INFLUENCE OF LAND COVER, FIRE AND HUMAN DISTURBANCE ON HABITAT SELECTION BY BOREAL CARIBOU IN THE NWT

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EXECUTIVE SUMMARY

Population declines of boreal caribou in Canada are thought to be linked to habitat disturbance from human development activity and wild fires. Both national and NWT recovery strategies for this threatened species recommend developing range plans to manage habitat disturbance at levels that can support self-sustaining populations. To meet critical habitat requirements defined in the national recovery strategy, at least 65% undisturbed habitat must be maintained within each local population range. Range planning also requires identifying areas that provide the habitat attributes that boreal caribou need to survive and reproduce. Currently, the definition of critical habitat for boreal caribou considers any fires less than 40 years old to be disturbed habitat. Unlike many boreal caribou ranges in southern Canada, wildfire is the main source of habitat disturbance in the NWT boreal caribou range. This project sought to better understand seasonal and annual habitat selection of boreal caribou in the NWT as a function of land-cover type, fire age, and human disturbance. Location data collected from >300 adult female boreal caribou collared between May 2002 and March 2018 within five regional monitoring areas were used in Resource Selection Function (RSF) models to assess habitat selection during 7 seasonal activity periods and on a year-round basis. Habitat selection was assessed at two spatial scales by defining habitat availability within: 1) broad scale polygons describing North and South NWT groups of caribou (2nd order selection), and 2) within individual annual home ranges (3rd order selection). RSF models included variables characterizing burn age (by decade) within specific land-cover types, landscape context (the proportion of sparse conifer and broadleaf land cover within a 1-km radius), and impacts from human disturbance (distance to major roads, settlements, and other polygonal features, and linear feature density (km/km^2)). Caribou generally showed higher selection for younger burns (<10 years old) and older burns (>30 years old) and avoided middle-aged burns (11–30 years old). Selection for burns by caribou in the NWT appeared to be strongest during the snow-free seasons, followed by increasing avoidance of burns ≤40 years old from early to late-winter. Preference for recent burns during the snow-free season may be associated with greater forage abundance or quality in these areas and the higher nutritional demands experienced by lactating females during this period. Human disturbance features also influenced caribou habitat selection. Caribou generally selected areas further away from major roads and polygonal disturbances such as well pads and cutblocks, but occurred closer to settlements than expected, perhaps an artifact of logistical constraints on deploying collars on animals far from settlements. Caribou avoided areas with high linear feature density during the snow-free season, but this trend was reversed during mid- to late winter. Second-order RSF models had excellent predictive performance, but there was greater seasonal variability in predictive performance of third-order RSF models, which likely reflects higher variability in habitat available to each individual at this scale. Our findings generally agree with recent research questioning the relative importance of fire effects on caribou demography and distribution. Animals are assumed to select habitat in a way that enhances their individual fitness, and in the NWT, female caribou appear to seek out recently burned land-cover types during the snow-free season, suggesting that these areas may have some benefit to caribou. Range plans should consider maintaining a mix of recently burned and unburned areas to meet the shifting seasonal requirements of caribou. Predictive habitat selection maps generated by this study can be used in range planning and other applications to help identify important areas for boreal caribou that may require more careful management of both human and fire disturbance.

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INTRODUCTION

Boreal caribou are currently listed as a threatened species both nationally (in 2003) and in the Northwest Territories ([NWT] in 2014) under federal and territorial species at risk legislation (Environment Canada 2012, Northwest Territories Conference of Management Authorities 2013). Declines of boreal caribou throughout most of Canada are thought to be caused by habitat disturbance and fragmentation (Environment Canada 2012). The hypothesized link between habitat disturbance and boreal caribou declines is through apparent competition, whereby human-caused disturbances and forest fires creates early-seral (or young forest) habitat that can support higher densities of other ungulate species (e.g., moose and deer), in turn leading to higher densities of predators (e.g. wolves), which subsequently prey on caribou at unsustainable rates (Environment Canada 2012). Linear disturbances such as roads and seismic lines can also facilitate movements of predators (and people) into boreal caribou habitat, making it more difficult for boreal caribou to maintain spatial separation from predators and harvesters (DeMars and Boutin 2018, Mumma et al. 2018). Wolves have been observed to travel farther and faster on linear features through forested habitat which increases the likelihood that they will encounter and kill boreal caribou (Dickie et al. 2017b).

In developing the national recovery strategy for boreal caribou (Environment Canada 2012), Environment and Climate Change Canada (ECCC) assessed the relationship between habitat disturbance and demographic performance of boreal caribou in order to define critical habitat (Environment Canada 2011). Critical habitat for boreal caribou is defined as:

- *"The area within the boundary of each boreal caribou range that provides an overall ecological condition that will allow for an ongoing recruitment and retirement cycle of habitat, which maintains a perpetual state of a minimum of 65% of the area as undisturbed habitat; and*
- *Biophysical attributes required by boreal caribou to carry out life processes."*

(Environment Canada 2012, p. vii)

Undisturbed habitat is considered any areas that have not been disturbed by fire within the last 40 years, and areas that are >500 m from human disturbance features digitized at a 1:50,000 scale from Landsat imagery (Environment Canada 2012). Disturbed habitat is thus defined as areas that are ≤40 years post-fire old, and areas that are within a 500 m buffer around human disturbance features.

The national recovery strategy identified the need for provinces and territories to develop range plans that would demonstrate how habitat disturbance from fire and human development activity will be managed in order to achieve or maintain at least 65% undisturbed habitat within each local population within their jurisdiction (Environment Canada 2012, Environment and Climate Change Canada 2016). The NWT recovery strategy for boreal caribou also recognizes the need to meet the management threshold for undisturbed habitat that defines critical habitat, and recommends that range plans be developed for the NWT to ensure that adequate habitat is maintained for boreal caribou. In 2019, the Government of the Northwest Territories (GNWT) developed a framework for boreal caribou range planning in the NWT, which states that the goal of the range plans as is "*to manage natural and human disturbance in order to provide adequate caribou habitat to ensure a healthy and sustainable boreal caribou population across their NWT range that offers harvesting opportunities for present and future generations*" (Government of the Northwest Territories 2019).

The NWT has one continuous boreal caribou range (called "NT1 in the national recovery strategy) that stretches from the border with Alberta and British Columbia north to the Inuvialuit Settlement Region, with the eastern and western boundaries of the range primarily defined by the extent of the Taiga Plains ecoregion (Ecosystem Classification Group 2009). As of fall 2017, the NT1 range had 69% undisturbed habitat, meaning there is some flexibility in defining which areas contribute to the 65% that is considered critical habitat. The second component of critical habitat includes "biophysical attributes", which the national recovery strategy defines as "*habitat characteristics required by boreal caribou to carry out life processes necessary for survival and recovery*" (Environment Canada 2012). Appendix H of the national recovery strategy describes the biophysical attributes of critical habitat in the Taiga Plains ecoregion according to different seasonal activity periods (Environment Canada 2012), but the GNWT lacks current range-wide maps of areas that might provide these biophysical attributes. Both the national boreal caribou range planning guidance (Environment and Climate Change Canada 2016) and NWT range planning Framework (Government of the Northwest Territories 2019) recommend identifying, describing and mapping important areas for boreal caribou. The national range planning guidance (Environment and Climate Change Canada 2016) further recommends using maps of habitat types that provide biophysical attributes to ensure that the 65% undisturbed habitat that is considered critical habitat is made up of habitat that includes these biophysical attributes. One of the challenges to translating the descriptions of biophysical attributes (Environment Canada 2012) into maps of habitat types that provide these attributes across the NT1 range is that they are partially based on previous studies of boreal caribou habitat selection that used land-cover data sets that were only available in limited areas of the range (e.g., Nagy et al. 2005, 2006) and which used different terminology and classifications than more up-to-date land-cover data sets that do provide range-wide coverage. The descriptions of biophysical attributes are also based on traditional knowledge, which can include very detailed, fine-scale descriptions of habitat features that are not easily translated to coarser resolution spatial data sets that provide broad-scale coverage.

Resource selection functions (RSFs) are a common analytical framework used to model and generate predictive maps of animal habitat selection (Manly et al. 2002, Morris et al. 2016). RSFs typically compare resource units associated with locations "used" by individuals to resource units associated with a random sample of locations that are available to individuals within a certain spatial scale of interest using logistic regression. Resource units are typically grid or pixel cells that can be characterized by a number of environmental attributes (e.g., land-cover type, distance to nearest forest edge; Lele et al. 2013). Outputs from RSF models can then be used to predict the relative probability that a resource unit is selected (i.e., used) or avoided by an individual animal when encountered (Lele et al. 2013). Most studies using RSFs are based on GPS locations of animals obtained by telemetry using VHF or satellite collars, with resource attributes derived from remotely sensed data layers in a Geographic Information System (GIS). There have been previous studies evaluating boreal caribou habitat selection in the NWT using RSFs, but they have been limited to sub-areas of the NT1 range and are not easily updated or extrapolated to the range as a whole. Nagy et al. (2005, 2006) used RSFs to evaluate habitat selection by boreal caribou in the Gwich'in region, using data developed by Ducks Unlimited to characterize land-cover. In 2014, RSFs were developed for an expanded study area that included the Gwich'in, Inuvialuit and Sahtu regions (Stantec Consulting Ltd 2014). This project used a longer time-series of boreal caribou collar data from a larger sample of individuals and modeled habitat selection the Earth Observation for Sustainable Development of Forests (EOSD; circa year 2000; Wulder et al. 2008) land cover data. The only NT1-wide RSF model for boreal caribou developed to date is from the science assessment in

support of the national recovery strategy (Environment Canada 2011). Environment Canada (2011) developed both national-scale and ecozone-specific RSF models using satellite telemetry data provided by jurisdictions across Canada. These models included data from 169 individual boreal caribou collared in the NWT that were monitored for various periods between 2000 and 2010. Although the national RSF model performed fairly well at predicting withheld collar locations within the Taiga Plains ecozone, the Taiga Plains-specific model had poor predictive performance (Environment Canada 2011). Since these earlier RSF studies took place, the GNWT has continued several of its collar-based monitoring programs for boreal caribou and has initiated programs in new areas of the NT1 range. There is now a much larger data set spanning a longer time period with which to develop an updated NT1-wide RSF model for boreal caribou to support range planning.

