Movement models reveal changing grizzly bear habitat use and functional connectivity in response to human disturbance in the southern Canadian Rocky Mountains

20 March 2024

Prepared for: Yellowstone to Yukon Conservation Initiative, Nature Conservancy of Canada,

and Wilburforce Foundation

Prepared by:

See author list on next page



Authors:

Eric C. Palm, corresponding author: Computational Ecology Lab, School of Public and Community Health Sciences, University of Montana, Missoula, MT, USA and Rocky Mountain Research Station, Aldo Leopold Wilderness Research Institute, US Forest Service, Missoula, MT, USA. <u>e2palm@gmail.com</u> and <u>epalm@mso.umt.edu</u>.

Tal Avgar: Wildlife Science Center, Biodiversity Pathways Ltd., Kelowna, British Columbia, Canada, and Department of Biology, Irving K. Barber Faculty of Science, University of British Columbia, Vancouver, BC, Canada. <u>tal.avgar@ubc.ca</u>

Melanie Dickie: Wildlife Science Center, Biodiversity Pathways Ltd., Kelowna, BC, Canada.

mvezina@ualberta.ca

Bruce N. McLellan: International Union for the Conservation of Nature, Bear Specialist Group, D'Arcy, BC, Canada <u>brucenmclellan@gmail.com</u>

Joseph M. Northrup: Wildlife Research and Monitoring Section, Ontario Ministry of Natural

Resources and Forestry and Environmental and Life Sciences Graduate Program, Trent

University, Peterborough, ON, Canada. Joseph.Northrup@ontario.ca

Michael A. Sawaya: Sinopah Wildlife Research Associates, Missoula, MT, USA.

sawaya.mike@gmail.com

Julie W. Turner: Wildlife Science Center, Biodiversity Pathways Ltd., Kelowna, BC, Canada. julwturner@gmail.com

Jesse Whittington: Parks Canada, Banff National Park Resource Conservation. Banff, AB, Canada. jesse.whittington@pc.gc.ca

Erin L. Landguth: Computational Ecology Lab and Center for Population Health Research, School of Public and Community Health Sciences, University of Montana, Missoula, MT, USA. erin.landguth@mso.umt.edu

Katherine A. Zeller: Rocky Mountain Research Station, Aldo Leopold Wilderness Research Institute, US Forest Service, Missoula, MT, USA. <u>katherine.zeller@usda.gov</u>

Clayton T. Lamb: Wildlife Science Center, Biodiversity Pathways Ltd., Kelowna, BC, Canada. <u>ctlamb@ualberta.ca</u>

Author contribution statement: CTL, KAZ and ECP conceived the study. ECP wrote the manuscript with help from CTL. ECP led the data analysis with help from CTL and KAZ. BNM, CTL, JMN, MAS, and JW collected GPS location data. All authors provided valuable feedback and contributed to the final manuscript.

Conflict of interest: The authors have no conflict of interest to declare.

Keywords: conservation, functional connectivity, habitat selection, human development, integrated step selection, movement ecology, utilization distribution

Target audience: This paper will be of interest to wildlife managers, conservation practitioners and wildlife ecologists.

Acknowledgements: We thank Cheryl Chetkiewicz, Tony Clevenger, Stephen Herrero, Clayton Apps, John Paczkowski and Gordon Stenhouse for sharing their grizzly bear GPS collar location data.

Acknowledgment of financial or institutional support: This research was supported in part by the USDA Forest Service, Rocky Mountain Research Station, Aldo Leopold Wilderness Research Institute. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or US Government determination or policy. Computational resources from the University of Montana's Computational Ecology Lab contributed to this research (NSF award numbers 2018112 & 1925267). We acknowledge support from Yellowstone to Yukon Conservation Initiative, Canadian National Program for Ecological Corridors, Nature Conservancy of Canada, Elk Valley Regional Land Trust, Habitat Conservation Trust Foundation, and Wilburforce Foundation.

Data accessibility statement: Data and code to run integrated step selection functions and simulate utilization distributions will be publicly available on Zenodo.org upon acceptance.

Word count:

Abstract: 199 Manuscript: 6324

Abstract

Individual-based movement models can help predict potential changes to animal movement behavior, habitat selection, and functional connectivity as human-caused habitat alteration increases. Functional connectivity plays a major role in the population viability of wide-ranging species, yet it is difficult to measure and predict. We used integrated step selection functions (iSSF) to model movement and habitat selection for 109 GPS-collared grizzly bears across 85,000 km² of southeast British Columbia and southwestern Alberta, where they face increasing habitat alteration from roads, human settlements, and mining. We then simulated individual grizzly bear movements from fitted iSSFs under three human disturbance scenarios to predict changes in population-level space use and functional connectivity in response to these disturbances. Bears generally avoided crossing highways, towns, and mines, but were attracted to areas alongside highways in regions with relatively low forage availability. Additional footprints of proposed mines and expanded human settlements in a future scenario would further decrease functional connectivity for grizzly bears on top of prior connectivity losses from existing human disturbance. Our results provide insights into grizzly bear movement and connectivity in an area of high conservation importance, and our predictive maps can be used to directly inform transboundary management actions and conservation planning.

Introduction

Wildlife movement is a fundamental ecological process that facilitates the acquisition of food, search for mates, and security from threats (Turchin 1998). Habitat change through loss, fragmentation and degradation can impede animal movement, thereby reducing access to resources and increasing their vulnerability to mortality while moving within and between habitat patches (Lindenmayer and Fischer 2013). Reductions in movements in response to

human influence have been documented across many species of mammals around the world, with far-reaching effects on multiple ecosystem processes (Tucker et al. 2018). Further, declining functional connectivity via reduced movement success among and between habitat patches can decrease the spatial distribution, abundance, and population persistence of animals (Bowne and Bowers 2004, Fahrig 2007).

The number of analytical approaches for assessing movement, habitat selection and connectivity has grown rapidly along with our ability to track animals at finer spatial and temporal resolutions and for longer durations (Northrup et al. 2022, Unnithan Kumar and Cushman 2022). Among these approaches, integrated step-selection analyses are attractive because they relax the assumption that movement and habitat selection are independent, simultaneously estimate parameters for both processes, and model interactions between the two (Avgar et al. 2016). Practitioners can simulate individual animal paths parameterized by these models to estimate population-level utilization distributions, which are more accurate than maps from traditional resource selection models that assume constant resource availability across space and time (Signer et al. 2017, 2024).

Individual-based simulations from fitted integrated step-selection functions (iSSFs) also provide a means to estimate Merriam connectivity, a type of functional connectivity defined as per-individual movement success between and within habitat patches (Fahrig et al. 2021). Merriam connectivity explicitly incorporates species-specific movement capability and structural landscape effects on connectivity. Quantifying connectivity directly from simulated trajectories obviates the need to separately predict landscape resistance (e.g., via transformed spatial predictions from a habitat selection model) for use in connectivity analyses such as cost-distance or circuit theory (Zeller et al. 2012), which require predefined path destinations, and assume animals have perfect knowledge of landscape resistance and exhibit consistent movement behavior.

Understanding how increasing human disturbance affects wildlife movement is essential for developing effective wildlife conservation and management strategies (Doherty and Driscoll 2018). Here, we focus on the movement, habitat selection, and connectivity of grizzly bears in the southern Canadian Rocky Mountains (**Figure 1**), where a growing footprint of roads, mines, human settlement, and other infrastructure has negatively affected their movements, behavior, and survival (McLellan and Shackleton 1988, Nielsen et al. 2004, Ciarniello et al. 2007, Northrup et al. 2012b). As a result, small subpopulations in this region have become increasingly isolated with minimal demographic interchange, and bears living in close proximity to humans rely on connectivity to nearby wilderness areas to offset human-caused mortality and to sustain viable populations (Proctor et al. 2012, Lamb et al. 2020). Understanding factors affecting grizzly bear habitat selection and mapping predicted space use in this region is key to preventing the near complete loss of connectivity between populations that has occurred farther south in Montana, Idaho and Wyoming (Sells et al. 2023).

We used a multi-step approach (**Figure 2**) to predict grizzly bear movements, habitat selection, and functional connectivity under past conditions (i.e., without human disturbance), current conditions, and a future scenario with increased human disturbance. First, we used iSSFs to estimate the degree to which a suite of habitat attributes affected grizzly bear movements, with a particular focus on how human infrastructure and broad-scale variation in habitat availability influenced movement and habitat selection. We then simulated individual movements from fitted iSSFs to predict population-level utilization distributions (UD) at a spatial extent large enough to help guide conservation planning at regional, national and international levels (Hilty et al. 2020,

Pither et al. 2023). Finally, we predicted changes to grizzly bear functional connectivity by calculating movement success of simulated animals within and between habitat patches in a subset of our study area with high amounts of existing and proposed human disturbance, high bear densities, and frequent human-bear conflicts.

Methods

Study area

Our study area consisted of 85,000 km² of southeastern British Columbia (BC) and southwestern Alberta (AB), including a large portion of the southern Canadian Rocky Mountains (Figure 1). At a broad spatial scale, this region provides important connectivity along the continental divide between highly fragmented animal populations in the south and larger ones to the north and west (Apps and Wildlife Conservation Society Canada 2007). The Rocky Mountains form a narrow (50-100 km) corridor between the developed prairies to the east and the settled valley of the Rocky Mountain Trench to the west, and encompass large swaths of protected areas, including several national parks, provincial parks, and provincial wildland areas. Several major highways cross the region, primarily along valley bottoms but also across several high mountain passes. Human settlement is largely confined to valley bottoms, low-elevation foothills, and prairies. Recent increases in tourism and associated traffic, ongoing development of coal mines, and human population growth have increased habitat alteration in the region. In AB, grizzly bear hunting was banned in 2006, and the species is listed as Threatened under the Wildlife Act (Government of Alberta 2022). Hunting of grizzly bears was legal outside of national parks in BC until it was banned in late 2017.

