Giroux *et al.*, 2023).

202 To assess the importance of including temperature as an explicit covariate (as opposed
203 to including its effects with time of day and day of year), we fit models with and without
204 smooth effects of temperature and compared the fits of the two sets of models via analyses
205 of deviance (a form of generalized likelihood ratio tests) following the methods of Section
206 3.3 in Wood (2017). See Appendix B for additional information.

207 **2.3.1 Effects of temperature on movement rates**

208 We estimated the effects of temperature on mammals' instantaneous movement state (mov-
209 ing or not) and speed when moving using two Hierarchical Generalized Additive Models
210 (HGAMs; Pedersen *et al.*, 2019 and Appendix B) with the `mgcv` package for R. The first
211 HGAM estimated the probability that an animal was moving, $P(M)$, with a binomial fam-
212 ily of distributions and logit link function. The second HGAM estimated an animal's speed
213 when moving with a gamma family of distributions and log link function. We fit the models
214 with fast Restricted Maximum Likelihood ('fREML') and discretized covariates (`discrete =`
215 `TRUE`) to optimize computational efficiency with no appreciable losses to model performance

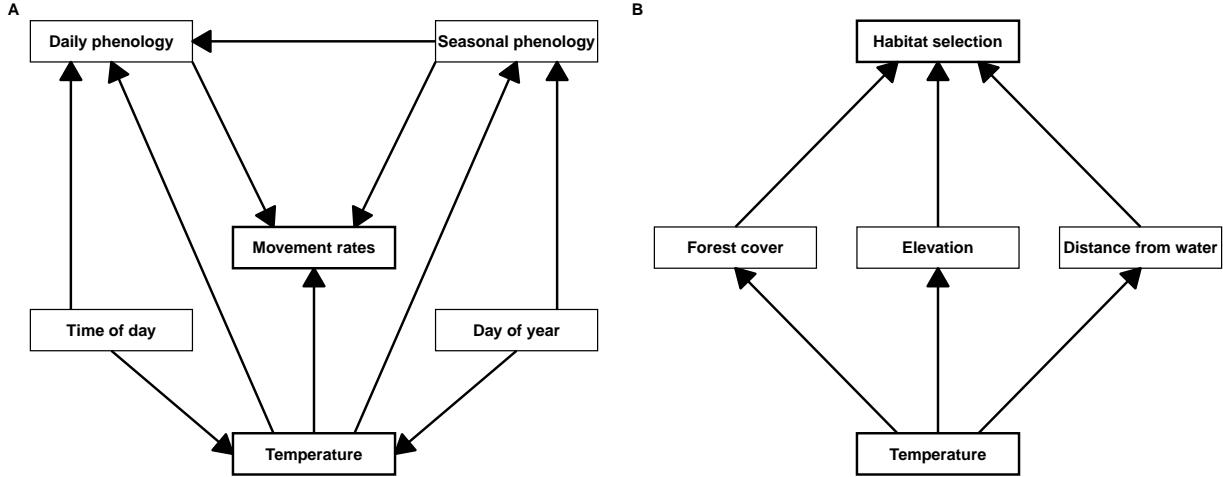


Figure 2: Directed Acyclical Graphs (DAGs) assumed for inferring the causal effects of temperature (red) on each species' movement behaviour. (A) Ambient temperature affects mammals' movement rates (i.e. probability of moving, speed when moving, and their product: hourly distance traveled). The effects of temperature on mammals' movement rates depend on daily and seasonal phenology, since animals may respond to temperatures differently at different times of day and or days of year. Additionally, both temperature and phenology depend on time of day and day of year. Finally, daily phenology changes with seasonal phenology due to changes in photoperiod (e.g., the time of twilight changes throughout the year, affecting crepuscular activity). (B) Similarly, habitat selection depends on the availability and selection of habitat variables (forest cover, elevation, and distance from water), but the selection strength for each variable is conditional on temperature. For example, an animal may select for more densely-forested areas at extreme temperatures.

216 (Appendix B; Wood *et al.*, 2015, 2017; Li & Wood, 2020). Together, the binomial HGAM
 217 and the gamma HGAM inform us on an animal's long-term average speed, since it is the
 218 product of the probability of moving and its average speed when moving.

219 The HGAMs (equations (2) and (3)) included fixed-effect intercepts for each species
 220 (β_s), random intercepts for each animal (Z_a), and species-level by smooths that allowed
 221 independent smoothness parameters for each species (model I in Figure 4 of Pedersen *et*
 222 *al.*, 2019). The by smooths accounted for trends in time of day (in Pacific Daylight Time;
 223 `tod_pdt`), day of year (`doy`), and temperature (`temp_c`). To account for the cyclicity of time
 224 of day and day of year, the smooth terms used cyclic cubic splines (p. 202 of Wood, 2017).
 225 The models also had three tensor product interaction terms by each species: (1) day of year
 226 and time of day, (2) temperature and time of day, and (3) temperature and day of year.
 227 These three terms accounted for smooth changes in: (1) daily behaviour across day of year,
 228 (2) the response to temperature over time of day (e.g., changes in nocturnality), and (3)

229 the response to temperature over day of year (e.g., the timing of molting, migration, and
 230 hibernation). Finally, two smooth terms of log-transformed sampling interval (dt ; hours)
 231 corrected for biases in speed estimates arising from irregular GPS sampling intervals, since
 232 longer intervals result in lower speed estimates (Nathan *et al.*, 2022; DeNicola *et al.*, 2025).
 233 A global smooth term of $\log(\text{dt})$ accounted for the overall effect of sampling interval, while
 234 a factor-smooth interaction term ($\text{bs} = \text{'fs'}$) of $\log(\text{dt})$ and species accounted for species-
 235 level deviations from the global term while assuming a common smoothness parameter across
 236 species (model GS in Figure 4 of Pedersen *et al.*, 2019). Formally, the model for movement
 237 state M , with $M = 0$ indicating no movement and $M = 1$ indicating movement, was

$$\left\{ \begin{array}{l} M \sim \text{Bin}(p) \\ \mathbb{E}(M) = p \\ \mathbb{V}(M) = p(1-p) \\ \log(p) = \beta_s + Z_a + f_{1,s}(\text{tod_pdt}) + f_{2,s}(\text{doy}) + f_{3,s}(\text{temp_c}) + \\ f_{4,s}(\text{doy}, \text{tod_pdt}) + f_{5,s}(\text{temp_c}, \text{tod_pdt}) + f_{6,s}(\text{temp_c}, \text{doy}) + \\ f_7(\log(\text{dt})) + f_{8,s}(\log(\text{dt})) \end{array} \right. , \quad (2)$$

238 while the model for movement speed when moving (i.e., $M = 1$, indicated with S) was

$$\left\{ \begin{array}{l} S \sim \text{Gamma}(\mu_S, \nu_S) \\ \mathbb{E}(S) = \mu_S \\ \mathbb{V}(S) = \mu_S^2 / \nu_S \\ \log(\mu_S) = \beta_s + Z_a + f_{1,s}(\text{tod_pdt}) + f_{2,s}(\text{doy}) + f_{3,s}(\text{temp_c}) + \\ f_{4,s}(\text{doy}, \text{tod_pdt}) + f_{5,s}(\text{temp_c}, \text{tod_pdt}) + f_{6,s}(\text{temp_c}, \text{doy}) + \\ f_7(\log(\text{dt})) + f_{8,s}(\log(\text{dt})) \end{array} \right. . \quad (3)$$

239 In both models, β_s indicates a fixed intercept for species s , Z_a indicates a Gaussian random
240 effect for animal a (of species s), $f_{j,s}$ indicates the j^{th} smooth function for species s , and
241 functions with two variables indicate tensor product interaction terms. The model code used
242 to fit the models is available in Appendix B.