In addition to developing up-to-date boreal caribou RSF models for the NT1 range, there is also a need to develop a more in-depth understanding of how wildfires and post-fire vegetation succession influence boreal caribou habitat selection and distribution. Within the NT1 range, wildfires are the main type of disturbance. As of fall 2017, which is close to the endpoint of the data used in this project (31 March 2018—see *Caribou Spatial Data* below), 31% of the NT1 range was considered disturbed habitat, of which wildfires accounted for 24% and 500 m-buffered human disturbance made up only 9% (note the "total disturbance" footprint is less than the sum of fire and human disturbance due to overlapping footprints; Government of the Northwest Territories 2019). The model used to define critical habitat for boreal caribou treats fire disturbance as a binary variable, with fires ≤40 years old considered as disturbed habitat, and those >40 years old considered as undisturbed (Environment Canada 2011). This classification is consistent with how wildfires were included as a covariate in the national and ecozone-specific RSF models developed by Environment Canada (2011), which found that boreal caribou consistently avoided fires <40 years old on an annual time scale. Avoidance of fire-disturbed habitat by boreal caribou has been attributed to either increased predation risk due to preference for recent fires by alternate prey such as moose (Courtois et al. 2007, Courbin et al. 2013), or to reduced availability of lichens, which are the primary winter forage of caribou (Schaefer and Pruitt Jr 1991, Dunford et al. 2006). The description of biophysical attributes of critical habitat for the Taiga Plains ecoregion (Environment Canada 2012, Table H-1 therein) suggests, however, that boreal caribou may select recently burned habitat in calving, post-calving and rutting seasons. This finding is likely based on Nagy et al. (2005), who found that boreal caribou used burns 10-29 years old more than expected by chance between June and November in the Gwich'in region of the NWT, and on evidence from traditional knowledge studies of boreal caribou from different regions of the NWT (Benson 2011, Dehcho First Nations 2011, Species at Risk Committee 2012).

There is also some skepticism that 40 years is an appropriate cut-off at which fires become undisturbed habitat again, given the shorter growing season and colder climate which may delay post-fire succession in the north. Less productive growing conditions may delay the period during which fires are attractive to alternate prey species such as moose, and delay the recovery of winter forage species for boreal caribou, which are mainly slow-growing terrestrial and arboreal lichens. However, there is recent evidence suggesting that fires may not contribute significantly to apparent competition between moose and boreal caribou, at least in some regions. DeMars et al. (2019) found that moose avoided fires ≤25 years in both upland and peatland habitat within boreal caribou ranges in northern British Columbia, Alberta, and Saskatchewan, but avoidance for burned peatlands was generally stronger than for burned uplands. They also found that there was no relationship between moose density and the proportion of

fires ≤40 years old within a moose survey unit. Similarly, McLoughlin et al. (2019) found that high levels of fire disturbance do not necessarily lead to a high availability of early-seral deciduous or mixedwood forests suitable for moose. They also found that boreal caribou populations can be self-sustaining in ranges with high levels of fire disturbance, and that lichens can recover after fires as early as 35-years post-disturbance. These findings all point to the need to better understand the role of fire in boreal caribou habitat selection, distribution and demographics, given that it is the dominant source of disturbance with the NT1 range.

Although anthropogenic disturbance makes up a smaller proportion of the total disturbance footprint within the NT1 range, previous studies within the NWT have found that it may affect boreal caribou habitat selection and movement behavior (Nagy et al. 2005, Nagy 2011, Stantec Consulting Ltd 2014). A review of traditional knowledge on boreal caribou also indicates that industrial development is thought to be responsible for the largest impacts on boreal caribou in some regions of the NWT, and that boreal caribou are relatively intolerant of noise, light and habitat disturbance from industrial activities (Species at Risk Committee 2012). Seismic lines account for the vast majority (~84%) of linear disturbance within the NT1 range, whereas public and industry all-season and winter roads, pipeline and utility corridors account for <16% (based on Environment and Climate Change Canada's 2015 anthropogenic disturbance data). Polygonal human disturbances are primarily from settlements, mining, oil and gas and timber harvesting, but contribute much less to the human disturbance footprint than linear features. Both Nagy et al. (2005) and Stantec Consulting Ltd (2014) found that boreal caribou avoided areas with higher densities of linear features, and were less likely to use areas close to seismic lines or where roads are present. The strength of avoidance of seismic lines by boreal caribou appears to vary according to the time of year, density of seismic lines, and predator/alternate prey diversity (Nagy 2011, also summarized in Species at Risk Committee 2012). Boreal caribou in the southern part of the NWT range (Dehcho and South Slave regions) avoided seismic lines more strongly in the summer, whereas caribou in the northern part of the range (Gwich'in region) avoided them during winter (Nagy 2011). The length of the avoidance period was longer where there was a higher density of seismic lines and a higher diversity of predators and alternate prey (Nagy 2011). Females also crossed seismic lines less than expected by chance, traveled faster when they did cross them, and used areas >400 m from seismic lines more than expected by chance during the avoidance period when they had access to such areas (i.e., when seismic line density was low enough that areas >400 m away from lines were available; Nagy 2011). To date, there has not been an evaluation of how boreal caribou respond to human-created polygonal disturbances in the NWT.

The objectives of this project are to gain a better understanding of how land-cover type, fire and human habitat disturbance influences seasonal habitat selection patterns of boreal caribou across the NT1 range, and to generate predictive maps of seasonal habitat selection to help identify important areas for boreal caribou and support the development of regional boreal caribou range plans within the NWT. Specifically, we sought to:

- Evaluate whether boreal caribou habitat selection varies according to fire age, and whether the fire occurred in upland versus lowland land-cover types;
- Evaluate whether selection for different post-fire age classes and land-cover types varies across different seasonal activity periods for boreal caribou; and,

- Evaluate whether habitat selection depends on the density or distance to different types of human disturbance.

METHODS

Study Area

The study area for this project was defined by a combination of the GNWT`s 2016 version of the NT1 boreal caribou range boundary, the extent of available collar data from different NWT boreal caribou monitoring programs (which includes areas within adjacent boreal caribou ranges in northern Alberta and northeastern British Columbia) and the extent of EOSD land-cover data (Wulder et al. 2008) that was updated by the GNWT and Natural Resources Canada (NRCan) in 2007 and 2010 (Natural Resources Canada and Government of Northwest Territories 2017; Fig. 1). The study area boundary was primarily defined by the extent of the circa 2007/2010 EOSD land-cover dataset, which covers the majority of the NT1 boreal caribou range except the northwestern corner of the range that extends into the Yukon territory, and the southeastern corner of the range which falls within Wood Buffalo National Park. Most of the western edge of the circa 2007/2010 EOSD data set extends beyond the western edge of the NT1 range boundary, but given some uncertainty about the western extent of the range it was not clipped to the range boundary. The eastern extent of the EOSD data also extends several kilometers east of the NT1 range boundary; however south of Great Bear Lake it extends significantly beyond the range boundary into the Taiga Shield ecoregion. Within this area south of Great Bear Lake, the NT1 range boundary was buffered by 15 km, and the edge of the buffer was used to clip the extent of the EOSD layer to keep it within a similar distance of the range boundary as the remainder of the study area. The NT1 range boundary is also clipped to the shoreline of Great Bear and Great Slave lakes; however, telemetry data and traditional knowledge indicate that there are offshore islands along within these lakes that are used by boreal caribou. To capture these areas, an internal buffer of 15 km was created within Great Bear and Great Slave lakes, and the EOSD layer was clipped to include a 15 km swath along the shore of each lake. The interior of Great Bear and Great Slave lakes beyond this 15 km buffer were omitted from the study area to prevent a large proportion of random locations used in the RSF analyses from falling within these lakes.

The study area encompasses five regional monitoring areas for boreal caribou: Inuvik, Sahtu, Dehcho, North Slave, and South Slave (Fig. 2). These regions are further divided into ten sub-regions (region in which the sub-region occurs in brackets): Gwich'in North (Inuvik), Gwich'in South (Inuvik), Sahtu (Sahtu), Dehcho North (Dehcho), Dehcho South (Dehcho), North Slave (North Slave), Mackenzie (South Slave), Hay River Lowlands (South Slave), Pine Point-Buffalo Lake (South Slave), and Cameron Hills (South Slave).