Telemetry data

We used GPS collar data from grizzly bears captured throughout the southern Canadian Rocky Mountains. Bears were captured using multiple methods, including darting from a helicopter, leg restraints, and culvert traps. Full details on bear capture methods and animal care protocols can be found in (Northrup et al. 2012a, McLellan 2015, Lamb et al. 2020, Whittington et al. 2022). Our initial dataset included 305,619 GPS locations from 159 GPS-collared grizzly bears whose collars collected data between 2000 and 2020. We resampled GPS location data to a relocation interval of ~6 hours to maintain a consistent sampling rate across individuals for our iSSFs and to maximize sample sizes throughout the study extent and across different collaring efforts. This relocation interval limited the spatial domain available to an animal at a given time step to be within a distance reachable within 6 hours. We captured seasonal differences in movement and habitat selection behavior by assigning location data into one of three time periods, which were modified slightly from seasons used in McLellan and Hovey (1995) that were based on changes in grizzly bear diet. Our seasons were: spring (den emergence–July 15), summer (July 16–Sept 15), and fall (Sept 15–den entrance). We fit separate iSSFs for each season (Avgar et al. 2016).



Figure 1. Focal area for grizzly bear movement and connectivity analyses in the southern Canadian Rocky Mountains showing locations of grizzly bear telemetry data, collected from 2000–2020, used in the integrated step-selection functions. Colors of telemetry locations indicate different regions within the study area that were used in spatial cross validation of the models. Assignment of individuals to regions was based on home range centroid.

Habitat covariates

A major focus of our analyses was to understand grizzly bear behavioral responses to different types of human disturbance, including mines, roads, and towns. We represented these disturbances using one or more of three different variable types: (1) footprint, a binary variable indicating whether the location intersected the disturbance feature itself, (2) distance-to, a continuous variable with transformed distances to a disturbance feature (see Appendix 1 for details on distance transformations), or (3) semi-permeable movement barrier, a binary variable indicating whether the straight lines connecting consecutive locations intersected a disturbance feature. We acknowledge that the straight-line 'steps' are modeling heuristics, that the bears did not in fact travel along these straight lines and, in some scenarios, they might easily move around the 'barrier'. Nevertheless, our approach provides a parsimonious way to estimate semipermeable barrier effects in iSSF. We ran separate models using either footprints or semipermeable barriers for mines and towns. We used separate distance-to variables for highways and non-highway roads, which we expected would have different effects on bears due to differences in vehicle speed and traffic volumes (Gibeau et al. 2002, Waller and Servheen 2005, Northrup et al. 2012a). We also represented highways as semi-permeable movement barriers. Finally, we included semi-permeable barriers for alpine areas that were either glaciated or predominantly rock, and for large $(> 2.5 \text{ km}^2)$ lakes and reservoirs. See Appendix 1 for additional details on creation of human footprint and semi-permeable barrier variables.

We also sought to quantify selection behavior in response to forage, terrain ruggedness index (TRI), and canopy cover. We predicted that grizzly bears would select areas with high vegetation greenness, measured using the enhanced vegetation index (EVI) and delta EVI (growing season EVI – winter EVI), which would strongly correlate with high quality forage such as deciduous shrubs and forbs. We compared log-likelihoods of full models using only one of these variables to determine which to use in top models.

We predicted that bears would avoid the most rugged terrain and generally select low to intermediate canopy cover. To help distinguish between deciduous shrubs and forbs versus

deciduous trees, we interacted greenness with canopy cover. In spring and summer models, we also included an interaction between greenness and elevation to help capture intermediate-to-high-elevation areas of high greenness such as avalanche paths and alpine meadows. We predicted bears would more strongly select these areas relative to low-elevation agricultural areas because they often contain an abundance of high-quality bear forage (Serrouya et al. 2011). We assumed the first spring location for each bear-year was near its den, and we included a 'distance to den' variable in all three seasonal models. We predicted that most bears in our dataset exhibited range-resident behavior and that the coefficient for distance to den would be negative. We resampled all raster data to 180-m resolution for iSSFs and subsequent simulations to balance spatial resolution with computation time. See **Table S1** for additional details on habitat covariates used in iSSFs.

Integrated step selection functions

We fit point-based iSSFs in a generalized linear mixed modeling (GLMM) framework using the R package 'glmmTMB', version 1.0.2.1 (Brooks et al. 2017, Muff et al. 2019). iSSFs discretize animal movement paths into individual steps and restrict the availability domain for each step based on the animal's current location and their typical movement behaviors. For each season, we fit a gamma distribution to used step lengths and a von Mises distribution to turning angles between consecutive used steps at the population level (step lengths and turn angles pooled across all animals). We generated 20 available locations per used location by making random draws from these distributions using the R package 'amt', version 0.1.2 (Signer et al. 2019). Each set of one used location and 20 available locations represented a stratum. We extracted habitat covariate values at the end of each step to characterize habitat selection and at the start of each step for movement-habitat interactions (Fieberg et al. 2021). We estimated stratum-specific intercepts as random effects with a fixed large variance in a conditional Poisson regression, following Muff et al. (2019). We included a random slope at the individual level for every covariate, except on generalized functional response interaction terms (see below) and terms where their inclusion prevented model convergence. We included interactions between movement parameters (log step length) and habitat covariates (canopy cover, EVI, TRI) at the start of steps to account for the degree to which animals adjust their speed of travel and directional persistence based on different habitat characteristics. We interacted cosine turn angle with log step length because directional persistence and step length are often positively correlated (Hodel and Fieberg 2022).

Generalized functional responses in iSSFs

Exploratory plots of selection ratios calculated within bins of several continuous variables (e.g., distances to roads and highways) showed pronounced variation in selection behavior across different portions of the study area (**Figures S1** and **S2**). We attempted to account for this broad-scale variation in grizzly bear behavior in our models by using generalized functional responses (GFR), which are interactions between habitat variables at the ends of steps with broader-scale habitat availability (Matthiopoulos et al. 2011). Using GFRs can improve a model's ability to accurately predict responses across heterogenous or novel environments while still capturing local extremes in resource availability (Matthiopoulos et al. 2011, Paton and Matthiopoulos 2016). We estimated the broad-scale availability of greenness, terrain ruggedness and canopy cover by calculating the average pixel value within a circular moving window of 315

km, which was large enough that it ensured the Pearson's correlation between a covariate and its broad-scale average was < 0.65 (see Appendix 1 for details), and which also roughly corresponds to the average seasonal home range size of a grizzly bear from past studies in the area (Graham and Stenhouse 2014). We did not include random slopes on the generalized functional response interaction terms themselves (e.g., canopy cover:broad scale greenness) because these terms account for broad-scale, population-level variation in responses across the entire study area, and there was relatively little variation in home-range level greenness encountered by an individual bear.

Model selection

For each season, we started with a full model structure that included quadratic terms for canopy cover, TRI, and elevation, predicting that bears would select for intermediate values of each of these variables. We also included greenness, all types of human disturbance, and semi-permeable barrier variables for rock/ice and water bodies. However, we prioritized accurate spatial predictions over consistency in model structure across seasons, and we removed or retained model terms depending on model performance (i.e., individual Spearman's rank correlations) in the spatial cross validation processes described below (see below).

Mapping utilization distributions using simulations from fitted iSSFs

We simulated movement paths from fitted iSSFs to predict seasonal population-level UDs across the entire study area (Signer et al. 2017). We lacked a spatially unbiased sample of den locations across our study extent to use as start locations for spring iSSF simulations. Instead, we ran a second-order resource selection function (RSF) using the same GPS location dataset as for our iSSFs to predict where bears placed home ranges within the broader region. We randomly sampled 100,000 locations from the top 30% of mapped predicted relative probabilities of use from the second-order RSF and used these as starting locations for the spring UD simulation. This process reflected bears' primary distribution within the mountains, foothills and mountain valleys, and their broad-scale avoidance of eastern prairies. Additional details on the second-order RSF can be found in Appendix 1.

We used the 'rvnorm' function in Program R to simulate a separate set of habitat coefficients for each simulated bear using the full variance-covariance matrices of our top models (Kerman and Gelman 2007). This accounted for individual variability in habitat selection responses and propagated model uncertainty to our simulated movement paths. However, we simulated coefficients for movement and movement-habitat interactions using the fixed-effect variance-covariance matrix only, as including additional uncertainty from random slopes sometimes resulted in a negative gamma distribution scale parameter when generating proposed step lengths, which is nonsensical (Valle et al. 2023). At each simulated bear's starting point in the spring simulation, we randomly generated an initial bearing and drew a random step length from the gamma distribution fitted to observed step lengths pooled across all animals for that season. We used the iSSF model coefficients from movement and movement-habitat interaction terms to update the distribution of available step lengths and turn angles to estimate the selection-free movement kernel at each subsequent step, as in Avgar et al. (2016). We then extracted habitat attributes at the endpoints of the 100 candidate steps and multiplied their values by the corresponding habitat coefficients to calculate relative probability of use for each location, conditional on the 100 candidate locations. We weighted each candidate location by its predicted relative probability of use, probabilistically selected one location, and continued to the next step

in the path for that animal. We repeated this process for all steps in the path. We terminated a path if > 60% of the 100 candidate locations for a step fell outside the study area and assigned steps that landed in either a large (> 2.5 km^2) waterbody or among cliffs (TRI > 30) as NA.

We simulated 1,000,000 paths with 4 locations per day within our study area for 68 days in the spring, 61 days in the summer, and 47 days in the fall (median season durations across all bear-years). We used the last location from each complete path from the spring simulation as start locations for summer and used the summer end locations as start locations for fall. We created a seasonal UD by summing the number of locations that fell in each 180-m raster pixel. We then created annual UDs by summing the three seasonal rasters and dividing each pixel's value by the total number of steps across all seasons. Additional details on individual-based simulations are in Appendix 1.