243 **2.3.2 Effects of temperature on habitat selection**

244 We estimated the effects of temperature on each species' selection for percent forest
245 cover (`forest_perc`), elevation (`elevation_m`, in meters), and distance from water
246 (`dist_water_m`, in meters) by fitting a Hierarchical Resource Selection Function (HRSF) for
247 each species (McCabe *et al.*, 2021). We fit each HRSF using an HGAM with a Poisson family
248 of distributions and log link function (Appendix B; Aarts *et al.*, 2008). After removing
249 non-resident individuals (Table B1), we accounted for the spatiotemporal autocorrelation
250 in the telemetry locations by weighting each point based on the telemetry's Autocorrelated
251 Kernel Density Estimate (Fleming & Calabrese, 2017; Noonan *et al.*, 2019b; Alston *et al.*,
252 2022) to produce estimates of second-order habitat selection (Johnson, 1980). Quadrature
253 points were used to approximate the likelihood function of a Poisson point process through
254 Monte-Carlo Markov chain-based integration (Aarts *et al.*, 2008; Fithian & Hastie, 2013;
255 Baddeley *et al.*, 2015) and were determined using the raster cells in each animal's 99.9%
256 AKDE percentile, with each raster cell having a weight of 1. The number of quadrature
257 locations greatly outnumbered the number of observed locations (Fig. B12), especially after
258 accounting for the AKDE weights (Fig. B13).

259 Each species' model had the same structure:

$$\left\{ \begin{array}{l} O \sim \text{Pois}(\lambda) \\ \mathbb{E}(O) = \mathbb{V}(O) = \lambda \\ \log(\lambda) = f_1(\text{forest_perc}) + f_2(\text{elevation_m}) + f_3(\text{dist_water_m}) + \\ Z_a + f_{4,a}(\text{forest_perc}) + f_{5,a}(\text{elevation_m}) + f_{6,a}(\text{dist_water_m}) + \\ f_7(\text{forest_perc}, \text{temp_c}) + f_8(\text{elevation_m}, \text{temp_c}) + \\ f_9(\text{dist_water_m}, \text{temp_c}) + f_{10}(\text{temp_c}) + f_{11,a}(\text{temp_c}) \end{array} \right. , \quad (4)$$

where O indicates whether an animal was observed ($O = 1$) or not ($O = 0$), and the species-level indices are omitted for readability, but each term in the model can be assumed to be species-specific. Smooth effects of percent forest cover (`forest_perc`), elevation (`elevation_m`, in meters), and distance to water (`dist_water_m`, in meters) accounted for the species-level selection strength for each resource. A Gaussian random effect for each individual animal (Z_a) corrected for uneven sampling across individuals, while factor-smooth interaction terms for each animal ($f_{j,a}$) accounted for animal-level resource selection (i.e., individual-level deviations from the species-level estimate; Jeltsch *et al.*, 2025). Tensor product interaction terms of the three resources and temperature (`temp_c`) estimated the smooth change in resource selection at different temperatures. Finally, marginal smooth terms of temperature and factor-smooth interaction terms of temperature and animal accounted for species- and individual-level sampling biases at different temperatures (e.g., sampling more during warm periods).

3 Results

Of the GPS fixes with finite speed estimates, 2.6% had temperatures lower than -20°C , while 6.5% had temperatures above 20°C , and temperature ranges differed across species (Table 2, Fig. B2). Sampling interval affected estimates of probability as well of as speed when

moving (Fig. B8). All species' estimated probability of moving and speed when moving decreased with sampling intervals above 1 hour, except for cougars' speed, although the estimated trends were highly uncertain (Fig. B8). Consequently, we present all results while predicting specifically for one-hour sampling intervals. At 0°C, species differed in estimated mean probabilities of moving ($\hat{P}(M = 1)$; range: 0.05 – 0.31), mean speed when moving ($\hat{\mathbb{E}}(S|M = 1)$; range: 0.42 – 2.67 km/h), and mean overall speed (i.e., $\hat{P}(M) \times \hat{\mathbb{E}}(S|M = 1)$, range: 0.04 – 0.61 km/h; Table 2). Grizzly bears had the lowest movement frequency ($\hat{P}(M) \approx 0.05$), while wolves and cougars moved most often ($\hat{P}(M) \geq 0.22$). Mountain goats and southern mountain caribou moved the slowest ($\hat{\mathbb{E}}(S|M = 1) \approx 0.43$ km/h), while wolves had the highest mean speed when moving ($\hat{\mathbb{E}}(S|M = 1) \approx 2.67$ km/h). Consequently, at 0°C, wolves traveled an average of 0.22×2.67 km/h ≈ 0.6 km/h; 2.5 to 16.7 times further than other species.

Table 2: Summary statistics for each species' GPS fixes with finite speed estimates, namely: the number fixes after data cleaning (n), the percentage of fixes with temperature (T) below -20°C and above 20°C , the estimated mean probability of moving ($\hat{P}(M = 1)$), the mean speed when moving ($\hat{\mathbb{E}}(S|M = 1)$; km/h), and the mean hourly distance travelled ($\hat{P}(M = 1) \times \hat{\mathbb{E}}(S|M = 1) = \hat{\mathbb{E}}(D)$; km/h), for a sampling interval of 1 hour and a temperature of $T = 0^{\circ}\text{C}$.

Species	n	T < -20°C (%)	T > +20°C (%)	$\hat{P}(M = 1 T)$	$\hat{\mathbb{E}}(S M = 1, T)$	$\hat{\mathbb{E}}(D T)$
Caribou (boreal)	187,679	6.8	7.9	0.18	0.73	0.13
Caribou (s. mountain)	26,518	1.3	3.4	0.11	0.42	0.05
Cougars	80,621	0.7	6.9	0.31	0.76	0.24
Elk	875,682	2.4	4.9	0.17	0.57	0.10
Grizzly bears	39,001	0.0	8.4	0.05	0.72	0.04
Mountain goats	65,219	0.7	2.8	0.13	0.42	0.06
Wolves	202,386	1.7	13.0	0.22	2.67	0.60
Total	1,477,106	2.6	6.5			

Across all species, Relative Selection Strength (RSS) was weakest for forest cover and strongest for elevation. At temperatures near 0°C, boreal caribou selected for forest cover between 50% and 75%, elevations near 500 m, and distances from water < 10 km, while southern mountain caribou selected for dense forest cover, elevations near 2 km, and distances from water $\lesssim 5$ km. Cougars selected for dense forest cover ($> 75\%$), an elevation of ~ 1

km, and distances from water < 7.5 km. Elk selected for intermediate forest cover (\approx 50%), elevations between 1 and 2 km, and distances from water of 10-15 km. Grizzly bears selected for relatively sparse forest cover (25-50%), elevation between 1 and 2 km, and distances from water < 3 km. Mountain goats selected for sparse forest cover (< 25%), elevations near 1.5 km, and distances from water < 5 km. Finally, wolves selected for forest cover (\gtrapprox 50%), elevations near 1 km, and distances from water < 5 km. There was relatively strong agreement between models with and without temperature (Figs. B3, and B14), but including temperature always resulted in better fits (all p-values $< 2.2 \times 10^{-16}$; all $\Delta AIC \geq 342$; Appendix B). Accounting for temperature even resulted in a simpler HRSF for mountain goats (lower model degrees of freedom due to simpler smooth terms) that fit the data better (lower deviance), and hence no test was necessary to show that the inclusion of temperature produced a better fit.