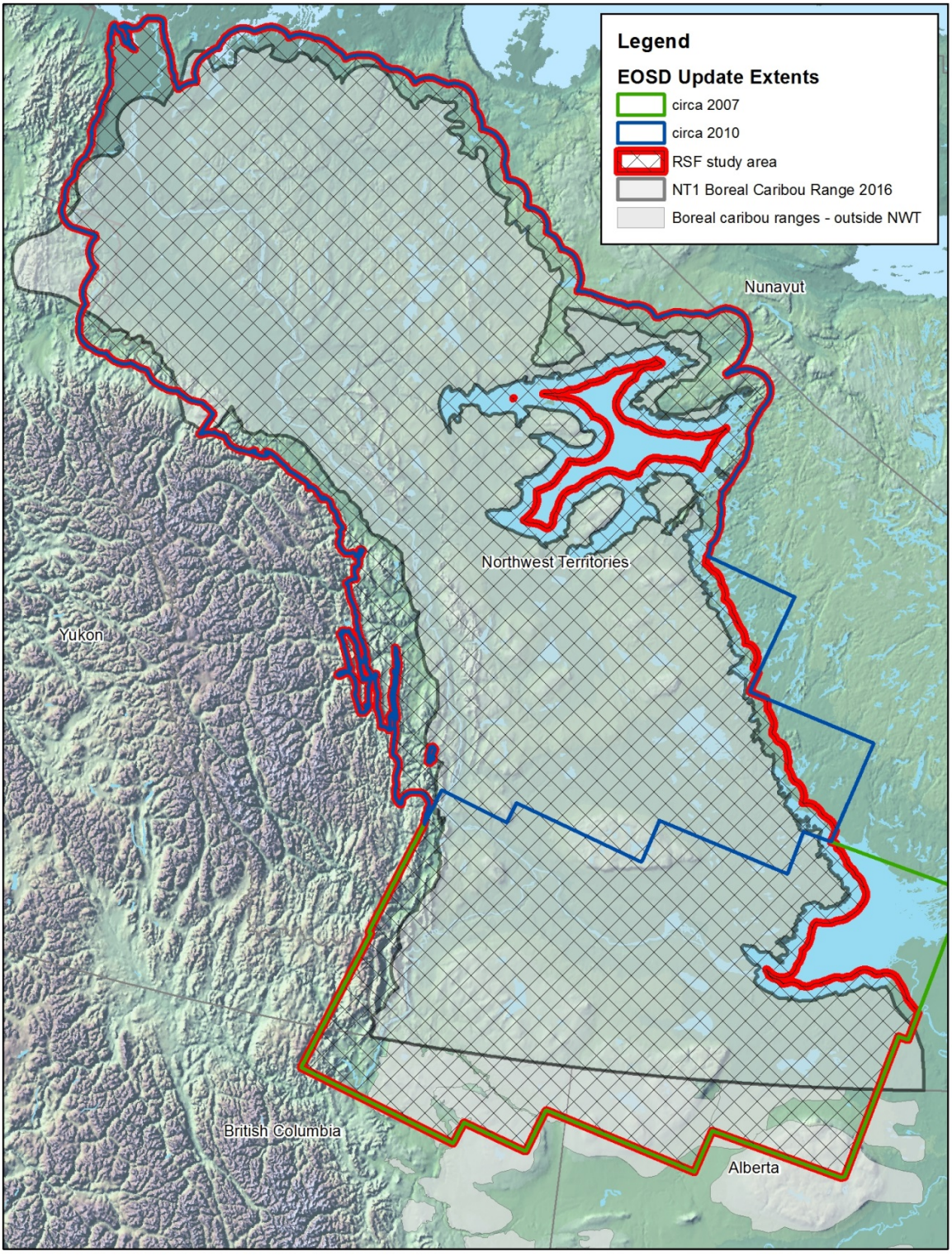

Figure 1: Study area for boreal caribou RSF analyses and predictive mapping (cross-hatched area). Study area boundaries were defined based on a combination of the extent of circa 2007 and 2010 EOSD land-cover data, the NT1 boreal caribou range boundary, and an interior buffer of 15 km along the shorelines of Great Bear and Great Slave lakes.

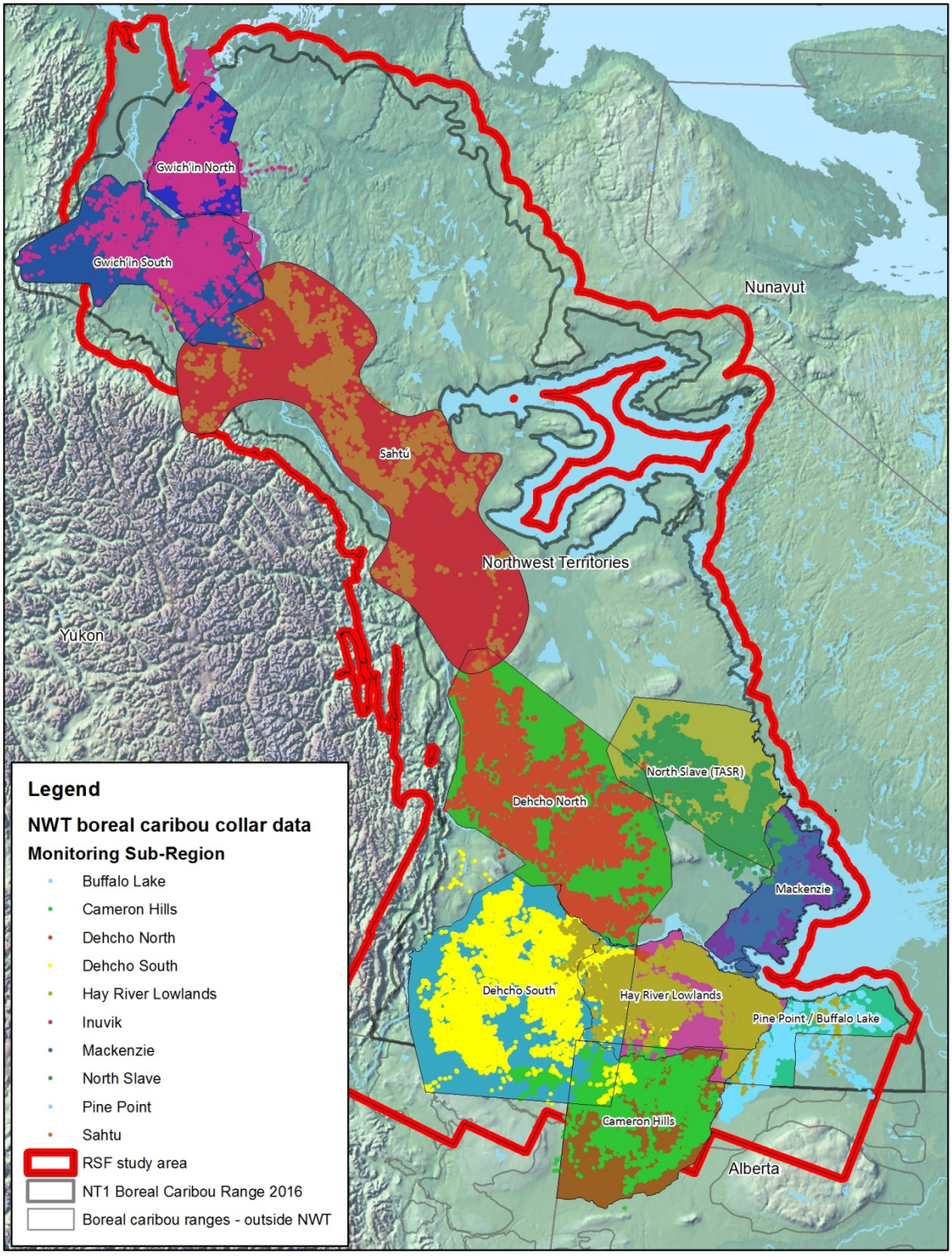

Figure 2: Regional boreal caribou monitoring areas within the NWT and extent of collar data from each sub-region (different coloured points represent collar locations from individuals collared within each sub-region).

Caribou Spatial Data

We used GPS location data collected from radio-collared boreal caribou captured in the Northwest Territories and monitored for various periods between 1 May 2002 and 31 March 2018. These data were accessed from the Movebank data repository (https://www.movebank.org/) where they were initially screened to exclude duplicate records, pre- and post-deployment locations (i.e., locations recorded when the collar was not on the animal), and erroneous locations that exceeded biologically plausible movement (see Appendix A). For our analyses, we excluded any locations that fell outside of the study area. This initial data set included 681,561 GPS locations distributed among 435 individual caribou (regional breakdown: Dehcho = 147 caribou, Inuvik = 43, North Slave = 25, Sahtu = 20, South Slave = 200). The mean monitoring interval per collar was 690 days (SD = 479, minimum = 3, maximum = 1969).

The acquisition rate of GPS locations (i.e., the fix rate) varied among radio-collars, ranging from one location per hour to one location every five days (for Doppler-shift collars), and many collars had fix rates that varied seasonally. Because we used statistical techniques that accounted for unequal sample sizes among individual caribou, we did not standardize the data to a common fix rate (e.g., every five days). However, within a given season (see *Defining Seasons* below), we standardized each individual's data set by subsampling to the collar's coarsest fix rate, which minimized potential spatiotemporal bias when inferring seasonal resource selection. To ensure a consistent sampling interval within the time-series of each individual-season, we assigned a missing value to locations removed by Movebank's screening procedures or when a scheduled GPS fix was not recorded by the radio-collar. To further minimize potential spatiotemporal bias, we also excluded individuals that were not monitored for at least half of the seasonal interval. For analyses using data across the entire year, we also excluded those individuals monitored for ≤231 days, a threshold where estimated sizes of annual home ranges reached an asymptote (see *Evaluating Resource Selection: General Framework* and Appendix B). From these data, we calculated the fix success rate (number of recorded GPS fixes / number of scheduled GPS fixes) of each individual collar for each season-year. For the seven seasons considered, the mean fix success rate was 0.88 for calving, 0.85 for summer, 0.88 for early fall, 0.88 for late fall, 0.88 for early winter, 0.90 for mid-winter and 0.91 for late winter (Table 1). Across caribou-years, the mean fix success rate was 0.90. For all analyses of resource selection, we excluded individual season-years with fix success rates <90% as rates below this threshold may result from habitat-induced biases (e.g., higher fix success rates in some land-cover types versus others), which can impact inferences on resource selection (Frair et al. 2010). Additional information on data screening and further statistics detailing radio-collar performance can be found in Appendix A.