Validation of iSSFs

We evaluated the seasonal iSSFs using two different spatial cross validation procedures with individual blocking (Roberts et al. 2017). First, we calculated a centroid from each animal's full set of locations across all seasons, and then classified animals into one of six validation regions, which contained between 9% and 19% of the total locations within a season: Banff National Park West (BNPW), Banff National Park East (BNPE) Kananaskis (KAN), Elk Valley North (EVN), Elk Valley South and Southeast (SE; **Figures 1 and S3**). For each of six validation folds, we withheld all data from animals in one test region (test data) and fit our top seasonal models to the remaining six regions (training data). We then simulated a population-level UD from each seasonal model fitted to the training data using the same procedure as above, categorized the raster pixel values into 10 roughly equal-area bins, and overlaid the GPS locations from the

withheld region. For each withheld individual, we calculated the Spearman's rank correlation between the area-adjusted proportion of used locations in a bin and the bin ranking (1–10; Boyce et al. 2002). We repeated this process for all six validation regions, and reported validation results broken down by season and region.

We also created used habitat calibration (UHC) plots as in Fieberg et al. (2018). These UHC plots provided a graphical (qualitative) assessment of how well our models predicted the observed frequency distribution of environmental space use. We used the same region-based training and test datasets as above for UHC plots, but omitted mines, town crossings and water crossings from top seasonal models because these features were not present in all six validation regions. We characterized the used habitat distribution under the models fit to training data by drawing 1000 samples from each habitat covariate.

Finally, we assessed the predictive capacity of our UDs beyond the spatial extent of our model input data by overlaying GPS location data from 17 grizzly bears in BC's Flathead Valley over our binned seasonal UDs and calculating Spearman's rank correlations of area-adjusted proportions in each bin.



- Figure 2. Steps for predicting annual space use and quantifying functional connectivity using individual-based simulations parameterized from fitted integrated step selection functions for 109 grizzly bears in the southern Canadian Rocky Mountains.

11 Assessing past and future land use scenarios

We predicted how habitat selection and space use have changed from a past "disturbance-free" 12 land-use scenario and may change under a future scenario. For the past scenario, we eliminated 13 distance to road and highway variables, mine footprints, and semi-permeable barriers for towns 14 15 and highways from our simulations. We filled in greenness and canopy cover values within the 16 footprints of these removed features using the average values from the surrounding raster pixels (see Appendix 1 for more details). For future conditions, we used a disturbance scenario where 17 all currently proposed coal mines were built and towns (>100 buildings/km²) extended their 18 19 footprint outward by 500 meters. This scenario is plausible in the next 25-50 years given the expansion of mining and housing developments in the study area over the last century, but it 20 21 does not include potential restoration of disturbed areas. We applied the average canopy cover and greenness values within existing mine footprints and towns, respectively, to the added 22 footprint of these features. 23

24

25 *Predicting changes in functional connectivity*

We quantified movement success of simulated paths between locations in and around the Elk 26 27 Valley in southeast BC under past conditions, current conditions and under a future scenario, and calculated the percent change in movement success across individuals between the scenarios. 28 Under the future scenario, this area encompassed 228 km² of proposed coal mines and 50 km² of 29 30 expanded human settlement. We categorized past, current, and future annual UDs into 10 equalarea bins, and generated 20 nodes from within patches of high predicted use (i.e., bins 8, 9 and 31 10) that occurred in all three UDs. We required all high-use patches to be $> 2 \text{ km}^2$ in area and >32 33 10 km apart. For each scenario, we counted the number of simulated paths that traveled between

all possible pairs of nodes. We considered a simulated path to have visited a node if any of its
locations fell within the intersection of a 1-km² buffer around the node and its associated highuse patch. Most (15 of 20) nodes fell in separate habitat patches, although a few occurred in the
same larger patch, so our predictions included both between- and within-patch movement
success, both of which are important for functional connectivity (Cavanaugh et al. 2014).

40 Results

41 *iSSFs*

42 After resampling tracks to one location every ~6 hours and removing bear-seasons with <21 days 43 of locations, our final iSSF dataset included 69,414 GPS locations from 109 bears (Table 1). We 44 did not include elevation in the fall model because Spearman's rank correlations declined across 45 most individuals in the spatial cross validation when it was included. We also did not include distance to roads or highways in the fall model, because there was no clear pattern in selection 46 ratios across a range of distances from these features (Figures S1 and S2). Log likelihood 47 48 supported using a footprint variable over a crossing variable for mines and a crossing variable 49 over a footprint variable for towns in all top models. Mine footprints in summer, lake crossings in all seasons, and town crossings in spring and summer were too rare on the landscape to fit 50 51 random slopes. We only retained GFR terms with broad-scale greenness, as they explained far 52 more variation than interactions with broad-scale canopy cover and TRI. See Table S2 for the 53 model structure of final seasonal iSSFs.

54

Table 1. Summary of GPS locations used in the integrated step-selection functions for 109
 grizzly bears from 2000–2020 in the southern Canadian Rocky Mountains.

Season	# of locations		# of bears		$ Mean \pm SD \ locations \\ per \ bear $		Mean ± SD days with location	
_	Female	Male	Female	Male	Female	Male	Female	Male
Spring	17,177	9,137	52	43	330 ± 238	212 ± 153	93 ± 63	62 ± 42
Summer	15,066	6,474	48	31	314 ± 209	209 ± 134	89 ± 55	59 ± 34
Fall	11,374	5,552	50	27	227 ± 155	206 ± 96	66 ± 43	57 ± 27

Cover, forage, and topography—We assessed behavioral responses to habitat conditions by 58 59 plotting relative selection strength (Avgar et al. 2017) predictions across the full range of values 60 for a covariate in the input dataset relative to its average value in that season, holding all other 61 covariates constant at their average values. Grizzly bears selected areas with high greenness $(\beta_{spring} = 0.71 \pm 0.05 \text{ [SE]}, \beta_{summer} = 0.61 \pm 0.05, \beta_{fall} = 0.38 \pm 0.04)$ and low-to-intermediate 62 terrain ruggedness in all seasons, although relative selection for greenness was higher in spring 63 and summer than in fall (Figures S4 and S5). Selection for high greenness increased at higher 64 65 elevations in spring and summer (greenness:elevation: $\beta_{spring} = 0.22 \pm 0.03$, $\beta_{summer} = 0.28 \pm 0.04$) and increased in open areas in the summer and fall (greenness:canopy cover: $\beta_{summer} = -0.06 \pm$ 66 0.03, $\beta_{\text{fall}} = -0.16 \pm 0.03$; Figure S5). Bears selected low to intermediate canopy cover in all 67 seasons (Figure S4). 68

69

Movement—Nearly 88% of all used locations in our final dataset were < 20 km from the first
location in that bear-year, suggesting strong range resident behavior, although we did observe
obvious exploratory forays (defined as > 40 km displacement) in 9 of 307 (< 3%) of bear-years.
Accordingly, the distance to den variable was strongly negative for all three seasonal models
(Figure S5). Faster movements were more directional, as indicated by positive coefficients for

the interaction between cosine turn angle and log step length. Grizzly bears moved slower in

- reas with more rugged terrain and higher canopy cover during all seasons (Figures S5 and S6).
- 77 During spring and summer, bears moved faster in areas with higher greenness (Figure S5).
- 78

Semi-permeable barriers and human footprint—Grizzly bears avoided crossing towns ($\beta_{spring} = -$ 79 0.59 ± 0.15 , $\beta_{summer} = -0.70 \pm 0.20$, $\beta_{fall} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$, $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$, $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$, $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$, $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), $\beta_{summer} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), highways ($\beta_{spring} = -0.09 \pm 0.24$), highways ($\beta_{spring} = -1.08 \pm 0.11$), highways (\beta_{spring} = -1.08 \pm 0.11), highways (\beta_{spring} = -1.08 \pm 0.11), highways (\beta_{spring} = -1.08 80 = -0.80 ± 0.13 , $\beta_{fall} = -0.69 \pm 0.11$), and high elevation rocky or glaciated areas ($\beta_{spring} = -0.89 \pm$ 81 0.15, $\beta_{summer} = -1.07 \pm 0.11$, $\beta_{fall} = -1.24 \pm 0.14$) during all three seasons (Figure 3), although 82 83 avoidance of crossing towns in fall was not statistically significant. The main effects of distance to highways and to roads were not statistically significant on their own in either summer or fall 84 models. However, the degree of selection or avoidance of these features in both spring and 85 summer depended on broad-scale variation in greenness (see Generalized Functional Responses 86 below; Figure 4). Bears avoided mine footprints in all seasons ($\beta_{spring} = -0.49 \pm 0.35$, $\beta_{summer} = -$ 87 1.56 ± 0.43 , $\beta_{\text{fall}} = -0.49 \pm 0.44$), although this avoidance was only statistically significant in the 88 summer. The lack of statistical significance in spring and fall was likely because mines were 89 relatively rare on the landscape and because two bears (one in each season) were habituated to 90 91 mining activity (Figure 3).