3.1 Effects of temperature on movement rates

Species' changes in movement rates to temperature varied in both direction and magnitude (Figs. 3, B4-B6), even after accounting for differences in daily and seasonal activity (e.g., sleeping, migration, hibernation; Figs. B4-B6). Smooth interaction terms were well-behaved and indicated clear shifts in activity over time of day and day of year for all species. The models had good in-sample prediction (Fig. B7) and explained reasonably high proportions of the deviance [79.3% for the gamma model and 10.7% for the binomial model, which is relatively high for a binomial model with binary responses]. All species altered their daily and seasonal movement behaviour to changes in temperature (Fig. 3). The response was most visible in cougars. In late spring (June 1st), they moved from evening to early morning if hourly temperatures were below 20°C, but if temperatures were above 20°C they moved mostly between 3:00 and 6:00 AM. Throughout the year, they tended to move more when it was colder, but what they perceived as "colder" was relative to the time of year. Overall, uncertainty around the estimated effects was generally higher at extreme temperatures due

320 to lower data availability (Figs. B4A, B5A, and B6A).

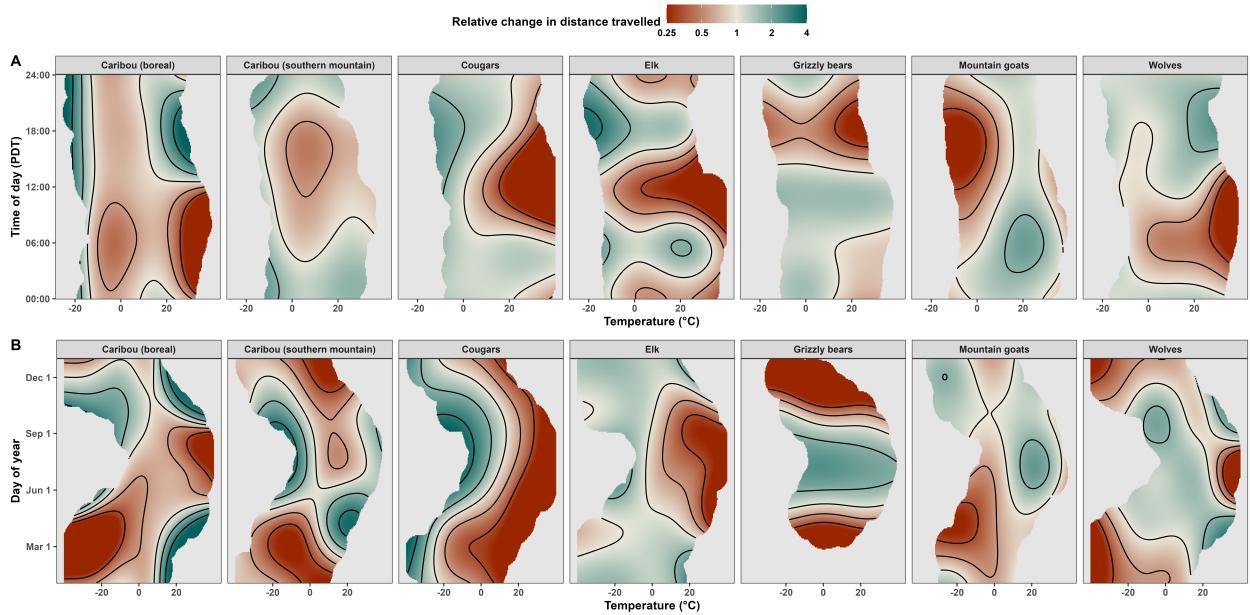


Figure 3: **Temperature is a strong driver of how far and when mammals travel.** The fill indicates the effects of temperature on the relative change in hourly distance travelled (probability of moving times mean speed when moving) over time of day on June 1st (**A**) and day of year at 12:00 PDT (**B**). Predictions in the surface plots extend to 10% of the range away from each datum. The color bar is on the log₂ scale to help visualize patterns in doubling, and values are capped to $2^{\pm 2}$ for ease of readability.

321 3.2 Effects of temperature on habitat selection

Species' RSS was generally strongest for elevation and weakest for forest cover, but RSS depended significantly on temperature for all species (all p-values < 2.2×10^{-16} ; Fig. 4). Changes in RSS with temperature were strongest for elevation and generally weakest for distance from water, but there were no common trends across all species for any of the three resources. All species except cougars exhibited clear temperature-dependent shifts in their preference for forest cover. At higher temperatures, wolves relaxed their preference for forested areas, while mountain goats relaxed their preference for open areas (cover < 50%). As temperatures warmed, elk and boreal caribou shifted towards more forest cover closer to 50%, while southern mountain caribou and grizzly bears selected for areas with 50% forest cover or less. All species shifted elevationally with temperature, although boreal caribou had a much sharper change in RSS across elevation. Elk, mountain goats, and cougars

moved to higher elevations with temperature, while wolves, southern mountain caribou, and grizzly bears moved to lower elevations. Wolves, elk, and southern mountain caribou moved closer to water with temperature, while mountain goats, cougars, and grizzly bears moved somewhat further away from water but remained mainly within 5-10 km of water. As with movement rates, estimated RSS was generally most uncertain at extreme temperatures, for which data were scarcer (Fig. B15).