Prior to analyses, we elected to exclude data from caribou in the Mackenzie sub-region. This area experienced large fires that occurred in 2014 and 2015 and radio-collars were deployed on caribou after these fires. Because much of the area available to these caribou consisted of these recent burns, we expected that the inclusion of the Mackenzie data might bias our models of resource selection towards recent burns. Exclusion of the Mackenzie caribou yielded final data sets of 448 caribou-seasons[1] for calving (*n* = 252 caribou), 336 caribou-seasons for summer (*n* = 211 caribou), 364 caribou-seasons for early fall (*n* = 221 caribou), 405 caribou-seasons for late fall (*n* = 242 caribou), 432 caribou-seasons for

[1] Many caribou were monitored for multiple years. A "caribou-season" refers to the number of caribou monitored within the season of interest within a given year.

early winter (*n* = 268 caribou), 623 caribou-seasons for mid-winter (*n* = 340 caribou), 659 caribou-seasons for late winter (*n* = 350 caribou), and 301 caribou-years (*n* = 194 caribou) for analyses conducted over the entire year (Table 1).

Table 1: Summary statistics of fix success rates (FSR) for radio-collars deployed on boreal caribou in the Northwest Territories and monitored between May 2002 and March 2018.

		FSR				FSR >90%		Final Data Set (FSR >90%;Mackenzie caribou excluded)	
Time Period	No. of Season-Years[†]	$\bar{x}$	SD	Min.	Max.	No. of Season-Years	No. of Caribou	No. of Season-Years	No. of Caribou
Calving	873	0.88	0.14	0.08	1.00	480	276	444	249
Summer	737	0.85	0.17	0.08	1.00	371	238	336	211
Early Fall	699	0.88	0.15	0.22	1.00	396	247	364	221
Late Fall	681	0.88	0.18	0.15	1.00	446	270	405	242
Early Winter	741	0.88	0.17	0.11	1.00	478	301	432	268
Mid-Winter	912	0.90	0.16	0.13	1.00	677	373	623	340
Late Winter	1001	0.91	0.14	0.18	1.00	718	383	659	350
All Year	1201[δ]	0.90	0.09	0.55	1.00	338	222	301	194

[†] The number of season-years meeting the minimum monitoring threshold for each season.

[δ] For All Year analyses, this value refers to the number of caribou-years

Evaluating Resource Selection: General Framework

We evaluated seasonal selection of habitat by boreal caribou using resource selection functions (RSFs), a widely used modelling approach that compares environmental attributes (or resources) associated with GPS (or "used") locations to environmental attributes of random (or "available") locations generated within the spatial scale of interest (Manly et al. 2002). Collectively, the environmental attributes considered are those thought to be important indicators of a species' habitat requirements. Individual attributes may be selected or avoided by the species. Selection occurs when the proportion of used locations associated with a given attribute is higher than the proportion of random locations associated with the same attribute (i.e., random expectation); avoidance occurs when use is proportionally lower than random expectation.

We estimated RSFs for caribou at second- and third-order scales (*sensu* Johnson 1980; Figs.3–4). Second-order selection generally evaluates how areas are selected within a population's range. Because spatial delineations of boreal caribou populations within the Northwest Territories are not well-defined, we used expert input from regional government biologists to define availability at this scale. We considered caribou occurring within the Inuvik and Sahtu monitoring regions to be part of a Northern group and caribou occurring within the Dehcho, North Slave and South Slave monitoring regions to be

part of a Southern group. For each group, we defined availability by fitting a minimum convex polygon (MCP) around all GPS locations pooled from radio-collared caribou within the group (Fig. 3; note: caribou GPS locations were all those available post-screening procedures and included caribou from the Mackenzie sub-region). We then buffered each MCP by 15-km, which approximated the maximum distance that caribou moved in a 24-hr period based on the GPS data (Appendix B), and clipped these buffered MCPs to the boundaries of the study area. Seasonal RSFs at a second-order scale therefore entailed a comparison of resources associated with caribou GPS locations falling within a given seasonal period to resources associated with random locations sampled within these buffered MCPs (Fig. 3).

Third-order selection evaluated how caribou selected seasonal areas within their annual home ranges (Fig. 4). For each individual caribou, the annual home range defined availability at this scale and we estimated home ranges using kernel density estimates (KDEs; also called utilization distributions; Worton 1989, Börger et al. 2006, Fleming et al. 2015), which represent a probability surface of an animal's space use (i.e., the probability of relocating an animal at a given spatial coordinate). Compared to MCPs, KDEs provide more robust estimates of animal home ranges because they are less sensitive to changes in collar fix rates and do not include areas where animal use may be low, which can occur with MCPs (Worton 1987, Börger et al. 2006). We estimated KDEs using recently developed methods that account for the autocorrelation that is inherent in GPS location data (Fleming et al. 2015). KDEs were calculated using all GPS locations collected from an individual caribou during a biological year, which we defined as starting on 1 May, a date that corresponds to the onset of the calving season, and ending on 30 April. We used the 95% isopleth (or contour line) from the KDE to spatially delineate the annual home range. Third-order RSFs therefore entailed a comparison of resources associated with caribou GPS locations falling within a given seasonal period to resources associated with random locations sampled within these estimated annual home ranges (Fig. 4). Because KDEs—and other home range estimators—are sensitive to monitoring time (i.e., the length of time an animal is monitored; Börger et al. 2006), we conducted a sensitivity analysis to determine the minimum monitoring time required for estimates of home range size to stabilize (Appendix B). This analysis suggested that the estimated area of annual KDEs stabilized after 231 days; therefore, we excluded caribou-years that did not meet this threshold from third-order resource selection analyses.

For each RSF scale, we used random points to sample availability. Because the number of random points sampled can influence RSF results (Northrup et al. 2013), we conducted sensitivity analyses to determine the minimum number of random points that needed to be sampled per caribou for RSF coefficients to stabilize (Appendix C). Based on these analyses, we used 3000 random points per caribou sampled within each population-level MCP for second-order RSFs and 3000 random points sampled within each individual caribou's annual home range for third-order RSFs.

Defining Seasons

In temperate climates, seasonal changes in resources (e.g., forage, thermal cover, refugia) and life history status (e.g., breeding versus the birthing season) can alter how a species selects habitat throughout the year (Nielsen et al. 2003, McLoughlin et al. 2010). We therefore evaluated how resource selection by boreal caribou potentially changed across seasonal periods that were thought to be biologically relevant for caribou. To identify such periods, we evaluated for breaks in the year-long distribution of mean daily movement rates (m/hr) of caribou in the Northern and Southern groups (Appendix D). To reduce potential spatial bias in movement behaviour (e.g., animals in one area may move more than those in another area), mean rates of daily movement were calculated across

individual caribou within each monitoring region (Dehcho, North Slave, South Slave, Inuvik and Sahtu). We then fit a generalized additive model to each group's data (Northern [Inuvik and Sahtu] and Southern [Dehcho, North Slave and South Slave]) and used the model predictions in a piecewise (or segmented) regression to identify break points in the temporal distribution of movement rates. These break points were assumed to be indicative of seasonal changes in caribou behaviour. Results from this analysis suggested minor differences in seasonal movement behaviour between the two regions with Southern caribou calving earlier and experiencing longer summers and shorter winters. The final delineation of seasons considered these results and seasons were further adjusted based on expert input from regional government biologists as well as seasonal delineations from other studies on boreal caribou (Ferguson and Elkie 2004a, Nagy 2011, Rudolph and Drapeau 2012). Eight seasons were identified—pre-calving dispersal, calving, summer, early fall, late fall, early winter, mid-winter, and late winter—with the start and end dates varying between the Northern and Southern groups (Table 2). Of these seasons, we developed RSF models for seven, excluding pre-calving dispersal when caribou movement rates are generally highest as females are dispersing to solitary calving sites (Ferguson and Elkie 2004b). We also developed an all-year model which included collar locations from throughout the year, including the pre-calving dispersal season.