Figure 3. Predicted relative selection strength of grizzly bears, shown by season, for potential 93 barriers and human footprint variables. Predictions are from integrated step-selection functions 94 fit to GPS collar data from 109 bears from 2000-2020 in the southern Canadian Rocky 95 96 Mountains. Transparent points show individual-level coefficients (random slopes), while points 97 with black outlines and error bars intervals depict fixed-effects coefficients and associated 95% confidence intervals based on fixed effects only. Selection strength for a covariate is relative to 98 99 its average value (from the model input data) during that season. All other covariates in the model were held constant at their average values. Points denoted with + indicate variables 100 101 without random slopes. 102

103 Generalized functional responses-Responses to canopy cover, greenness, roads, highways, and 104 rock/ice barriers varied as a function of the broad-scale greenness in an area (Figure 4). In spring 105 and summer, lower broad-scale greenness consistently increased the relative selection for areas 106 near roads and highways (d hwy:greenness broad: $\beta_{spring} = 0.09 \pm 0.02$, $\beta_{summer} = 0.06 \pm 0.02$; d_road:greenness_broad: $\beta_{spring} = 0.11 \pm 0.01$, $\beta_{summer} = 0.13 \pm 0.02$). Lower broad-scale 107 108 greenness was also associated with selection of lower canopy cover in all seasons 109 (canopy cover: greenness broad: $\beta_{summer} = 0.14 \pm 0.03$, $\beta_{fall} = 0.32 \pm 0.04$) and higher greenness 110 in fall (greenness: greenness broad: $\beta_{\text{fall}} = -0.13 \pm 0.03$; Figure 4). In spring and summer, bears 111 were more likely to move across highways and rock-ice features in areas with lower broad-scale greenness, although the increased avoidance of crossing highways in these areas was not 112 113 statistically significant (Figure S5).



··· Low broad-scale greenness — High broad-scale greennes

Figure 4. Predicted relative selection strength of grizzly bears, shown by season, across a range 115 of habitat covariates as a function of broad-scale greenness (enhanced vegetation index). 116 Predictions are from integrated step-selection functions fit to GPS collar data from 109 bears 117 from 2000–2020 in the southern Canadian Rocky Mountains. Variable ranges on the x-axis 118 119 include the middle 95% of values available to bears in iSSFs (excluding values below and above the 2.5% and 97.5% quantiles, respectively). Selection strength for a covariate is relative to its 120 average value (from the model input data) during that season, which is 1. Shaded regions 121 indicate 95% confidence intervals based on fixed effects only. All other covariates in the model 122 were held constant at their average values. 123



Figure 5. Predicted annual utilization distribution under current conditions for the entire study extent (A), estimated as the sum of 125 126 three seasonal utilization distributions (spring, summer, and fall). Predicted annual utilization distributions under past conditions (no human disturbance), current conditions, and a future scenario of additional human footprint (B), and the relative percent change in 127 128 predicted probabilities of use between past and current conditions, and between current conditions and a future scenario (C), in a subset of the study area outlined in red in (A). Utilization distributions were created using individual-based simulations from 129 130 integrated step-selection functions fit to GPS collar data from 109 grizzly bears from 2000-2020 in the southern Canadian Rocky Mountains. We calculated the 99% quantile of mapped predictions in the utilization distributions and set all higher pixel values to this 131 132 value to ease visual interpretation. Similarly, we calculated the 1% and 99% quantiles of relative percent change and set all pixel 133 values lower, and higher, respectively, to these values.

135 Simulated utilization distributions from iSSFs

136 The annual UD under current conditions showed areas of high predicted use mostly occurred in 137 mountain valleys in the northern portion of the study area, which included large expanses of 138 high-elevation rock and ice (Figure 5). Predicted use was more evenly distributed across 139 elevations in southern areas. We calculated the areas within 50% and 95% volume contours of 140 simulated UDs as we increased the number of paths simulated and found that these areas 141 remained relatively stable above \sim 750,000 paths (Figure S7). We also found that the relative 142 percent change in pixel values of UDs approached zero as the simulation duration increased (e.g., 10 days to 68 days for spring; Figure S8). Across seasons, an average of 3.3% (range = 143 144 2.1% to 4.0%) of the proposed steps for each model were not realized because simulated 145 movement paths reached the study area boundary. Simulated paths had very similar step length 146 distributions as real paths, but less directional persistence (Figures S9 and S10), and visual 147 inspection of a random sample of simulated versus real GPS paths showed similar areas of use 148 and avoidance (Figure S11). Simulating movements on a future landscape surrounding BC's Elk 149 Valley with human disturbance footprints resulted in correspondingly larger areas that were 150 avoided by bears, while the UD for a past human disturbance-free landscape highlighted the degree to which roads and highways impeded movements throughout the area (Figure 5). 151





Figure 6. Predicted percent change in connectivity for grizzly bears from past to current 153 conditions (left panel), and current conditions to a future scenario with additional coal mines and 154 expanded town footprints (right panel) in the Elk Valley, British Columbia. Nodes were sampled 155 156 from the top 30% of pixel values in all three of the past, current, and future annual utilization distributions. Relative connectivity was defined as the relative number of simulated trajectories 157 that successfully transversed a pair of nodes in the start period for each panel. Relative node use 158 was defined as the relative number of successful simulated trajectories whose locations fell 159 within the intersection of a 1-km radius around the node and the habitat patch containing that 160 161 node at the start period for each panel. Percent change was estimated by counting the number of simulated trajectories that successfully transversed a pair of nodes in the start (nstart) and end 162 (nend) periods, and calculating $(1 - \text{nend} / \text{nstart}) \times 100$. We calculated the 1% and 99% 163 164 quantiles of percent change and set all pixel values lower, and higher, respectively, to these values, to ease visual interpretation. 165

167 Predicted changes in functional connectivity

168 Predicted movement success within and between habitat patches declined throughout much of

169 the Elk Valley, BC area from a past scenario free of human disturbance to current conditions

- 170 (Figure 6). Eighty-four percent of edges connecting nodes showed declines in predicted
- 171 connectivity, with a median (\pm SD) difference of $-16.3\% \pm 15.9\%$, including declines for all
- 172 connections that spanned highways. Predicted movement success declined for 67% of edges
- 173 from current conditions to a future scenario with larger town footprints and proposed coal mines,

although the magnitude of losses (median difference = $-3.6\% \pm 9.3\%$) were generally lower than the past to current changes. The largest predicted declines from current conditions to the future scenario occurred in the northern end of the valley near the town of Elkford. We predicted slight increases in functional connectivity to some habitat patches to the east and southeast under the future scenario, likely reflecting simulated bears that circumvented the entire area containing additional disturbance footprints.

180

181 *Validation of iSSFs*

182 The mean Spearman's rank correlation across individuals using the binned seasonal UDs for 183 each of the six validation regions ranged from 0.75 to 0.86 in spring, 0.68 to 0.90 in summer, and 184 0.65 to 0.83 in fall (Figure S12). Model predictive capacity was consistently high across individuals for all three seasons in both Banff regions (east and west) and lower in the Southeast. 185 For each region, UHC plots depicted the degree to which models fit using training data from all 186 187 other regions predicted used habitats accurately (Figures S13, S14, S15, S16). In spring, the 188 model generally predicted canopy cover distributions for used locations well across all regions 189 except the Southeast (Figure S13). The spring model struggled to predict used distributions of 190 terrain ruggedness in Elk Valley North and South. In both summer and fall, there were 191 mismatches in the predicted versus observed distributions for used locations for canopy cover in 192 Banff National Park East, Elk Valley South, and Kananaskis. The fall model failed to accurately 193 predict the used distribution for terrain ruggedness in Elk Valley South (Figure S15). The external validation of seasonal UDs using GPS locations from the Flathead Valley, BC showed 194 195 better predictive performance in the spring (Sr = 0.82) and summer (Sr = 0.84) than in the fall 196 (Sr = 0.52; Figure S17).

198 Discussion

199 We simulated individual animal movements from fitted iSSFs to predict habitat selection 200 and functional connectivity for grizzly bears across a large swath of the southern Canadian 201 Rocky Mountains and adjacent areas under three scenarios of human disturbance. Comparing 202 movement success from simulations across these scenarios highlighted declining functional 203 connectivity in an important movement corridor with high bear densities and frequent human-204 bear conflicts. Our mixed-effects iSSFs allowed us to simultaneously estimate population-level 205 movement and habitat selection responses while explicitly accounting for individual-level 206 variation in these responses (Avgar et al. 2016, Muff et al. 2019). By simulating individual 207 movements directly from fitted iSSFs, we predicted grizzly bear space use and connectivity that 208 resulted from a realistic movement process.

209 We observed considerable variation in behavioral responses to varying conditions 210 throughout our study area. For example, generalized functional responses showed that bears 211 avoided areas near highways and roads when they had an abundance of productive vegetation 212 within their home range, but bears whose home ranges had lower vegetation productivity 213 strongly selected areas closer to highways and roads. The increased selection for roadsides in 214 low productivity areas was typified by the highly-protected Alberta park bears (those in the 215 BNPW, BNPE and KAN validation regions), where roadsides provided attractive foods such as 216 buffaloberry (*Shepherdia canadensis*), especially relative to the dry pine stands along with 217 expanses of rock and ice that largely composed these landscapes. Outside of protected areas, 218 increased use of roadsides by bears struggling to meet nutritional demands could represent an 219 ecological trap (Nielsen et al. 2004, Lamb et al. 2017). These results suggest conservation

actions such as highway crossing structures that augment habitat may be most effective at
reducing grizzly bear mortality risk in areas with generally low broad-scale vegetation
productivity. If grizzly bear movements and behaviors within home ranges reflect those during
longer-distance movements, these targeted actions could also increase broader scale connectivity
across the region.