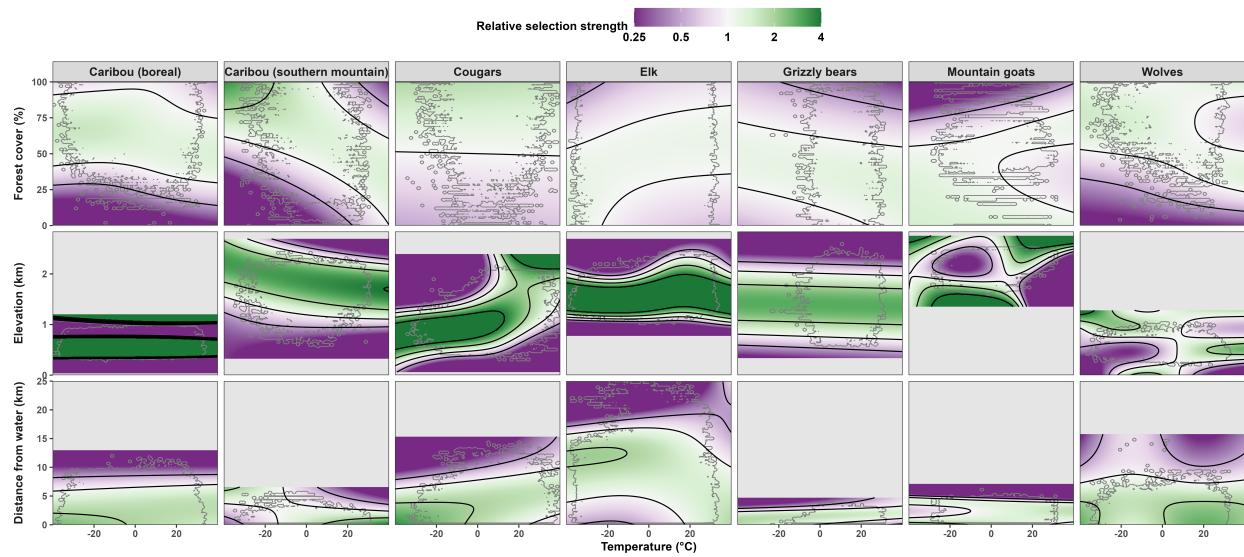


Figure 4: Mammals' habitat selection depends on ambient temperature. Estimated relative selection strength (RSS) for forest cover (%), elevation (km), and distance from water (km) as a function of temperature. The grey contours indicate the extent of each species' observed data. RSS values were re-centered and capped to between 0.25 and 4 ($2^{\pm 2}$) to improve readability.

The three habitat variables were nonlinearly correlated. Within the boreal caribou range (Fig. 5A), locations with an elevation of 0.9-1.1 km had a median forest cover of 100% and a median distance to water of 1.8 km. In contrast, elevations above 1750 m did not have forest cover above 90% and had a median distance to water of 1.5 km. Local predictions of RSS revealed that boreal caribou and wolves selected for similar habitats (Fig. 5B), but caribou tended to avoid the river system that wolves strongly selected for. Both species selected for the same loop of low-elevation habitat (< 500 m), but their selection strength for the area varied with temperature. For caribou, selection for the area was stronger at -20°C and weaker at warmer temperatures, while, for wolves, selection was stronger at +20°C. Both species' HRSFs indicated selection against elevations approximately between 0.5 km and 0.9

349 km but selection for elevations approximately above 0.9 km. After data cleaning and the
350 removal of non-range-resident animals, the highest observed elevations were 1 km for caribou
351 and 1.733 km for wolves. Quadrature points had maximum elevations of 1.1 km for caribou
352 and 1.3 km for wolves.

353 **3.3 Predicted changes in movement behaviour during the 21st century**

354 Predicted changes in movement rates with future climate change varied across species in both
355 magnitude and direction, but worse SSPs always corresponded to greater absolute changes
356 (Fig. 6). Additionally, species that were predicted to move less often did not necessarily
357 have lower speeds when moving, and vice versa (Figs. B9 and B10). Estimated changes in
358 average yearly distance traveled were negligible for boreal caribou and grizzly bears, although
359 both species showed seasonal changes in seasonal movement rates. As temperatures warmed,
360 boreal caribou were predicted to move more in winter, spring, and fall but less in summer
361 (Fig. 3), while grizzly bears were predicted to show a clear shift towards earlier emergence
362 from hibernation (Fig. B4) and greater movement earlier in the year but less movement in
363 early fall. Southern mountain caribou and mountain goats are projected to travel further by
364 2100, although the estimates for southern mountain caribou varied greatly over space (Fig.
365 7). Cougars, elk, and wolves were projected to move less by 2100, with cougars showing as
366 much as a 24% decrease in mean yearly distance travelled.

367 Absolute relative changes in predicted yearly distance travelled were small under the
368 best-case SSP (0-4% change in 2100 relative to 2025). Under the worst-case SSP, absolute
369 changes by 2100 (relative to 2025) ranged from ~2% (grizzly bears) to ~24% (cougars).
370 Projected changes in 2100 varied spatially due to spatial heterogeneity in climate change
371 projections (Fig. 7). Again, absolute changes were generally greatest under worse SSPs, but
372 the direction of change at each location also varied across SSPs (most visible in cougars).

373 Median RSS was projected to decrease over time within each species' observed range, but,
374 again, changes were stronger under worse SSPs (Fig. 8). Decreases were most pronounced

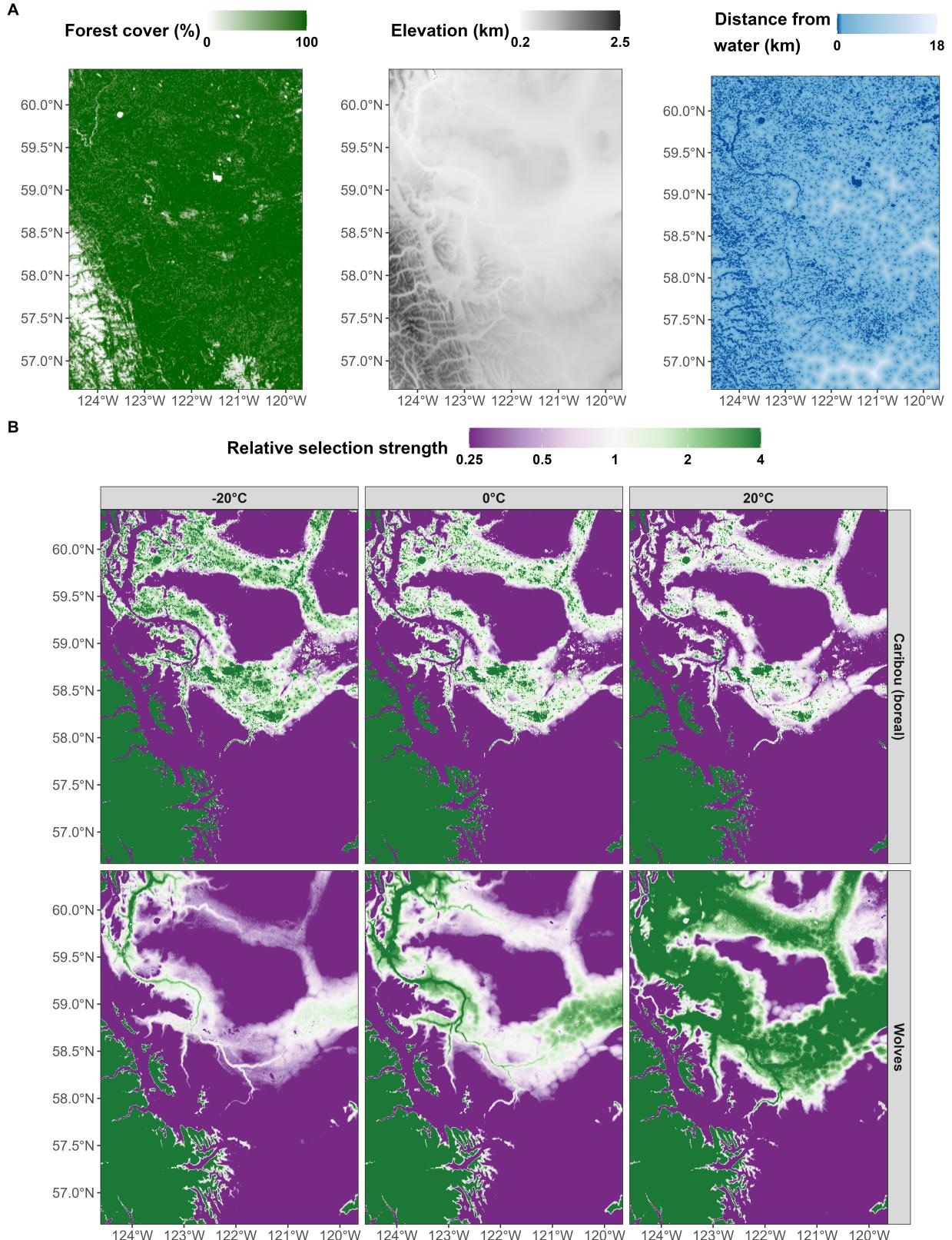


Figure 5: Temperature affects boreal caribou's and wolves' habitat selection and, consequently, their encounter rates. Panel A shows the rasters of the three habitat variables used in the hierarchical resource selection functions, while panel B shows the relative selection strength (RSS) for boreal caribou and wolves, as a function of temperature. RSS values were re-centered and capped to between 0.25 and 4 ($2^{\pm 2}$) to improve readability.