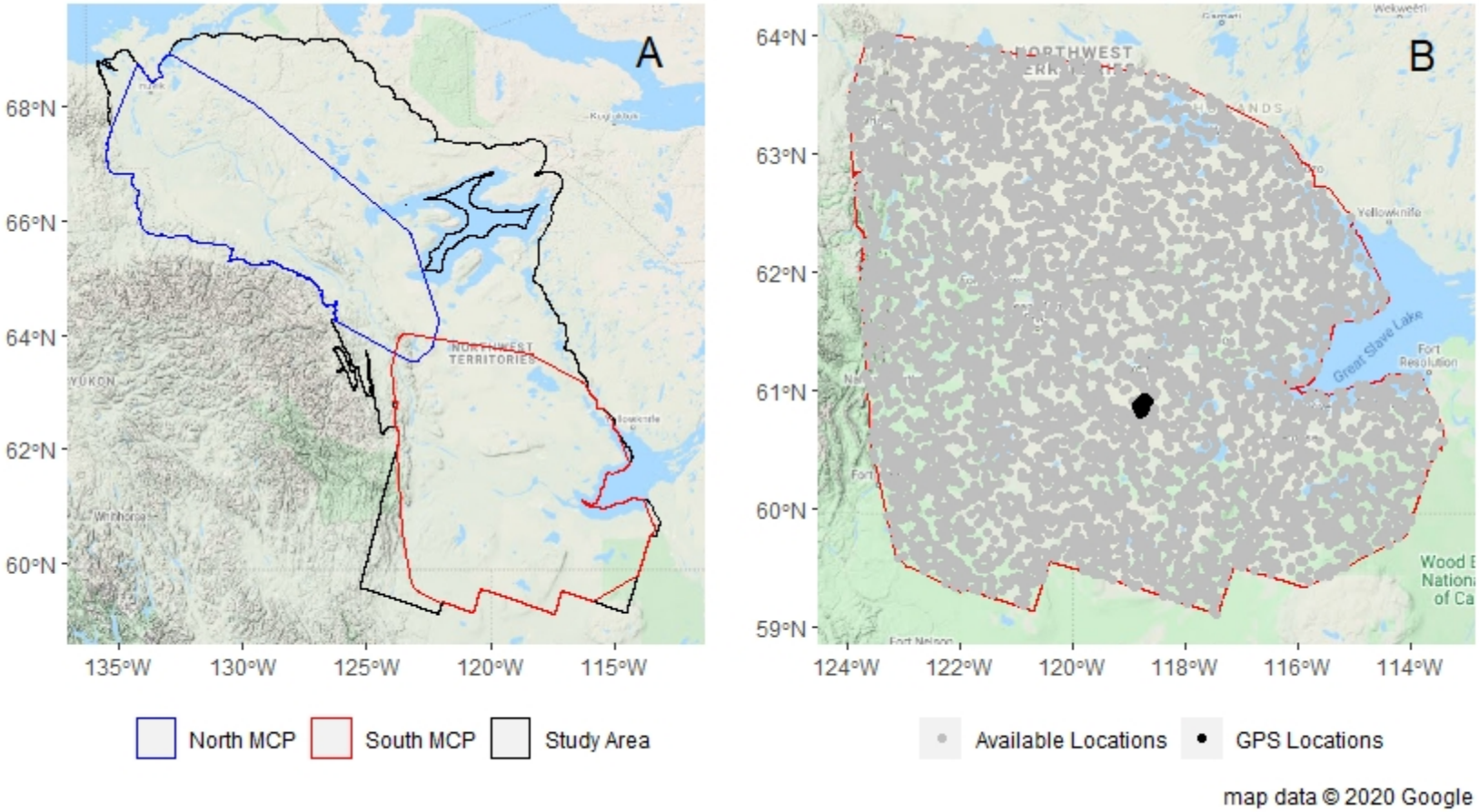

Figure 3: The spatial scale of second-order selection. Availability at this scale was delineated by two 100% minimum convex polygons (MCPs): one fit around all GPS locations from caribou in the Southern group and one fit around all GPS locations from caribou in the Northern group (panel A). These MCPs were then buffered by 15-km, the estimated maximum distance caribou moved in a 24-hr period. In panel B, GPS locations collected during the calving season for an individual caribou from the Southern group are shown within the South MCP. Availability within each MCP is sampled using random locations.

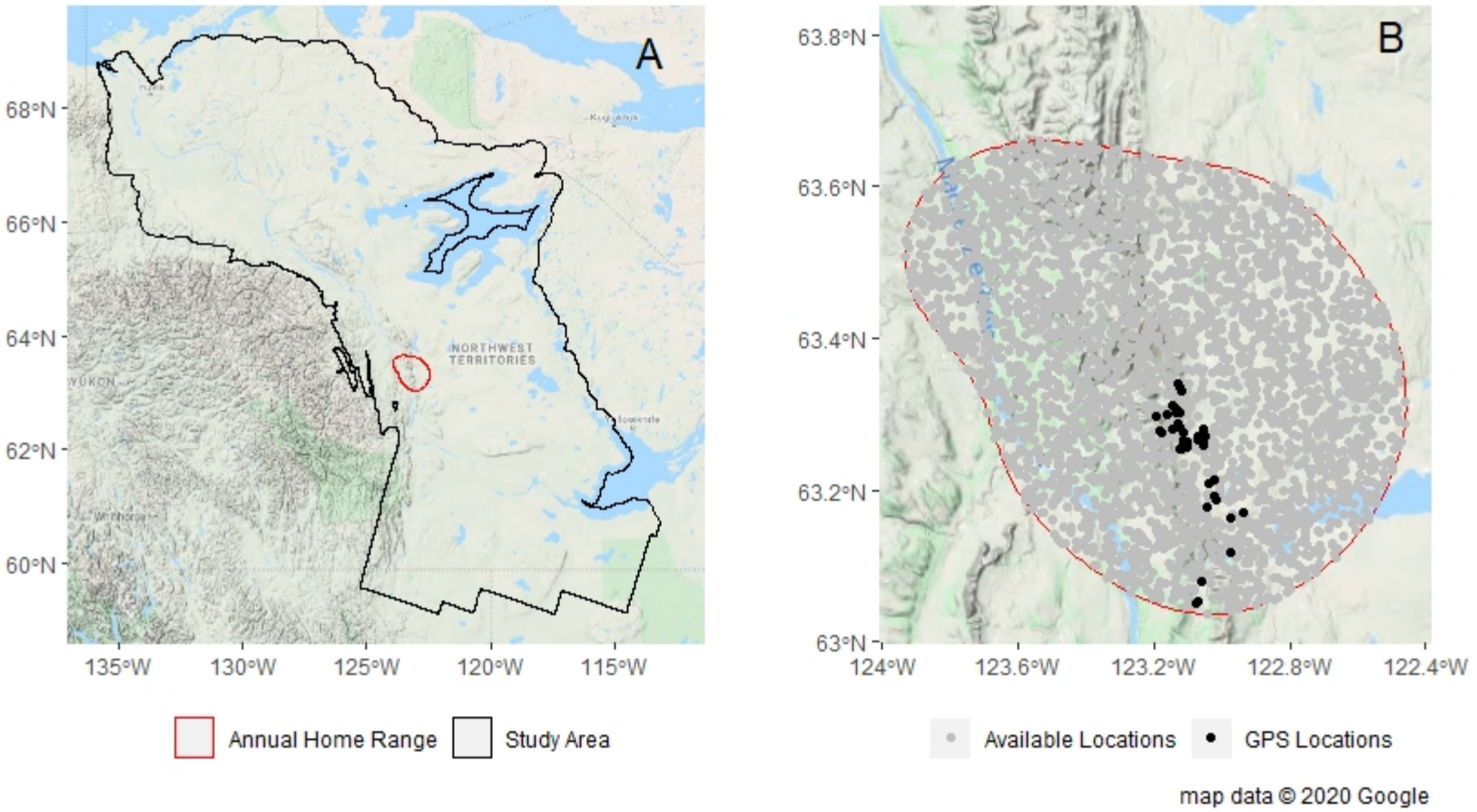

Figure 4: The spatial scale of third-order selection. For each individual caribou, availability at this scale is defined by the annual home range, which is characterized by the 95% isopleth (or contour line) of a kernel density estimate calculated using all of an individual's GPS locations collected during a biological year (1 May–30 April). In panel A, the estimated annual home range of an individual caribou is shown within the study area. In panel B, GPS locations collected during the calving season for this individual caribou are shown within the annual home range. Availability within the home range is sampled using random locations.

Table 2: Seasonal delineations for modelling resource selection by boreal caribou in the Northwest Territories.

	Region			
	South		North	
Season	Date Range	No. of Days		No. of Days
Pre-calving Dispersion[†]	2 Apr–30 Apr	28	6 Apr– 30 Apr	24
Calving	1 May–30 Jun	60	1 May–12 Jul	72
Summer	1 Jul–12 Sept	73	13 Jul–8 Sept	57
Early Fall	13 Sep–20 Oct	37	9 Sept–25 Sept	16
Late Fall	21 Oct–30 Nov	40	26 Sept–25 Oct	29
Early Winter	1 Dec–25 Jan	55	26 Oct –12 Jan	78
Mid-Winter	26 Jan–15 Mar	48	13 Jan–21 Mar	67
Late Winter	16 Mar– 1 Apr	16	22 Mar–5 Apr	14

[†] RSF models were not developed for pre-calving dispersion

Environmental Variables

We used circa 2007/2010 EOSD land-cover data (Natural Resources Canada and Government of Northwest Territories 2017; Fig. 5) to characterize different land-cover types available to boreal caribou. The original EOSD land-cover data (Wulder et al. 2008), which included 21 different land-cover classes, was generated from Landsat satellite data at a 25-m resolution and reflected land-cover across Canada's forested ecozones as they existed in circa year 2000. The GNWT and NRCan updated the EOSD data within the Taiga Plains ecozone of the NWT in three phases (Natural Resources Canada and Government of Northwest Territories 2017). Phase 1 (circa 2007) covered the southern NWT and was undertaken using Landsat TM imagery from 2006 to 2008. Phase 2 and 3 (circa 2010) covered the northern portion of the Taiga Plains ecozone and was undertaken using Landsat TM imagery collected from 2007 to 2013. The updated EOSD layer (circa 2007/2010) was validated using a large collection of aerial survey data, forest inventory datasets and high resolution satellite imagery, and represented the most up-to-date and validated land -over data available for the Taiga Plains ecozone. The extent of the circa 2007/2010 EOSD data generally exceeded the extent of the NT1 boreal caribou range boundary, and captured the majority of the extent of collar data available for boreal caribou within the NWT. Small portions of the northwestern and southeastern corners of the NT1 range were not covered by the updated EOSD data, and were omitted from the study area for this project. The 2007/2010 EOSD data contains 24 land-cover classes, 23 of which occur within the study area (the "Broadleaf Sparse" class was deemed absent from the Taiga Plains). The "Snow/Ice", "Rock/Rubble", "Exposed land", and "Developed" categories were combined into a "Non-Vegetated" category, which accounted for ~1% of the study area. Areas classified as "NoData", "Shadow", and "Cloud" represented ~0.04% of the study area and were also collapsed into the "Non-Vegetated" category.