225 Bears consistently avoided crossing highways in all seasons and regions, including 226 regions such as Banff National Park West and Kananaskis where they selected areas near roads. 227 Comparisons of predicted space use and movement success from past to current conditions 228 highlighted the degree to which highways have heavily impeded grizzly bear movements. Bears 229 also strongly avoided moving across high-elevation rocky terrain, glaciers, and towns in all 230 seasons. A portion of semi-permeable barrier crossings in our dataset were likely false positives 231 due our relocation interval of 6 hours and the highly mobile nature of grizzly bears. Therefore, we may have underestimated their avoidance of crossing these features. Semi-permeable barriers 232 233 collectively constrained grizzly bear movements to relatively narrow corridors in some areas, 234 such as the Elk and Bow River valleys. Avoidance of towns and mines was partially captured by 235 the positive greenness coefficients, which likely explains the lack of statistical significance for 236 the mine coefficients in spring and fall. Bears used lower elevation areas in the spring and fall 237 compared to the summer months (Figure S2), likely in response to a combination of snowpack 238 and forage availability (McLellan and Hovey 2001a). Some valley bottoms are particularly 239 attractive to bears in the fall, due to an abundance of carcasses and fruit trees (Lamb et al. 2017, 240 2023).

Any predictions of animal space use across a large area, and those in areas beyond the
spatial extent of model input data, should always be interpreted with caution (Beyer et al. 2010),

243 perhaps especially for a highly-mobile omnivore. Grizzly bears in this region are known to exhibit considerable dietary plasticity to help meet their high energetic requirements (Roberts et 244 245 al. 2014), sometimes relying on locally-abundant foods, such as fish (Mowat et al. 2013) or 246 whitebark pine (Pinus albicaulis) seeds (Hamer 2021), that are not captured by remotely-sensed 247 GIS layers such as those used in our models. Therefore, our predictions may underestimate the 248 relative importance of certain areas for grizzly bear habitat use. Further, our results may be 249 biased towards bears that frequently use valley bottoms, as most capture efforts were focused in 250 these areas.

251 Our simulated UDs largely represented within-home-range movements necessary to carry 252 out daily requirements (Riordan-Short et al. 2023) rather than long-distance dispersal, which is 253 rarely captured in animal movement data. However, given that grizzly bear dispersal in our study 254 area primarily occurs in gradual range shifts or expansions over a period of months to years (McLellan and Hovey 2001b, Proctor et al. 2004), some areas of high predicted use in our UDs 255 256 may overlap with dispersal corridors. Our simulations did not incorporate mortality risk, which 257 would be higher in areas near highways, human settlements, and agricultural areas (Northrup et 258 al. 2012, Lamb et al. 2023). Further, we did not explicitly account for extrinsic factors such as 259 competition or conspecific population density, which can influence movement and habitat 260 selection (Smith et al. 2023). Despite these potential limitations, our UDs generally performed 261 well in rigorous spatial cross-validation and external validation (Figures S13-S17), and the 262 should be valuable for informing large-scale conservation planning.

We focused our assessment of changing space use and functional connectivity on BC's Elk Valley and the adjacent eastern slopes of the Rocky Mountains, which collectively form an area of existing and proposed mining of rich metallurgical coal deposits, along with dispersed

266	human settlements that also rely on agriculture, forestry, and tourism. The area is situated where
267	the Rocky Mountains narrow to less than 70 km, and may serve as an important north-south
268	corridor facilitating broad-scale genetic connectivity (Palm et al. 2023). Future simulations
269	suggest that the combined effects of new coal mines and expanded settlements will lead to
270	further declines in local functional connectivity along the length of the Elk Valley but may
271	increase connectivity towards the east into presumably lower-quality habitat. Given the
272	magnitude of existing connectivity declines predicted by our simulations, even modest
273	connectivity losses in this area could eventually limit the movements of bears from adjacent
274	undisturbed areas that currently help avert local extirpations (Lamb et al. 2020).
275	Existing grizzly bear connectivity in the southern Canadian Rocky Mountains
276	demographically supports populations that would rapidly decline without it. Areas where bears
277	and extensive human development (towns, transportation corridors, and agriculture) overlap can
278	act as sink habitats where bears are not able to reproduce fast enough to offset high mortality.
279	Currently, connectivity in this region allows for population persistence in these areas through
280	both within-home-range movement and immigration from adjacent areas (Lamb et al. 2020).
281	This source-sink dynamic and demographic rescue has been observed widely across our study
282	area (Nielsen et al. 2004, Northrup et al. 2012b, Braid and Nielsen 2015, Lamb et al. 2020). If
283	future human-caused habitat alteration impedes functional connectivity to the point that
284	dispersing animals can no longer offset in situ demographic losses, grizzly bear populations in
285	these sink areas will decline.
200	

Grizzly bears are a wide-ranging keystone species (Tardiff and Stanford 1998), and
mitigating human disturbances that impede their movements should also improve connectivity
for other wildlife species. Conservation groups and resource companies targeting land purchases

289	can use our spatial predictions to optimize parcel selection, protect existing movement corridors,
290	and avoid degradation of areas where future connectivity is predicted to increase. At a minimum,
291	restoring degraded land or increasing landscape permeability using a combination of highway
292	crossing structures and fencing could help reduce potential negative effects of future
293	development on wildlife connectivity in the region (Clevenger and Ford 2010, Sawaya et al.
294	2014).
295	
296	References
297	Alberta Biodiversity Monitoring Institute. 2019. The Human Footprint Inventory 2019.
298	Apps, C. D., B. N. McLellan, J. G. Woods, and M. F. Proctor. 2004. Estimating Grizzly Bear
299	Distribution and Abundance Relative to Habitat and Human Influence. The Journal of
300	Wildlife Management 68:138–152.
301	Apps, C. D., and Wildlife Conservation Society Canada. 2007. Carnivores in the Southern
302	Canadian Rockies: Core Areas and Connectivity Across the Crowsnest Highway.
303	Wildlife Conservation Society Canada, Toronto, Ontario.
304	Avgar, T., S. R. Lele, J. L. Keim, and M. S. Boyce. 2017. Relative Selection Strength:
305	Quantifying effect size in habitat- and step-selection inference. Ecology and Evolution
306	7:5322–5330.
307	Avgar, T., J. R. Potts, M. A. Lewis, and M. S. Boyce. 2016. Integrated step selection analysis:
308	bridging the gap between resource selection and animal movement. Methods in Ecology
309	and Evolution 7:619–630.
310	Beyer, H. L., D. T. Haydon, J. M. Morales, J. L. Frair, M. Hebblewhite, M. Mitchell, and J.
311	Matthiopoulos. 2010. The interpretation of habitat preference metrics under use-

- availability designs. Philosophical Transactions of the Royal Society B: Biological
 Sciences 365:2245–2254.
- Bowne, D. R., and M. A. Bowers. 2004. Interpatch movements in spatially structured
 populations: a literature review. Landscape Ecology 19:1–20.
- Boyce, M. S., P. R. Vernier, S. E. Nielsen, and F. K. A. Schmiegelow. 2002. Evaluating resource
 selection functions. Ecological Modelling 157:281–300.
- **318** Braid, A. C. R., and S. E. Nielsen. 2015. Prioritizing Sites for Protection and Restoration for
- 319 Grizzly Bears (Ursus arctos) in Southwestern Alberta, Canada. PLOS ONE 10:e0132501.
- 320 Brooks, M. E., K. Kristensen, A. M. Koen J. van Benthem, C. W. Berg, A. Nielsen, H. J. Skaug,
- 321 M. Maechler, and B. M. Bolker. 2017. glmmTMB Balances Speed and Flexibility
- Among Packages for Zero-inflated Generalized Linear Mixed Modeling. The R Journal
 9:378–400.
- 324 Cavanaugh, K. C., D. A. Siegel, P. T. Raimondi, and F. Alberto. 2014. Patch definition in
- metapopulation analysis: a graph theory approach to solve the mega-patch problem.
 Ecology 95:316–328.
- 327 Ciarniello, L. M., M. S. Boyce, D. R. Seip, and D. C. Heard. 2007. Grizzly bear habitat selection
 328 is scale dependent. Ecological Applications 17:1424–1440.
- 329 Clevenger, A. P., and A. T. Ford. 2010. Wildlife Crossing Structures, Fencing, and Other
- Highway Design Considerations. Page *in* J. P. Beckmann, A. P. Clevenger, M. P. Huijser,
- and J. A. Hilty, editors. Safe passages : highways, wildlife, and habitat connectivity.
 Washington, DC.
- 333 Doherty, T. S., and D. A. Driscoll. 2018. Coupling movement and landscape ecology for animal
 334 conservation in production landscapes. Proceedings of the Royal Society B: Biological

- 335 Sciences 285:20172272.
- Fahrig, L. 2007. Non-optimal animal movement in human-altered landscapes. Functional
 Ecology 21:1003–1015.
- 338 Fahrig, L., V. Arroyo-Rodríguez, E. Cazetta, A. Ford, J. Lancaster, and T. Ranius. 2021.

Landscape connectivity. The Routledge Handbook of Landscape Ecology:67–88.

- 340 Farr, T. G., P. A. Rosen, E. Caro, R. Crippen, R. Duren, S. Hensley, M. Kobrick, M. Paller, E.
- 341 Rodriguez, L. Roth, D. Seal, S. Shaffer, J. Shimada, J. Umland, M. Werner, M. Oskin, D.
- 342 Burbank, and D. Alsdorf. 2007. The Shuttle Radar Topography Mission. Reviews of
- Geophysics 45:RG2004.
- 344 Fieberg, J. R., J. D. Forester, G. M. Street, D. H. Johnson, A. A. ArchMiller, and J.
- Matthiopoulos. 2018. Used-habitat calibration plots: a new procedure for validating
 species distribution, resource selection, and step-selection models. Ecography 41:737–
 752.
- 348 Fieberg, J., J. Signer, B. Smith, and T. Avgar. 2021. A 'How to' guide for interpreting
- parameters in habitat-selection analyses. Journal of Animal Ecology 90:1027–1043.
- 350 Gibeau, M. L., A. P. Clevenger, S. Herrero, and J. Wierzchowski. 2002. Grizzly bear response to

351 human development and activities in the Bow River Watershed, Alberta, Canada.