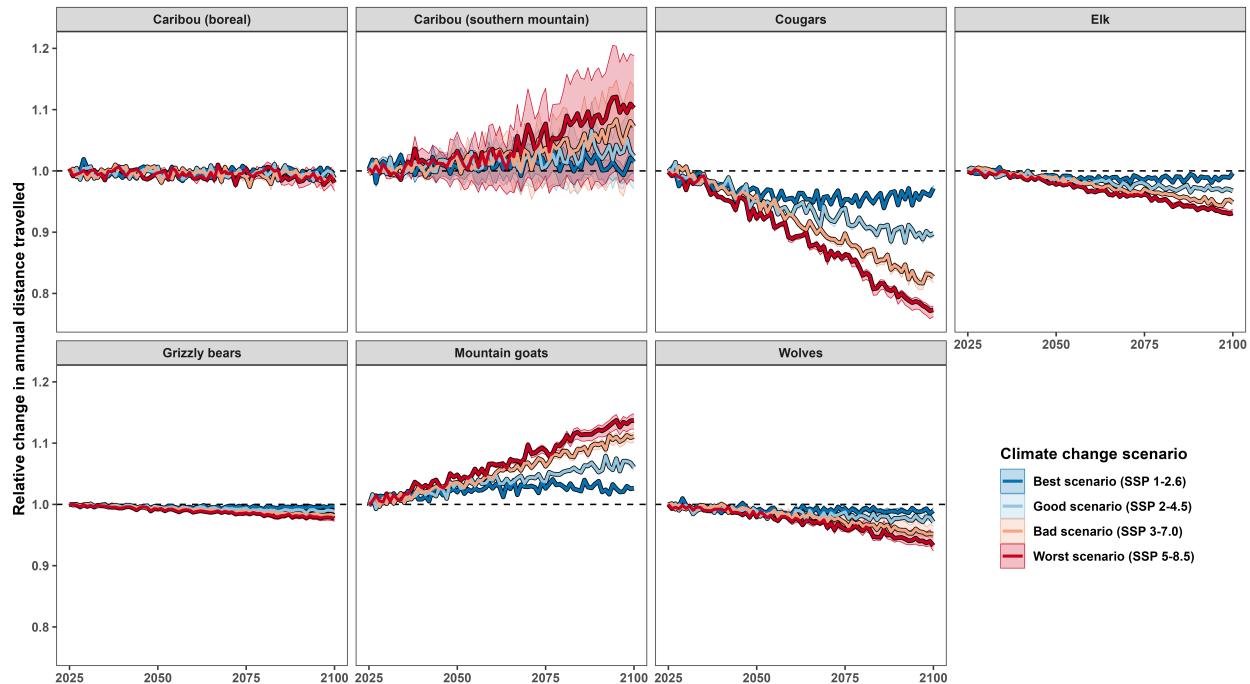


Figure 6: Species are predicted to alter their movement rates differently in response to climate change, and worse climate-change scenarios will result in the greatest change. Bold lines indicate the median change in yearly distance travelled (probability of moving times speed when moving) due to predicted changes in temperature within each species' study area. Shaded areas indicate the 95th and 5th percentiles. Changes are relative to the mean predicted distance travelled at each location in 2025, averaged across the four Shared Socioeconomic Pathways (SSPs). Values > 1 indicate an increase, while values < 1 indicate a decrease. The projections only account for changes in movement frequency and speed, and they ignore changes in physiology or movement costs.