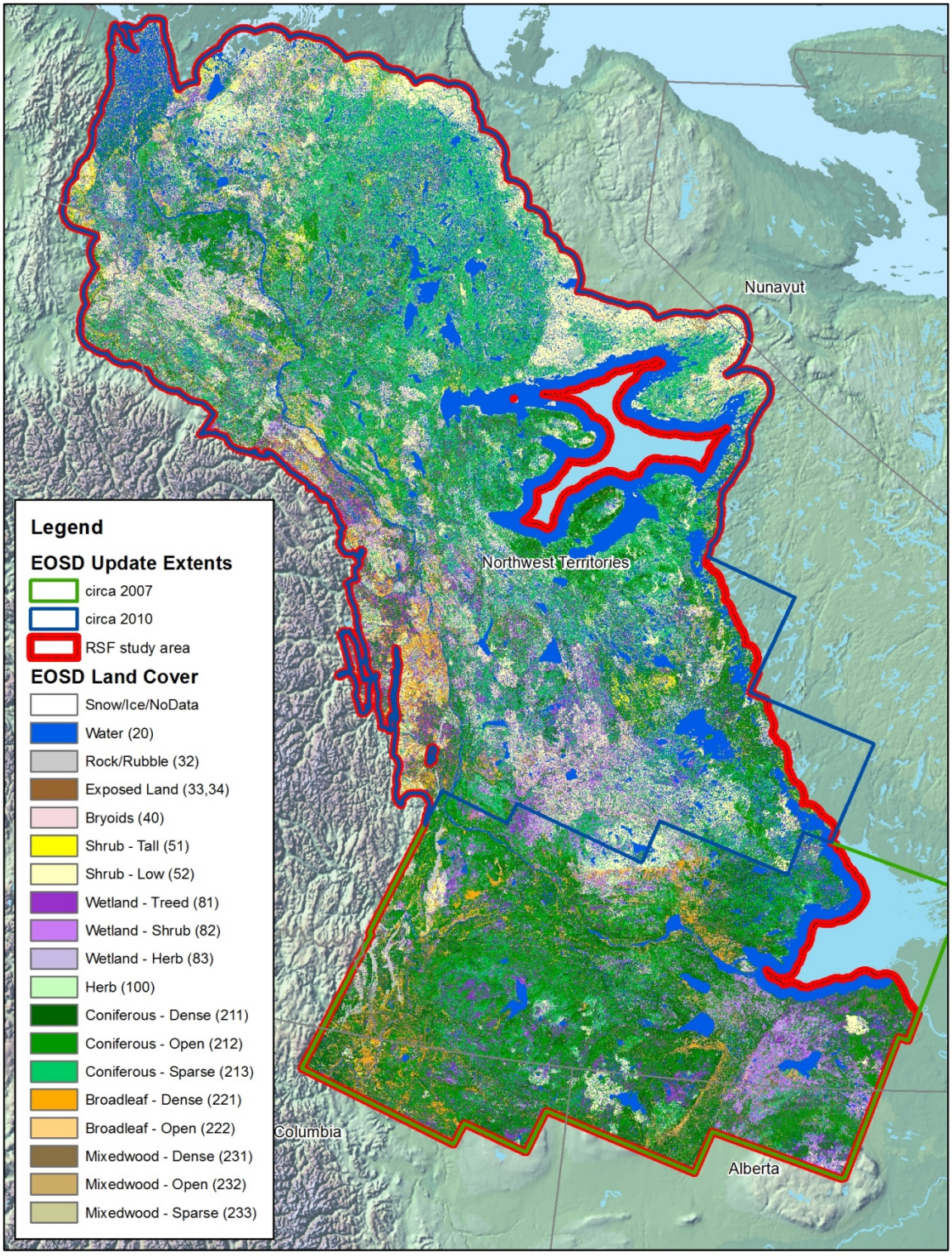

Figure 5: Earth Observation for Sustainable Development (EOSD) land-cover data updated using circa 2007 (area outlined in orange) and circa 2010 (area outlined in blue) Landsat TM imagery.

We accessed two data sources to model historical fires in the study area. For fires occurring between 1955 and 1985, we accessed fire perimeter data (polygons) from the Canadian National Fire Database (NFDB; Natural Resources Canada: https://cwfis.cfs.nrcan.gc.ca/ha/nfdb). For fires occurring between 1986 and 2017, we accessed fire perimeter data from the National Burn Area Composite (NBAC; Natural Resources Canada: http://cwfis.cfs.nrcan.gc.ca/datamart/datarequest/nbac; 2017b; Skakun et al. 2017; Fig. 6). Both datasets represent a compilation of fire boundaries provided by provinces, territories and Parks Canada. The NBAC data provides more precise fire polygons for fires occurring from 1986 onwards, using a semi-automated process that compares Landsat TM imagery before and after fires occur and excludes residual unburned terrestrial habitat and water bodies within the fire polygons. The combined NFDB/NBAC data set was converted from polygons to raster format. Where there were overlaps between fire polygons from different years, we assigned the most recent fire year to the raster cell value.

Anthropogenic disturbance within the study area (Fig. 7) was based on linear and polygonal disturbance features mapped from 30-m resolution Landsat imagery by ECCC in 2010 (methodology described in Appendix 7.2 of Environment Canada (2011)) and 2015 (Environment and Climate Change Canada: http://data.ec.gc.ca/data/species/developplans/2015-anthropogenic-disturbance-footprint-within-boreal-caribou-ranges-across-canada-as-interpreted-from-2015-landsat-satellite-imagery/). The 2015 data did not cover the entire extent of the study area, leaving small gaps near the southern boundary. Where such gaps existed, we backfilled the 2015 data with data from 2010. Polygonal disturbances included cutblocks, mines, reservoirs, built-up areas, well sites, agriculture, oil and gas facilities, and unknown features. Linear disturbances included roads, railways, powerlines, seismic exploration lines, pipelines, dams, air strips, and unknown features. As the public road network within the NWT represents the only type of linear feature that has seen continuous vehicular traffic throughout the duration of the collar data, we were particularly interested in how they influenced habitat selection. We used major road segments merged from the National Road Network data (Natural Resources Canada: https://open.canada.ca/data/en/dataset/2dac78ba-8543-48a6-8f07-faeef56f9895) from across the NWT, Yukon, Alberta and BC to represent the public road network, as the ECCC human disturbance data does not distinguish between public vs. private sector roads.