- Biological Conservation 103:227–236.
- Government of Alberta. 2022. Alberta Wildlife Act. Page Revised Statutes of Alberta 2000
 Chapter W-10. Edmonton, AB.
- 355 Government of British Columbia. 2021. Digital Road Atlas (DRA) Master Partially-Attributed
 356 Roads.
- 357 Government of Canada. 2016. National Road Network (NRN) AB, Alberta.

358	Graham, K., and G. B. Stenhouse. 2014. Home range, movements, and denning chronology of
359	the Grizzly Bear (Ursus arctos) in west-central Alberta. The Canadian Field-Naturalist
360	128:223–234.

Hamer, D. 2021. Use of Whitebark Pine (*Pinus albicaulis*) seeds by GPS-collared Grizzly Bears
 (*Ursus arctos*) in Banff National Park, Alberta. The Canadian Field-Naturalist 135:61–
 67.

Hilty, J., G. Worboys, A. Keeley, S. Woodley, B. Lausche, H. Locke, M. Carr, I. Pulsford, J.

365 Pittock, J. W. White, D. Theobald, J. Levine, M. Reuling, J. Watson, R. Ament, and G.

366 Tabor. 2020. Guidelines for conserving connectivity through ecological networks and

367 corridors. Best practice protected area Guidelines Series 30:122.

- Hodel, F. H., and J. R. Fieberg. 2022. Circular–linear copulae for animal movement data.
 Methods in Ecology and Evolution 13:1001–1013.
- Kerman, J., and A. Gelman. 2007. Manipulating and summarizing posterior simulations using
 random variable objects. Statistics and Computing 17:235–244.
- 372 Lamb, C. T., A. T. Ford, B. N. McLellan, M. F. Proctor, G. Mowat, L. Ciarniello, S. E. Nielsen,
- and S. Boutin. 2020. The ecology of human–carnivore coexistence. Proceedings of the
 National Academy of Sciences 117:17876–17883.

375 Lamb, C. T., G. Mowat, B. N. McLellan, S. E. Nielsen, and S. Boutin. 2017. Forbidden fruit:

human settlement and abundant fruit create an ecological trap for an apex omnivore.Journal of Animal Ecology 86:55–65.

378 Lamb, C. T., L. Smit, G. Mowat, B. McLellan, and M. Proctor. 2023. Unsecured attractants,

379 collisions, and high mortality strain coexistence between grizzly bears and people in the

380 Elk Valley, southeast British Columbia. Conservation Science and Practice 5:e13012.

- Lindenmayer, D. B., and J. Fischer. 2013. Habitat Fragmentation and Landscape Change: An
 Ecological and Conservation Synthesis. Island Press.
- 383 Manly, B. F. J., L. L. McDonald, D. L. Thomas, T. L. McDonald, and W. P. Erickson. 2002.
- 384 Resource Selection by Animals. Springer.
- Matthiopoulos, J., M. Hebblewhite, G. Aarts, and J. Fieberg. 2011. Generalized functional
 responses for species distributions. Ecology 92:583–589.
- 387 McCune, B., and D. Keon. 2002. Equations for potential annual direct incident radiation and heat
 388 load. Journal of Vegetation Science 13:603–606.
- 389 McLellan, B. N. 2015. Some mechanisms underlying variation in vital rates of grizzly bears on a
- multiple use landscape. The Journal of Wildlife Management 79:749–765.
- 391 McLellan, B. N., and F. W. Hovey. 1995. The diet of grizzly bears in the Flathead River
- drainage of southeastern British Columbia. Canadian Journal of Zoology 73:704–712.
- McLellan, B. N., and F. W. Hovey. 2001. Habitats Selected by Grizzly Bears in a Multiple Use
 Landscape. The Journal of Wildlife Management 65:92–99.
- 395 McLellan, B. N., and D. M. Shackleton. 1988. Grizzly Bears and Resource-Extraction Industries:
- Effects of Roads on Behaviour, Habitat Use and Demography. Journal of Applied
 Ecology 25:451–460.
- Mowat, G., D. C. Heard, and C. J. Schwarz. 2013. Predicting Grizzly Bear Density in Western
 North America. PLoS ONE 8:e82757.
- 400 Muff, S., J. Signer, and J. Fieberg. 2019. Accounting for individual-specific variation in habitat-
- 401 selection studies: Efficient estimation of mixed-effects models using Bayesian or
- 402 frequentist computation. Journal of Animal Ecology 89:80–92.
- 403 Nielsen, S. E., J. Cranston, and G. B. Stenhouse. 2009. Identification of Priority Areas for

404	Grizzly Bear Conservation and Recovery in Alberta, Canada. Journal of Conservation
405	Planning 5:38–60.

- 406 Nielsen, S. E., S. Herrero, M. S. Boyce, R. D. Mace, B. Benn, M. L. Gibeau, and S. Jevons.
- 407 2004. Modelling the spatial distribution of human-caused grizzly bear mortalities in the
- 408 Central Rockies ecosystem of Canada. Biological Conservation 120:101–113.
- 409 Northrup, J. M., J. Pitt, T. B. Muhly, G. B. Stenhouse, M. Musiani, and M. S. Boyce. 2012a.
- 410 Vehicle traffic shapes grizzly bear behaviour on a multiple-use landscape. Journal of
 411 Applied Ecology 49:1159–1167.
- 412 Northrup, J. M., G. B. Stenhouse, and M. S. Boyce. 2012b. Agricultural lands as ecological traps
- 413 for grizzly bears: Agricultural lands as ecological traps. Animal Conservation 15:369–
 414 377.
- 415 Northrup, J. M., E. Vander Wal, M. Bonar, J. Fieberg, M. P. Laforge, M. Leclerc, C. M.
- 416 Prokopenko, and B. D. Gerber. 2022. Conceptual and methodological advances in
- 417 habitat-selection modeling: guidelines for ecology and evolution. Ecological Applications
 418 32:e02470.
- 419 Palm, E. C., E. L. Landguth, Z. A. Holden, C. C. Day, C. T. Lamb, P. F. Frame, A. T.
- 420 Morehouse, G. Mowat, M. F. Proctor, M. A. Sawaya, G. Stenhouse, J. Whittington, and
- 421 K. A. Zeller. 2023. Corridor-based approach with spatial cross-validation reveals scale-
- 422 dependent effects of geographic distance, human footprint and canopy cover on grizzly
- 423 bear genetic connectivity. Molecular Ecology 32:5211–5227.
- Paton, R. S., and J. Matthiopoulos. 2016. Defining the scale of habitat availability for models of
 habitat selection. Ecology:14-2241.1.
- 426 Pither, R., P. O'Brien, A. Brennan, K. Hirsh-Pearson, and J. Bowman. 2023. Predicting areas

427	important for ecological connectivity throughout Canada. PLOS ONE 18:e0281980.
428	Proctor, M. F., D. Paetkau, B. N. Mclellan, G. B. Stenhouse, K. C. Kendall, R. D. Mace, W. F.
429	Kasworm, C. Servheen, C. L. Lausen, M. L. Gibeau, W. L. Wakkinen, M. A. Haroldson,
430	G. Mowat, C. D. Apps, L. M. Ciarniello, R. M. R. Barclay, M. S. Boyce, C. C. Schwartz,
431	and C. Strobeck. 2012. Population fragmentation and inter-ecosystem movements of
432	grizzly bears in western Canada and the northern United States. Wildlife Monographs
433	180:1–46.
434	Roberts, D. R., V. Bahn, S. Ciuti, M. S. Boyce, J. Elith, G. Guillera-Arroita, S. Hauenstein, J. J.
435	Lahoz-Monfort, B. Schröder, W. Thuiller, D. I. Warton, B. A. Wintle, F. Hartig, and C.
436	F. Dormann. 2017. Cross-validation strategies for data with temporal, spatial,
437	hierarchical, or phylogenetic structure. Ecography 40:913–929.
438	Roberts, D. R., S. E. Nielsen, and G. B. Stenhouse. 2014. Idiosyncratic responses of grizzly bear
439	habitat to climate change based on projected food resource changes. Ecological
440	Applications 24:1144–1154.
441	Sawaya, M. A., S. T. Kalinowski, and A. P. Clevenger. 2014. Genetic connectivity for two bear
442	species at wildlife crossing structures in Banff National Park. Proceedings of the Royal
443	Society B: Biological Sciences 281:20131705.
444	Sells, S. N., C. M. Costello, P. M. Lukacs, L. L. Roberts, and M. A. Vinks. 2023. Predicted
445	connectivity pathways between grizzly bear ecosystems in Western Montana. Biological
446	Conservation 284:110199.
447	Serrouya, R., B. N. Mclellan, G. D. Pavan, and C. D. Apps. 2011. Grizzly bear selection of
448	avalanche chutes: Testing the effectiveness of forest buffer retention. The Journal of
449	Wildlife Management 75:1597–1608.