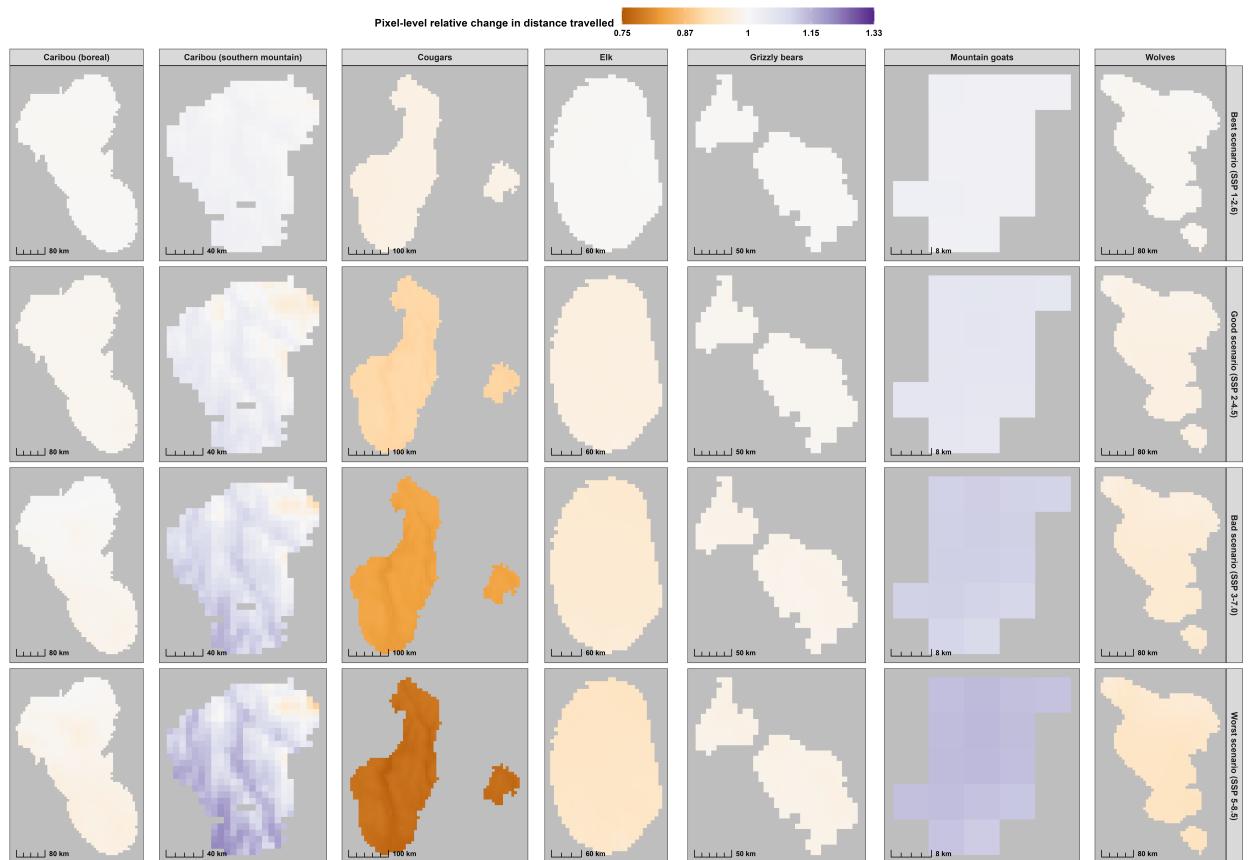


Figure 7: Climate change is predicted to impact each species' movement rates differently, but changes will also vary spatially. The color of each pixel indicates the predicted changes in distance traveled in 2100 at that pixel, relative to the value in 2025, averaged across all four scenarios. Values < 1 indicate a decrease, and values > 1 indicate an increase. For ease of readability, the color bar is on the \log_2 scale to help visualize patterns in doubling). The predictions only account for the predicted temperature throughout the areas and ignore environmental factors such as terrain slope, soil type, and forest cover. All maps extend to each species' study area (Fig. 1) and are shown in the BC Albers Equal Area Conic projection (EPSG:3005).

375 in areas with the lowest RSS and most severe for elk, mountain goats, cougars, and southern
 376 mountain caribou. Changes for boreal wolves and caribou were negligible. Elk, cougars,
 377 and grizzly bears were predicted to increase their selection strength for top-RSS areas, and
 378 elk, mountain goats, cougars, and southern mountain caribou were predicted to further
 379 decrease their selection for areas with low RSS. Unsurprisingly, the predicted change in
 380 RSS between 2025 and 2100 also varied spatially for all species (Fig. 9). Overall, RSS
 381 decreased throughout most of each species' current range, although elk, cougars, and bears
 382 were predicted to increase their selection for higher-altitude habitats. Still, none of the
 383 species were projected to increase RSS throughout their habitat (10).

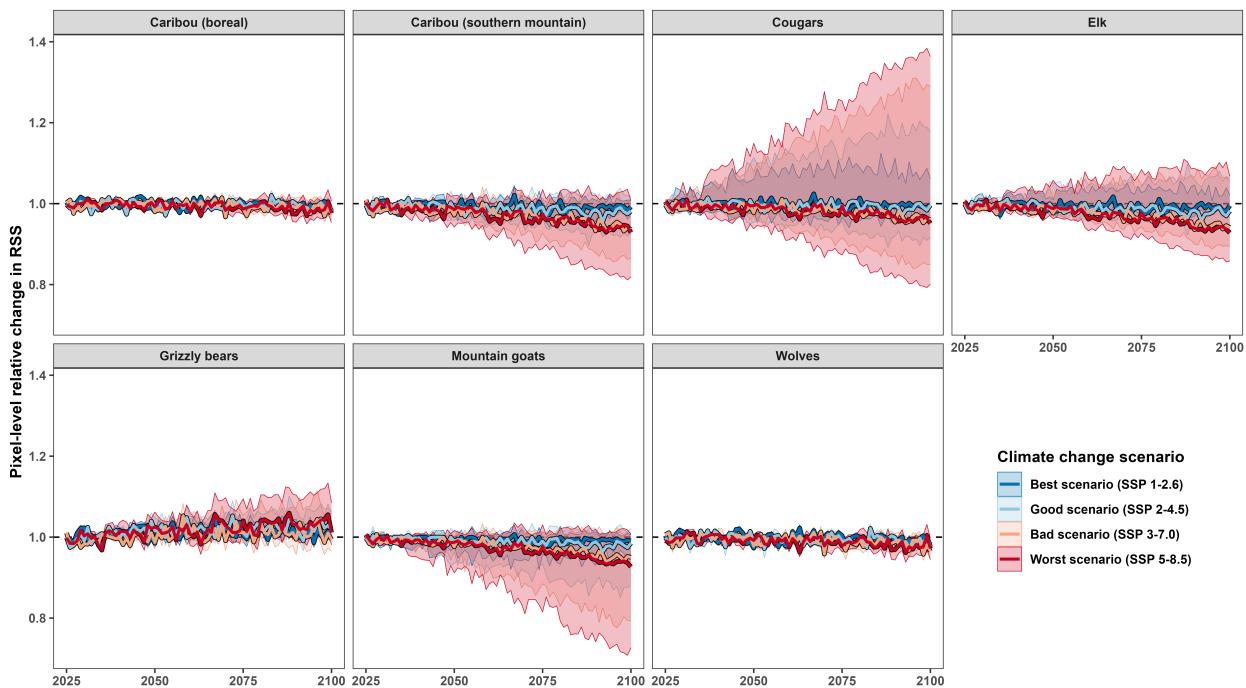


Figure 8: Species are predicted to alter their habitat selection differently in response to climate change, and worse climate-change scenarios will result in the greatest change. Bold lines indicate the change in median RSS due to predicted changes in temperature within each species' study area. Shaded areas indicate the 95th and 5th percentiles in change in RSS. Values > 1 indicate an increase, while values < 1 indicate a decrease. Changes are relative to each location's mean RSS in 2025, averaged across the four Shared Socioeconomic Pathways (SSPs).



Figure 9: Climate change will impact each species' relative selection strength (RSS) differently. The color scale indicates the predicted changes in RSS in 2100, relative to each location's average RSS in 2025 across all four scenarios (i.e., not relative to other pixels). Values < 1 indicate a decrease and values > 1 indicate an increase. For ease of readability, the color bar is on the \log_2 scale to help visualize patterns in doubling, and values are capped to 0.8 and 1.25 ($\approx 2^{\pm 0.322}$; original data ranged 0.71 to 1.93). All maps extend to each species' study area and are shown in the BC Albers Equal Area Conic projection (EPSG:3005).