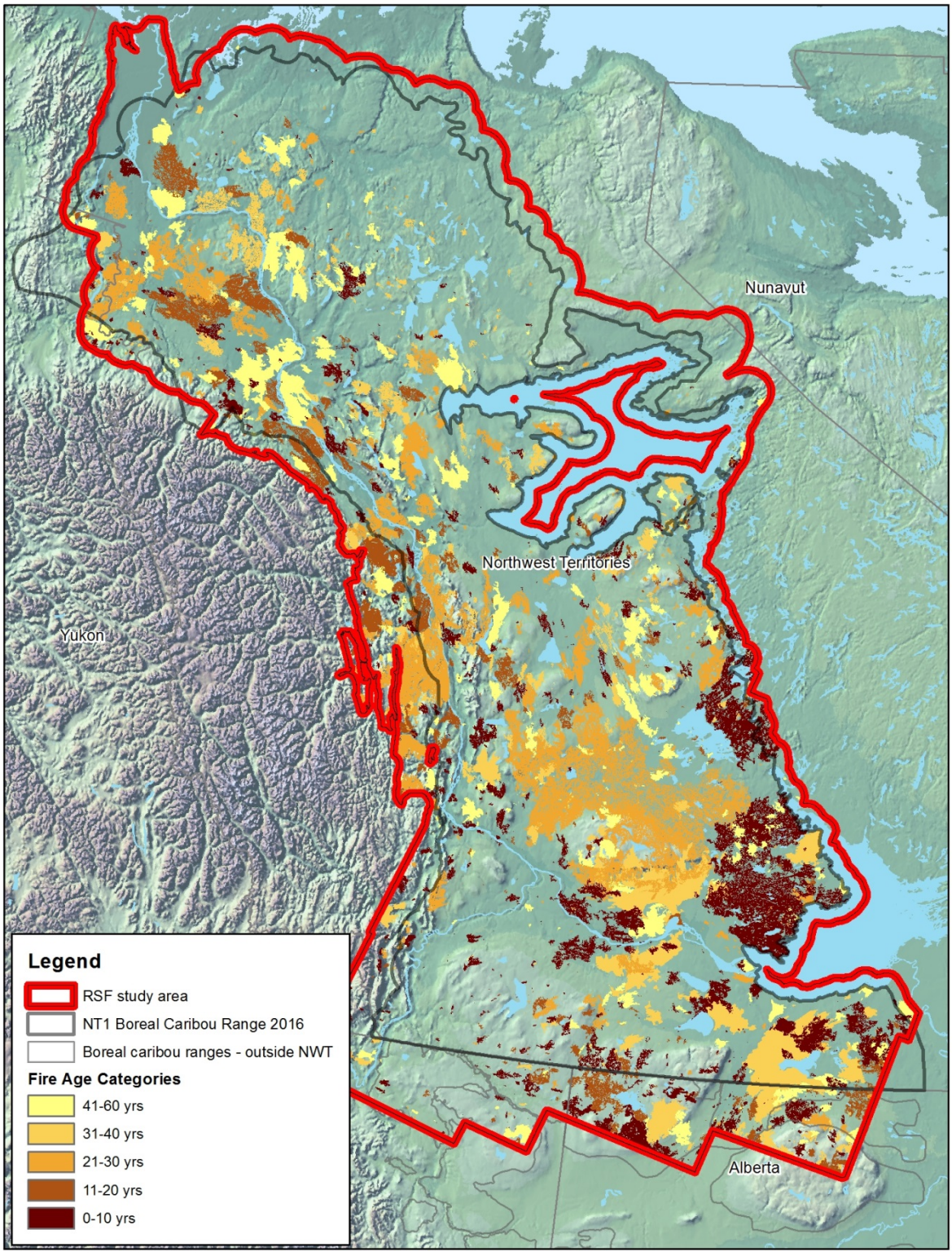

Figure 6: Fires by decadal age category within the study area based on fire polygons from 1955-1985 the Canadian National Fire Database, and fire polygons from 1986-2017 from National Burn Area Composite data. Fire age categories displayed in the figure were calculated based on a reference year of 2017.

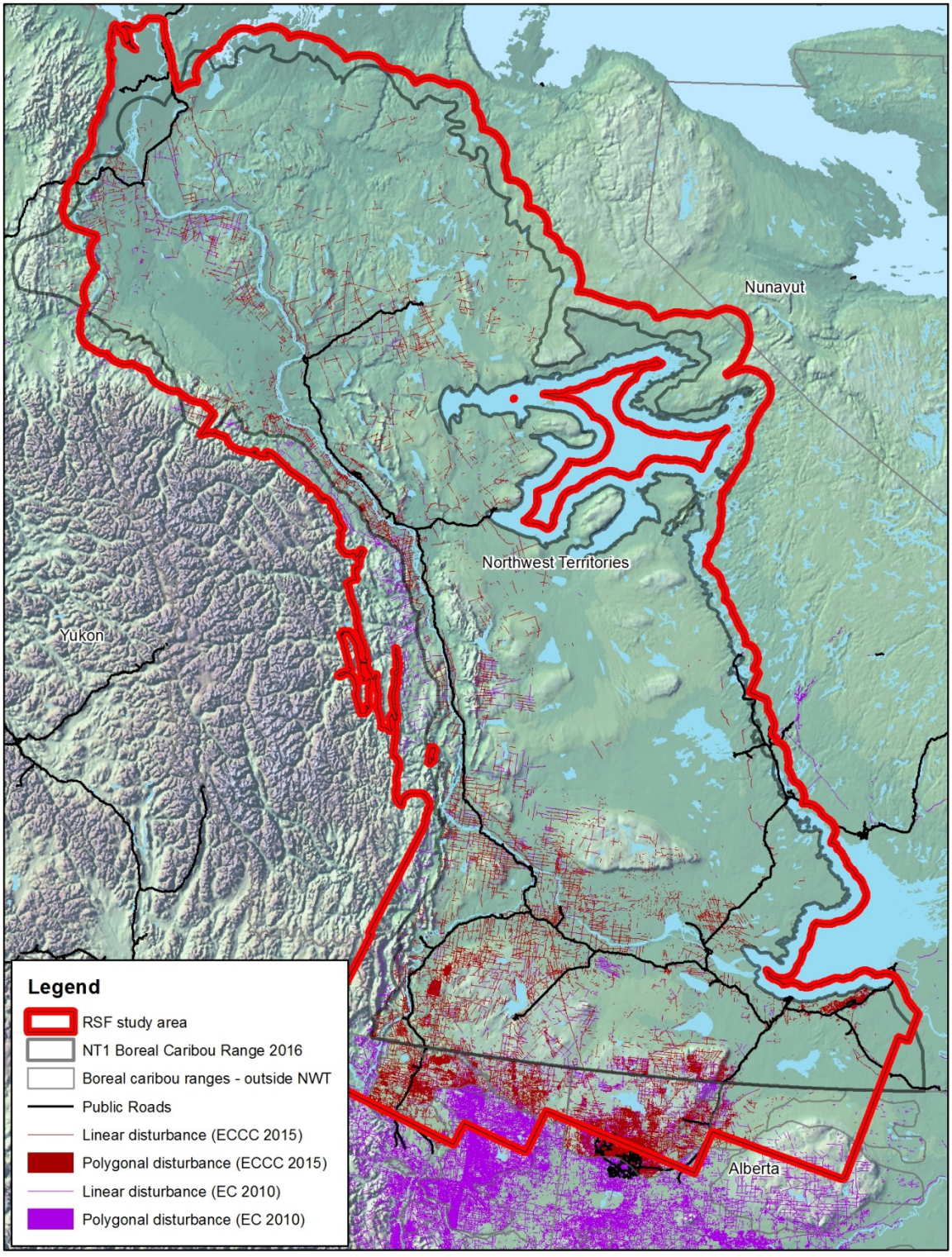

Figure 7: Linear and polygonal anthropogenic disturbance as mapped by ECCC in 2010 and 2015, and the public road network within the RSF study area.

Data Analyses

We estimated seasonal RSFs using generalized linear mixed effect models (GLMMs; Gillies et al. 2006, Zuur et al. 2009), which account for the hierarchical structure inherent in GPS location data (i.e., caribou are grouped within a monitoring sub-region, each caribou has a unique set of GPS locations) and unequal sample sizes among individual caribou. For all second- and third order GLMMs, we assigned individual caribou-year as a random grouping effect (i.e., a random intercept). These models took the form

$$ln\left[\frac{\pi(y_i=1)}{1-\pi(y_i=1)}\right] = \beta_0 + \beta_1 x_{1ij} + \ldots + \beta_n x_{nij} + \gamma_{0j} \qquad \text{(Eqn. 1; Gillies et al. 2006)}$$

where the left-hand side of the equation is the logit transformation for location y_i, β_0 is the fixed-effect intercept, β_n is the fixed-effect coefficient for each resource covariate x_n, and γ_{0j} is the random intercept for caribou-year j. From this base model, we also tested for hierarchical (or "groups within groups") structures of random grouping effects. We considered caribou-year grouped within monitoring sub-region, caribou-year grouped within the subpopulations defined for second-order RSFs analyses (i.e., North and South), and a three-level structure with caribou-year grouped within monitoring sub-region grouped within North or South group. Using the summer data, which constituted the longest season for the more data-rich Southern group, we fit second-order RSFs with each of these random-effect structures—keeping the fixed-effect structure the same for all models—and used Akaike's Information Criterion (AIC) to identify the structure with the most explanatory power (Zuur et al. 2009). The top model structure was caribou-year grouped within monitoring sub-region with this structure being 1.3 AIC units lower than the three-level structure and >57 AIC units lower than the other two structures [note: lower AIC values equate to better model performance; Burnham and Anderson 2002). Although the three-level structure was competitive with the top structure, the additional complexity did not significantly improve model performance (Arnold 2010). We therefore used caribou-year grouped within monitoring sub-region as the random effects structure and kept this structure constant across all RSF models to make seasonal comparisons of model outputs more straightforward.

The fixed-effect coefficients of the GLMMs yield insights as to how a typical caribou selects resources and can be interpreted within the classic use-availability design of

$$\omega(x_i) = \exp(\beta_1 x_1 + \beta_2 x_2 + \ldots \beta_n x_n) \qquad \text{(Eqn. 2; Manly et al. 2002)}$$

where $\omega(x_i)$ is the relative selection value of a resource unit (or pixel) in category i as a function of the explanatory covariates (x_n) and their estimated coefficients (β_n). We caution that robust inferences on caribou response to specific covariates usually requires fitting GLMMs with random coefficients for each covariate of interest (i.e., random slopes) as random-intercept-only GLMMs produce standard errors that are too narrow and do not reflect the individual animal as the sampling unit (Schielzeth and Forstmeier 2009, Muff et al. 2020). Fitting a maximal GLMM (i.e. a random slope for each covariate; Barr et al. 2013), however, was computationally infeasible with our large data set. Nonetheless, outputs from random-intercept-only GLMMs can be useful for generating predictions of animal space use (Schielzeth and Forstmeier 2009) and a primary objective of our project was to generate predictive maps of seasonal space use by caribou.