- 450 Signer, J., J. Fieberg, and T. Avgar. 2017. Estimating utilization distributions from fitted step451 selection functions. Ecosphere 8.
- 452 Signer, J., J. Fieberg, and T. Avgar. 2019. Animal movement tools (amt): R package for
- 453 managing tracking data and conducting habitat selection analyses. Ecology and Evolution
 454 9:880–890.
- 455 Signer, J., J. Fieberg, B. Reineking, U. Schlägel, B. Smith, N. Balkenhol, and T. Avgar. 2024.
 456 Simulating animal space use from fitted integrated Step-Selection Functions (iSSF).
 457 Methods in Ecology and Evolution 15:43–50.
- 458 Tardiff, S. E., and J. A. Stanford. 1998. Grizzly Bear Digging: Effects on Subalpine Meadow

459 Plants in Relation to Mineral Nitrogen Availability. Ecology 79:2219–2228.

- 460 Turchin, P. 1998. Quantitative Analysis of Movement: Measuring and Modeling Population
 461 Redistribution in Animals and Plants. Oxford University Press.
- 462 Unnithan Kumar, S., and S. A. Cushman. 2022. Connectivity modelling in conservation science:
 463 a comparative evaluation. Scientific Reports 12:16680.
- 464 Valle, D., N. Attias, J. A. Cullen, M. B. Hooten, A. Giroux, L. G. R. Oliveira-Santos, A. L. J.
- 465 Desbiez, and R. J. Fletcher. 2023, June 1. Bridging the gap between movement data and
 466 connectivity analysis using the time-explicit Step Selection Function (tSSF). bioRxiv.
- Waller, J. S., and C. Servheen. 2005. Effects of transportation infrastructure on grizzly bears in
 northwestern Montana. Journal of Wildlife Management 69:985–1000.
- 469 Whittington, J., M. Hebblewhite, R. W. Baron, A. T. Ford, and J. Paczkowski. 2022. Towns and
- 470 trails drive carnivore movement behaviour, resource selection, and connectivity.
- 471 Movement Ecology 10:17.
- 472 Wilson, M. F. J., B. O'Connell, C. Brown, J. C. Guinan, and A. J. Grehan. 2007. Multiscale

473	Terrain Analysis of Multibeam Bathymetry Data for Habitat Mapping on the Continental
474	Slope. Marine Geodesy 30:3–35.
475	Zeller, K. A., K. McGarigal, and A. R. Whiteley. 2012. Estimating landscape resistance to
476	movement: a review. Landscape Ecology 27:777–797.
477	
478	
479	
480	
481	
482	
483	
484	Appendix 1
485	Creation of habitat covariate layers
486	Topography, greenness and canopy cover
487	We calculated the terrain ruggedness index (TRI) using elevation data from NASA's
488	Shuttle Radar Topography Mission (Farr et al. 2007) using the mean elevation difference
489	between each pixel and its eight neighboring pixels (Wilson et al. 2007). We used semi-decadal
490	canopy cover data from NASA's Global 30-m Landsat Tree Canopy Version 4. For vegetation
491	greenness, we used Landsat 8 enhanced vegetation index (EVI) data to create a static layer that
492	represented the average EVI for years 2013–2016, and created annual layers for each year in the

- 494 2013–2020, so we backcasted EVI to 2000. We associated both EVI metrics with time since
- disturbance (logging, mine, or fire) using the 2013–2022 data, and backcasted disturbances for

496 the 2000–2012 period using average time since disturbance relationships for each feature. We assigned the average EVI and delta EVI values for undisturbed areas prior to disturbance during 497 498 the backcasting. 499 500 Annual mines layers 501 We hand digitized mines using 30-m resolution annual Landsat 7 imagery. Road and highway data was compiled using federal and provincial repositories (Government of Canada 502 2016, Alberta Biodiversity Monitoring Institute 2019, Government of British Columbia 2021). 503 504 505 Semi-permeable barrier variables We defined the boundaries of towns using building densities calculated from Microsoft's 506 507 building footprint layer (https://www.microsoft.com/en-us/maps/building-footprints) using the "kernel density" tool in ArcMap with a search radius of 500 m; we classified densities above 100 508 buildings/km² as 1 and all others as 0. We created the alpine rock/ice barrier layer using the 509 510 "barren" and "snow and ice" categories from the 30-m resolution North American Land Cover 511 Change Monitoring System's 2015 land cover layer and only included areas >2000 m in 512 elevation. 513 Distance-to transformations for roads and highways 514 515 To create distance-to variables for roads and highways, we calculated selection ratios 516 (Manly et al. 2002) for each season across a range of distances to roads to determine the distance 517 beyond which grizzly bear responses to roads changed from avoidance to selection (or vice 518 versa). We then estimated the decay rate α in the exponential decay equation 1-exp($-\alpha d$), where

519 d is the distance to roads, where the decay curve asymptotes at this distance (Nielsen et al. 2009), 520 and used that equation to transform distances to roads in our models. Transformed distance 521 values ranged from 0 at the road to near 1 at the asymptote, so a positive selection coefficient 522 would indicate selection for greater distances from roads. 523 524 Creating past (human disturbance-free) layers for greenness and canopy cover 525 To create past layers, we filled greenness and canopy cover values within existing disturbance 526 footprints using moving windows of 5 pixels for highways and roads, and 15 pixels for mines 527 and towns). We then calculated a past broad-scale greenness layer using the past greenness layer. 528 529 Additional details on integrated step selection functions 530 Model selection We did not include a quadratic term for greenness, as we predicted that bears would select for 531 high greenness across all seasons. For canopy cover (first-order) and greenness, we included 532 533 interactions with either broad-scale greenness (i.e., a generalized functional response) or 534 elevation, as the two were highly correlated, and used Spearman's rank correlations in the spatial 535 cross validation procedure to determine which interactions performed best in the model. We used log likelihood to determine whether top models would include footprint or semi-permeable 536 537 barrier variables for towns and mines. We also used log likelihood to determine whether to use 538 static or annual EVI values, and whether to use EVI or delta EVI. 539 540 Second-order (broad-scale) resource selection function for determining simulation start 541 locations

542 To estimate home ranges for the broad-scale resource selection function (RSF), we first filtered out bear-years with less than three months of data. We then used net squared displacement 543 curves to identify bears that engaged in dispersal movements or exploratory movements and 544 545 omitted these bears from the data set. We subsampled the GPS data for each bear to one point 546 every 24 hours to reduce the effect of spatial autocorrelation in the resulting model. We then 547 omitted bears with less than 40 GPS locations, which resulted in 109 individuals for the analysis. We randomly sampled 10% of these individuals to use as a hold-out testing data set to assess the 548 predictive power of our models. This resulted in 98 individuals for the final training data and 11 549 individuals for the testing data. 550

551 For each bear, we estimated a home range polygon with 90% kernel density utilization 552 distributions using the 'adehabitatHR' package and the reference bandwidth. We created a buffer 553 area around the spatial union of all individual bear locations to fully capture broad-scale availability of resources in the study area. To do this, we sampled 'used' points for each bear 554 555 randomly within the home range polygons. The number of points sampled was the same number 556 of points that went into estimating the home range polygon for each bear. We then calculated the maximum distance among GPS points for each bear and used the 90th percentile of the 557 558 population level distribution of distances to create a buffer around the bear home ranges. We 559 sampled available points across this area in a 1:1 ratio with the used points. We ran RSFs using a 560 generalized linear model using the 'glm' function in R.

561 Studies have shown that bears respond to environmental characteristics and resources at 562 different spatial scales (Apps et al. 2004, Ciarniello et al. 2007). Therefore, we developed multi-563 scale models using different neighborhood averages of variables (1000-m, 2500-m, and 5000-m) 564 so as not to confound selection across the different levels. We took the mean of each variable within each uniform buffer around each used and available point. We developed multi-scale
logistic regressions with Generalized Linear Models and the 'glm' function in R. We first ran a
single model for each variable at each scale and identified the scale with the highest log
likelihood. These were carried forward into the multiple regression models to create a multi-scale
model where each variable was included at its characteristic scale.

570 Variables in the 2nd order RSF included building density, roads, highways, mine footprints, canopy cover, enhanced vegetation index (EVI), forest age, heat load (i.e., potential 571 572 annual direct incident solar radiation centered around the southwest aspect; McCune and Keon 573 2002), summer precipitation, elevation, terrain ruggedness index (TRI), topographic position index (TPI), northness, along with barren, crop, grass and shrub land cover classes (as dummy 574 coded binary variables). We included all variables at the 5000-m scale except for grass, which 575 576 we included at the 1000-m scale. We found statistically significant avoidance of high building 577 densities, crop lands and high TPI (ridgetops). Bears strongly selected for higher elevation areas with higher values of EVI, summer precipitation, and heat load (generally southwest facing 578 579 slopes) at this broad scale.

- 581 *Supplementary tables*
- 582
- **Table S1.** Summary of habitat covariate data, including model variables, data types, availability, temporal and spatial resolution for
- 584 covariates included in integrated step selection functions for 109 grizzly bears marked between 2000 and 2020 in Canada's Southern
- 585 <u>Rocky Mountains.</u>

Model term(s)	Variable type	Original data	Original source	Data availability		Native resolution	Ι
evi_start; evi_end	Continuous	Raster	Landsat 7/8	https://developers.google.com/earth- engine/datasets/catalog/LANDSAT_LC08_C01_T1_8DAV_FVI	Static or	30m	7 91
evi_broad_end	Continuous	Raster	Landsat 7/8	https://developers.google.com/earth- engine/datasets/catalog/LANDSAT_LC08_C01_T1_8DAV_FVI	Static	30m	Bro
cc_start; cc_end	Continuous	Raster	NASA	https://developers.google.com/earth- engine/datasets/catalog/NASA_MEASURES_GECC_TC_v3	Static	30m	
tri_start; tri_end	Continuous	Raster	NASA SRTM	https://developers.google.com/earth- engine/datasets/catalog/USGS_SRTMGL1_003	Static	30m	TR
elev_end	Continuous	Raster	NASA SRTM	https://developers.google.com/earth- engine/datasets/catalog/USGS_SRTMGL1_003	Static	30m	
d_hwy_450m_end	Continuous	Raster	BC/AB	https://www2.gov.bc.ca/gov/content/data/geographic-data-	Static		
d_road_450m_end	Continuous	Raster	BC/AB	services/topographic-data/roads https://abmi.ca/home/data- analytics/da-top/da-product-overview/Human-Footprint-	Static		
barrier_hwy_end	Binary	Polyline	BC/AB	Products/HF-inventory.html	Static		
barrier_town_end	Binary semi-	Polygon	Microsoft building	https://github.com/microsoft/CanadianBuildingFootprints	Static		B
town_end	Binary footprint	Raster	Microsoft building	https://github.com/microsoft/CanadianBuildingFootprints	Static		B
barrier_water_end	Binary semi-	Raster	CEC land	http://www.cec.org/north-american-environmental-atlas/land- cover-2010-landsat-30m/	Static	30m	La
barrier_rock_ice_end	Binary	Raster	CEC land	http://www.cec.org/north-american-environmental-atlas/land- cover-2010-landsat-30m/	Static	30m	Roc
mine_end	Binary footprint	Raster	Landsat 7	https://developers.google.com/earth- engine/datasets/catalog/LANDSAT_LE07_C02_T1_L2	Annual	30m	dioit

Table S2. Model formulas for final seasonal integrated step selection functions for 109 grizzly bears marked between 2000 and 2020
 in Canada's Southern Rocky Mountains.