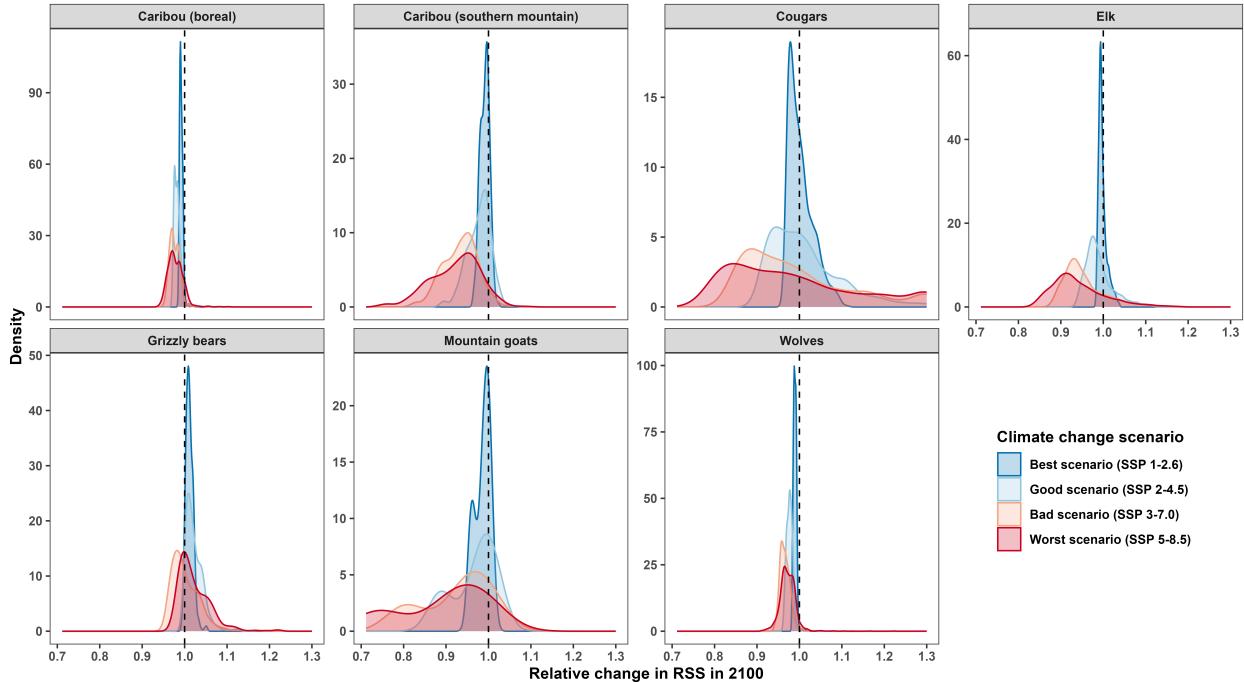


Figure 10: Climate change is predicted to cause species to decrease their selection strength for their current habitats, and worse climate change scenarios will have the greatest impact. The density plots indicate each species’ change in RSS in 2100 for their current habitat (Fig. 8), relative to each location’s RSS in 2025. Values < 1 indicate a decrease and values > 1 indicate an increase. For ease of readability, values > 1.3 were changed to 1.3 (original maximum: 1.93).

384 4 Discussion

385 We have demonstrated that temperature is an important driver of how and where large
 386 mammals move, and that it affects mammals’ seasonal and daily movement behaviour in
 387 complex and nonlinear ways. However, predicting mammals’ responses to climate change
 388 remains a challenge, as habitats are warming rapidly and mammals are exposed to increas-
 389 ingly novel and extreme conditions (Diffenbaugh & Field, 2013; Botero *et al.*, 2015; IPCC,
 390 2023). We leveraged the flexibility and interpretability of HGAMs to estimate mammals’
 391 nonlinear responses to temperature without imposing rigid assumptions about the shape of
 392 the responses (Simpson, 2018, 2025). In particular, tensor product interaction terms were
 393 crucial for estimating smooth, nonlinear changes in daily and seasonal trends with tem-
 394 perature with data from multiple individuals. By allowing interaction terms to be smooth
 395 bivariate functions, we were able to quantify changes in movement behaviour without the

need to discretize time into windows (e.g., day/night and seasons). We were thus able to present results using relatively simple and interpretable surface plots (Figs. 3 and 4) that conveyed nuanced, continuous-time estimates of change. This framework was essential for estimating how mammals behave at extreme temperatures. In fact, despite the recent increase in frequency of extreme heat events in western Canada, including a severe heat wave in 2021 (Kienzle, 2018; Thompson *et al.*, 2022; Zhang *et al.*, 2023), such events remain relatively rare, so estimating mammals' nonlinear responses required the flexibility provided by HGAMs (Wood, 2017). Additionally, the hierarchical approach allowed us to leverage data from multiple individuals in a single model while accounting for differences in behaviour and data availability across individuals (Pedersen *et al.*, 2019; Muff *et al.*, 2020; McCabe *et al.*, 2021; Jeltsch *et al.*, 2025; Silva *et al.*, 2025). Still, GAMs' flexibility and complexity can be a frustrating limitation if used too generously, so we suggest choosing each smooth term's basis size (k) carefully. While penalized splines and REML can help avoid unruly smooth terms, the penalty terms can struggle to restrict model complexity when datasets are as large as those presented here (Wood, 2017; Wood *et al.*, 2017).

The effects of warming temperatures on movement rates varied across species, seasons, and space due to differences in species' behavior and physiology as well as their habitats' phenology. For boreal caribou, hotter temperatures decreased movement rates summer but increased them otherwise, mirroring previous studies (Stien *et al.*, 2012; Leclerc *et al.*, 2021; Lessard *et al.*, 2025). The increase in movement rates with temperature during the cold months is likely partly due to shallower snow depth, which results in greater mobility (Pedersen *et al.*, 2021), but warmer temperatures during snowy seasons also increase the risk of rain-on-snow events, which limit forage availability and increase time spent foraging (Stien *et al.*, 2012; Berger *et al.*, 2018; Mezzini *et al.*, 2025). The reduced movement rates during warmer summers are likely mainly due to more frequent resting and use of thermal refugia, given ungulates' elevated risk of hyperthermia (Alston *et al.*, 2020; Verzuh *et al.*, 2023). Therefore, although we predict that boreal caribou's yearly average movement rates

423 will remain approximately unchanged throughout the 21st century, the projections do not
424 show the changes in seasonal movement phenology. This is an important caveat, since the
425 effects of extreme temperatures are exacerbated by phenological mismatches with seasonal
426 photoperiod (Walker *et al.*, 2019), including the timing of molting and reproduction. Earlier
427 growth seasons in boreal and arctic regions have resulted in lower calf birth and survival
428 (Post & Forchhammer, 2008), while the lengthening of the growth season has allowed moose
429 (*Alces alces*) and deer to encroach on boreal caribou habitat and increase the density of coy-
430 otes (*Canis latrans*), cougars, and wolves (Barber *et al.*, 2018; DeMars *et al.*, 2023), whose
431 movement behaviour also depends on ambient temperature.

432 Boreal wolves responded to temperature similarly to boreal caribou, and habitat selec-
433 tion strength was not projected to change noticeably by 2100, but wolves were predicted
434 to move less in future decades. In contrast, cougars showed markedly different seasonal
435 responses to temperature, with warmer temperatures always resulting in less travel, which
436 resulted in strong predicted decreases in movement rates over the 21st century. However,
437 spatial heterogeneity in habitat, climate, and cougar behaviour may cause boreal individuals
438 to respond to temperature differently from those in our study. Still, rising temperatures
439 clearly affect more than each individual species' movement behaviour; they have complex
440 and interconnected effects on entire communities and their trophic structures.

441 Cunningham *et al.* (2021) discuss the importance of adopting a community-level per-
442 spective when assessing the effects of climate change on animals' movement behaviour and
443 phenology. For example, as temperatures warm and both boreal caribou and wolves in-
444 crease their movement rates in fall, winter, and spring, they also increase their encounter
445 rates (Martinez-Garcia *et al.*, 2020), which will likely increase predation risk when caribou
446 are pregnant or with young calves. Additionally, while both species saw reduced movement
447 rates during hot summer days, boreal wolves' use of anthropogenic linear features (e.g., roads,
448 seismic lines) may allow them to reduce the total thermal costs of movement by moving for
449 shorter periods while increasing the chances of encountering heat-stressed prey (Whittington

450 *et al.*, 2011; Dickie *et al.*, 2017; Dickie *et al.*, 2022). Furthermore, caribou that attempt to
451 reduce predation risk from wolves by avoiding wolf habitat may still risk increasing predation
452 pressure from bears, cougars, and coyote (Leblond *et al.*, 2016; DeMars *et al.*, 2023; Labadie
453 *et al.*, 2023).