		Final model terms	
	Spring	Summer	Fall
Topograph y and vegetation	evi_end + canopy_cover_end + canopy_cover_end ² + tri_end + tri_end ² + northness_end + evi_end:canopy_cover_end + elev_end + elev_end ² + canopy_cover_end:elev_end + evi_end:elev_end +	evi_end + canopy_cover_end + canopy_cover_end ² + tri_end + tri_end ² + northness_end + evi_end:canopy_cover_end + elev_end + elev_end ² + canopy_cover_end:elev_end + evi_end:elev_end +	evi_end + canopy_cover_end + canopy_cover_end ² + tri_end + tri_end ² + northness_end + evi_end:canopy_cover_end +
Human disturbance s and semi- permeable barriers	d_hwy_end + d_road_end + hwy_cross + mine_end + town_cross + water_cros s+ rock_ice_cross	d_hwy_end + d_road_end + hwy_cross + mine_end + town_cross + water_cross + rock_ice_cross	hwy_cross + mine_end + town_cross + water_cross + rock_ice_cross
Generalize d functional responses	<pre>d_hwy_end:evi_broad_end + d_road_end:evi_broad_end + hwy_cross:evi_broad_end + rock_ice_cross:evi_broad_end +</pre>	<pre>canopy_cover_end:evi_broad_end + d_hwy_end:evi_broad_end + d_road_end:evi_broad_end + hwy_cross:evi_broad_end + rock_ice_cross:evi_broad_end +</pre>	evi_end:evi_broad_end + canopy_cover_end:evi_broad_end + hwy_cross:evi_broad_end + rock_ice_cross:evi_broad_end +
Movement variables	log_sl + cos_ta + log_sl:cos_ta + log_sl:cc_start + log_sl:tri_start + log_sl:evi_start + d_den_end	log_sl + cos_ta + log_sl:cos_ta + log_sl:cc_start + log_sl:tri_start + log_sl:evi_start + d_den_end	log_sl + cos_ta + log_sl:cos_ta + log_sl:cc_start + log_sl:tri_start + log_sl:evi_start + d_den_end



- **Figure S1.** Selection ratios, shown by season and region, as a function of distance to (non-highway) roads for 109 grizzly bears
- 597 marked between 2000–2020 in the southern Canadian Rocky Mountains. The size of points depicts the relative number of locations in
- that distance bin. Values above 1 indicate selection and values below 1 indicate avoidance.
- 599
- 600



- **Figure S2.** Selection ratios, shown by season and region, as a function of distance to highway for 109 grizzly bears marked between
- 603 2000–2020 in the southern Canadian Rocky Mountains. The size of points depicts the relative number of locations in that distance bin.
- 604 Values above 1 indicate selection and values below 1 indicate avoidance.



Figure S3. Home range centroids for 109 grizzly bears with GPS collar data from 2000–2020 in the southern Canadian Rocky Mountains, shown by spatial validation region and sex.



Figure S4. Predicted relative selection strength of grizzly bears, shown by season, across a range of values for three habitat covariates included in integrated step-selection functions (iSSF) fit to GPS collar data from 109 bears from 2000–2020 in the southern Canadian Rocky Mountains. Variable ranges on the x-axis include the middle 95% of values available to bears in each season, excluding values below and above the 2.5% and 97.5% quantiles, respectively. Selection strength for a covariate is relative to its average value (from the model input data) during that season. All other covariates in the model were held constant at their average values. Shaded regions indicate 95% confidence intervals based on fixed effects only. Note the different y-axis for each season.



Figure S5. Selection coefficients for all model terms included in integrated step-selection

630 functions fit to GPS collar data from 109 grizzly bears from 2000–2020 in the southern Canadian

631 Rocky Mountains. Transparent points show individual-level responses (random slopes; if

applicable), while points with black outlines and error bars intervals depict fixed-effects

633 coefficients and associated 95% confidence intervals.



Figure S6. Predicted distributions of net displacement per hour as a function of canopy cover(top panels) and terrain ruggedness (bottom panels) across three seasons from integrated step-

- 638 selection functions fit to GPS collar data from 109 grizzly bears from 2000–2020 in the southern
- 639 Canadian Rocky Mountains.



Figure S7. Area of utilization distribution isopleths as a function of the number of animals (paths) in simulations from integrated step

647 selection functions fit to 109 grizzly bears from 2000–2020 in the southern Canadian Rocky Mountains.



Figure S8. Maps showing the relative percent change in the spring season utilization distribution, simulated from an integrated step
 selection function fit to 109 grizzly bears in the Southern Canadian Rocky Mountains from 2000–2020, as a function of simulation

length. Values are relative to the maximum pixel change across all 10-day periods, excluding the bottom 0.5% and top 0.5% of values

to aid visualization. Note the last period is 8 days instead of 10.



Figure S9. Step length distribution for real steps from 109 grizzly bears in the southern Canadian
Rocky Mountains versus those for simulated steps from seasonal integrated step selection
functions. The time interval between successive steps was 4.5 to 6 hours for real steps and 6
hours for simulated steps.

658



Figure S10. Turn angle distribution for real steps from 109 grizzly bears in southern Canadian
 Rocky Mountains versus those for simulated steps from seasonal integrated step selection
 functions. The time interval between successive steps was 4.5 to 6 hours for real steps and 6
 hours for simulated steps.



Figure S11. Observed (real) grizzly bear movements from GPS collar data for specific areas and
seasons in the southern Canadian Rocky Mountains compared to simulated movements under
current conditions from fitted integrated step-selection functions. GPS collar data was not
randomly distributed with respect to bear density across the landscape due to capture methods
and access; therefore some areas not used by collared bears that were predicted as used in
simulations likely represent areas where bears were present but were not sampled via collaring
efforts.



Figure S12. Spatial cross validation for six regions showing the area-adjusted average proportions of used locations that fell into each of the 10 (nearly equal-area) bins of utilization distributions, where each individual line is a separate bear and validation results are depicted by season and region. Utilization distributions were created from individual-based simulations of integrated step-selection functions fit to GPS collar data from 109 bears from 2000–2020 in the southern Canadian Rocky Mountains. Models were fit to training data that excluded the focal region and predictions were made to that withheld region. Bolded points and error bars indicate mean values ± 1 standard deviation across all individuals for each map bin. Text annotation displays the mean ± 1 standard deviation of Spearman's rank correlations across all individuals in that season-region.



Figure S13. Used-habitat calibration plots for the spring season integrated step-selection function fit to GPS collar data from 95 grizzly bears from 2000–2020 in the southern Canadian Rocky Mountains. Panels depict the distribution of available and used locations for continuous variables in the test data sets (withheld region), along with 95% simulation envelopes for the predicted distribution of these habitat covariates at the used locations from the step-selection functions fitted to the training data sets (the remaining five regions). Models are well calibrated if the used location distributions fall within the simulation envelopes.



Figure S14. Used-habitat calibration plots for the summer season integrated step-selection function fit to GPS collar data from 79 grizzly bears from 2000–2020 in the southern Canadian Rocky Mountains. Panels depict the distribution of available and used locations for continuous variables in the test data sets (withheld region), along with 95% simulation envelopes for the predicted distribution of these habitat covariates at the used locations from the step-selection functions fitted to the training data sets (the



remaining five regions). Models are well calibrated if the used location distributions fall within the simulation envelopes.



Figure S15. Used-habitat calibration plots for the fall season integrated step-selection function fit to GPS collar data from 109 grizzly bears from 2000–2020 in the southern Canadian Rocky Mountains. Panels depict the distribution of available and used locations for continuous variables in the test data sets (withheld region), along with 95% simulation envelopes (model predictions) for the predicted distribution of these habitat covariates at the used locations from the step-selection functions fitted to the training data sets (the remaining five regions). Models are well calibrated if the used location distributions fall within the simulation envelopes.



Figure S16. Used-habitat calibration plots for integrated step-selection functions fit to GPS collar data from 109 grizzly bears from

- 705 2000–2020 in the southern Canadian Rocky Mountains. Panels depict the distribution of available and used locations for binary
- variables in the test data sets (withheld region), along with 95% simulation envelopes (model predictions) for the predicted
- 707 distribution of these habitat covariates at the used locations from the step-selection functions fitted to the training data sets (the
- remaining five regions). Models are well calibrated if the used location distributions fall within the simulation envelope.



Figure S17. External validation of seasonal utilization distributions using GPS location data from 17 grizzly bears in the Flathead Valley, BC, showing the area-adjusted average proportions of used locations that fell into each of the 10 (nearly equal-area) bins of utilization distributions. Each individual line is a separate bear. Utilization distributions were created from individual-based simulations of integrated step-selection functions fit to GPS collar data from 109 bears from 2000–2020 in the southern Canadian Rocky Mountains. Bolded points and error bars indicate mean values ± 1 standard deviation across all individuals for each map bin. Text annotation displays the mean ± 1 standard deviation of Spearman's rank correlations across all individuals in that season.