454 Considerations about changes in trophic interactions leads to another important caveat
455 about the results we present. The estimated changes in movement behaviour cannot be fully
456 attributed to physiological responses to temperature alone, since other aspects of habitats'
457 seasonal phenology are (nonlinearly) correlated with temperature. For example, mountain
458 goats' lower movement rates at temperatures near 0°C in winter may be in part due to
459 increased movement difficulty, since melting snow and rain-on-snow events increase the en-
460 ergetic costs of movement (White, 2025) and encounter rates with predators (Sullender *et*
461 *al.*, 2023). However, milder temperatures can also increase plant growth, which allows goats
462 to spend more time foraging within and less time travelling across patches (Charnov, 1976;
463 White *et al.*, 2025). Therefore, figure 3 illustrates an estimate of the total effects of temper-
464 ature on each species' movement rates, but it does not explicitly account for energetic costs.
465 Similarly, species' changes in habitat selection do not explicitly account for any changes in
466 physiological or energetic costs. Additionally, forest cover, elevation, and distance from water
467 are often correlated, so the estimated effects should be interpreted carefully, and they may
468 not be applicable outside the study areas used here. For example, both mountain goats and
469 elk selected for higher elevation as temperatures warmed, but our models did not account
470 for differences in forage availability at different elevations.

471 Climate change has also had extensive impacts on plant growth and phenology (Cleland *et*
472 *al.*, 2007; Denny, 2019; Tysor, 2025) with consequences on herbivores' behaviour and fitness
473 (Post & Forchhammer, 2008; Aikens *et al.*, 2017). Additionally, plants' limited ability to
474 disperse to and establish in new habitats is often a limiting factor for herbivores' ability to
475 escape hotter temperatures by moving to higher altitudes or latitudes, and the advance of
476 herbivores can further limit plants' ability to establish (Speed *et al.*, 2012; Diffenbaugh &

477 Field, 2013). Consequently, mammals that move to higher elevations may be forced to spend
478 more time foraging (Mezzini *et al.*, 2025), which will increase both their energetic expenditure
479 and encounter rates with predators and competitors (Kohl *et al.*, 2019; Martinez-Garcia *et*
480 *al.*, 2020; Tórrez-Herrera *et al.*, 2020; Smith *et al.*, 2023). If local peaks become unsuitable
481 habitat, and moving to nearby higher peaks requires traveling across low-quality and high-
482 risk habitat (Figure 9), habitat fragmentation may prevent movement across ranges (White
483 *et al.*, 2025).

484 Growing evidence suggests that mammals' exposure, sensitivity, and adaptability to cli-
485 mate change will limit their ability to adapt to change (Ameca y Juárez *et al.*, 2012; Diffen-
486 baugh & Field, 2013). Exposure to warming temperatures is widespread throughout western
487 Canada (Bunnell *et al.*, 2011; Kienzle, 2018; Eum *et al.*, 2023), and changes in temperature
488 and phenology may be too rapid for many species to respond to (Diffenbaugh & Field, 2013).
489 Species' adaptability is further challenged by the difficulty in responding to concurrent, mul-
490 tifarious, and interconnected changes (Diffenbaugh & Field, 2013; Polazzo *et al.*, 2024). In
491 the future, landscapes may thus become unable to support species and population sizes they
492 supported historically, and species may begin selecting against historical ranges (Williams
493 & Blois, 2018). Therefore, it is crucial for conservationists to distinguish between a species'
494 ideal environmental space and its best available geographic space (*sensu* Matthiopoulos,
495 2022).

496 Accelerating multifarious change in species' movement behaviour and energetic costs re-
497 quire conservation measures that are proactive and anticipate future changes. Polazzo *et al.*
498 (2024) present a framework for estimating species' responses to multifarious change using
499 GAMs that is particularly useful when estimating species' (nonlinear) responses to inter-
500 actions between environmental variables (e.g., changes in both temperature and limiting
501 nutrients). By accounting for the effects of multiple variables at once, they demonstrate
502 how a species' response to one variable can depend on other concurrent changes. Estimat-
503 ing responses to multifarious change is crucial in assessing mammals' responses to hotter

504 temperatures, altered phenology, and novel community dynamics.

505 Protected areas must support populations not only in present conditions but also as
506 species' needs and behaviour change over the decades (Simmons *et al.*, 2021; Livingstone *et*
507 *al.*, 2023). Recent evidence has questioned whether current protected areas will be effective
508 in the long term (Loarie *et al.*, 2009; Diffenbaugh & Field, 2013; Williams & Blois, 2018),
509 and increasingly more experts have been calling for proactive and long-term conservation.
510 By identifying and actively protecting climate change refugia and corridors, we may be able
511 to reduce the effects of climate change on mammalian movement behaviour and community-
512 level responses and ensure that protected areas may be viable for decades to come (Michalak
513 *et al.*, 2018; Graham *et al.*, 2019; Stralberg *et al.*, 2020; Hua *et al.*, 2022).

514 Future work should develop models that account for covariates that are specific to the
515 study species and area, such as forest age and disturbance (DeMars *et al.*, 2023), terrain
516 ruggedness (White & Gregovich, 2017), anthropogenic linear features (Dickie *et al.*, 2017),
517 and growing human presence in wild spaces (Sih *et al.*, 2011; Rice, 2022), including the
518 growing risk of human-wildlife conflict (Abrahms *et al.*, 2023; Weststrate *et al.*, 2024). In
519 particular, forests in western Canada are highly dynamic over time (Zhang *et al.*, 2015), and
520 fires size and burn severity have increased in western Canada in recent decades (Whitman *et*
521 *al.*, 2022; Parisien *et al.*, 2023; Wang *et al.*, 2025). Thus, while our use of a static raster of
522 forest cover allowed for simpler models and climate change projections, future studies should
523 account for mammals' responses to temporal forest dynamics, including the impacts of fire
524 (Whitman *et al.*, 2022; Parisien *et al.*, 2023; Wang *et al.*, 2025), logging (Lochhead *et al.*,
525 2022) and other extractive industries (Dickie *et al.*, 2017, 2024). However, the inclusion of
526 temporally dynamic variables will require that any future projections of species' behaviour
527 depend on temporally dynamic estimates of how such variables will change over time with
528 changes in climate and anthropogenic activity.

529 We have demonstrated that temperature has complex and nonlinear effects on how and
530 where mammals move. Rising temperatures have impacted mammals' daily and seasonal

movement cycles, and changes are expected to intensify throughout the 21st century. Quantifying how temperature affects mammalian behavior and fitness is a first step towards developing an understanding of the effects of climate change on landscape dynamics and the effectiveness of protected areas in the future. By leveraging the flexibility and statistical power of Hierarchical Generalized Additive Models, we have provided researchers with malleable and data-driven methods for assessing species' responses to climate change. We hope that future work will develop more species-specific models with the intent of developing a community-level framework for quantifying and predicting how communities will respond to climate change.

Author contributions

SM performed the data cleaning, ran the analyses, and wrote the manuscript. CHF wrote code for estimating instantaneous movement speeds. MJN conceived of the project idea and supervised SM throughout the project. All other authors contributed telemetry data and reviewed the interpretation of the results for their species of interest. KH and SD contributed substantially to manuscript review. All authors contributed to reviewing the manuscript.

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