To assess how resource selection varied seasonally, we used the same fixed-effects structure for each seasonal RSF at both the second- and third-order scales (Table 3). We developed this model structure using summer data at a second-order scale and considered explanatory covariates that included local land-cover type (the EOSD data; 30-m pixel scale), landscape context variables, burn variables, and four variables characterizing anthropogenic disturbance: linear feature density, distance-to-major road, distance-to-polygonal disturbance, and distance-to-settlement. For variables with time-dependent data sets, we matched the time stamp of the caribou location to the appropriate data set. For example, caribou locations occurring in 2010 and earlier were matched to ECCC 2010 disturbance data whereas caribou locations occurring after 2010 were matched to ECCC 2015 disturbance data. Similarly, burn age variables (see below) were matched to time stamp of the caribou location (e.g. for a caribou location occurring in 2007, a fire that burned in 1995 would be classified as 12 years old). For local land-cover type, we created a binary variable for each type and set 'conifer dense' as the reference category by omitting it from the models. For landscape context, we calculated the proportion of each land-cover type in a 1-km radius around each 30-m pixel in the study area. We then estimated univariate RSFs with each landscape context variable and used AIC to select the variable with the most explanatory power. Because variables with a broadleaf component were four of the top five variables and all were negative, we combined the proportions of 'broadleaf dense', 'broadleaf open', 'mixedwood open', and 'mixedwood dense' into one landscape variable describing the proportion of forest with a broadleaf component in a 1-km radius. We retained this variable and the proportion of 'spare conifer forest' in a 1-km radius, which showed the strongest selection by caribou among landscape context variables, for all seasonal RSF models.

For burns and linear feature density, we considered multiple formulations of each variable and used AIC to identify the formulation with the most explanatory power. For burns, we considered four formulations:

i. a decadal formulation where burns were partitioned into age classes (1–10 years old, 11–20 years old, 21–30 years old, 31–40 years old and 41–60 years old) but the type of land-cover burned was not considered (hereafter, 'burn-decade-only');

ii. a decadal formulation with the above age classes but also identified whether the burn was in an upland conifer forest (EOSD categories 'conifer dense' and 'conifer open'), upland broadleaf forest (EOSD categories 'broadleaf dense', 'broadleaf open', 'mixedwood open', and 'mixedwood dense'), non-treed upland (EOSD categories 'bryoids', ' tall shrub', and 'short shrub') or lowland (EOSD categories 'treed wetland', 'shrub wetland', 'herb wetland', 'herb', and 'sparse conifer forest') (hereafter, 'burn-decade-by-land-cover');

iii. a continuous formulation that interacted the four broad land-cover classes above (upland conifer, upland broadleaf, non-treed upland and lowland) with time since fire (in years) (hereafter, 'continuous-by-land-cover');

iv. a continuous formulation that interacted the four broad land-cover classes above (upland conifer, upland broadleaf, non-treed upland and lowland) with time since fire (in years) as a quadratic (hereafter, 'quadratic-by-land-cover').

In the first two formulations, burns—and their interactions with land-cover—became new local land-cover types. Among the four formulations, the 'burn-decade-by-land-cover' (formulation ii above) had

the most explanatory power as it was >1200 AIC units lower than the next best formulation ('burn-decade-only'; note: as a general rule, only models within 2 AIC units are considered suitable for inference, Burnham and Anderson 2002). We therefore used the 'burn-decade-by-land-cover' formulation in all subsequent RSF models.

For linear feature density, we considered two formulations: one where density was measured in a 400-m radius and one where it was measured in a 1-km radius. The smaller radius reflects a common spacing for natural resource exploration lines (i.e., seismic lines) whereas the larger radius reflects the most common metric for quantifying linear feature density (km/km^2). To determine which scale was more relevant to predicting caribou space use, we estimated univariate RSFs with each variable and compared AIC values. Caribou response was stronger for the 1-km radius (>1000 AIC units lower) and we retained this scale for all seasonal RSFs.

For the remaining anthropogenic disturbance variables—distance-to-major-road, distance-to-polygonal-disturbance, and distance-to-settlement—, we used exponential decay transformations to place increased emphasis on areas in close proximity to the feature (Nielsen et al. 2009; Fig. 8). These transformations took the form

$$1 - e^{-\alpha d} \qquad \text{(Eqn. 3; Nielsen et al. 2009)}$$

where d is the distance (in meters) to the feature and α is the decay rate. By subtracting the decay function from 1, distances at the feature have a value of 0 whereas very large distances away from the feature have values approaching 1. We consulted the available literature to determine appropriate values for α for each variable. For distance-to-major-road, Leblond et al. (2011) found that boreal caribou in Quebec avoided roads by 1.25-km so we set α at 0.0025, which caused values to erode precipitously beyond 1.25-km. For distance-to-polygonal-disturbance, caribou response has varied depending on the type of disturbance (e.g. well pad versus cut block) and responses have varied by subpopulation (Johnson et al. 2015). Given that reported values ranged from 1-km (Smith et al. 2000) to >13-km (Vors et al. 2007, Boulanger et al. 2012), we used a conservative value of 0.003 for α, which resulted in values decaying rapidly after 1-km. For distance-to-settlement, Polfus et al. (2011) suggested that northern mountain caribou avoided settlements by 3-9-km, depending on the season. We therefore set α at 0.000625, which resulted in values decaying rapidly after an intermediate distance of 5-km. We acknowledge that further research is likely warranted to determine the potential zone of influence for various types of disturbances on boreal caribou in the Northwest Territories.

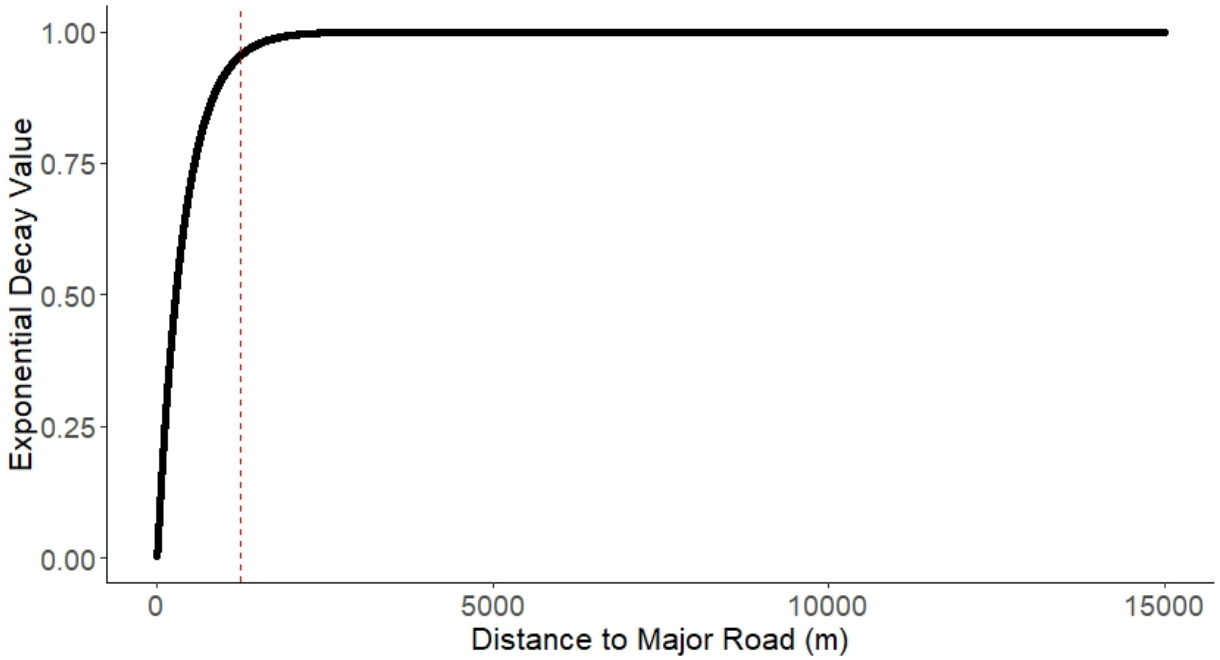

Figure 8: Example of an exponential decay transformation applied to a continuous "distance-to" variable. For distance to major roads, the shape parameter (or α) of the exponential decay function (see Eqn. 3 in main text) was set to 0.0025 to ensure that distances beyond 1250-m (red dashed line) decayed rapidly and transformed to similar values.

For each seasonal RSF, we assessed predictive performance using *k*-fold cross validation (Boyce et al. 2002). This iterative process entailed randomly partitioning the data by individual caribou into five folds, using four folds (i.e., data from 80% of the individuals) to estimate the RSF (i.e., the training set), then testing model predictions on the GPS locations from withheld caribou (i.e., the testing set). We tested model predictions using two different methods, which primarily differed in how RSF values were partitioned into discrete bins (Fig. 9). In the first, which we term model-based cross validation, we used the fixed-effects output from the RSF (Eqn. 2) to predict values for the random locations and the GPS locations for each individual caribou in the testing set. Recall that the random locations for each individual caribou index that individual's spatial domain of availability—at the second-order scale, availability was the buffered MCPs created for the Northern and Southern groups whereas the third-order scale, availability was an individual's annual home range. For each caribou, predicted values for the random locations were partitioned into decile bins (i.e., 10 ordinal bins containing an equal number of random locations) and we then calculated the number of caribou GPS locations falling within each bin. The frequency of caribou GPS locations within each bin were summed across all testing caribou and model prediction was assessed by comparing the proportional frequency of predicted values for caribou locations falling within a bin to bin rank using Spearman's correlation coefficient (r_S; DeCesare *et al.* 2012). In the second method, which we term map-based cross validation, we used random locations (*n* = 40,000) sampled from the combined North and South MCPs (Fig. 9). As with the other method, we used the fixed-effects from the RSF to predict values for these random locations, partitioned these into decile bins, then calculated $\bar{r}_S$ by comparing the proportional frequency of predicted values of testing caribou locations falling within a bin to bin rank. For all seasonal RSFs, we completed 10 iterations of the validation process then calculated $\bar{r}_S$ for each method with higher $\bar{r}_S$ values indicating better predictive performance. The two methods yield different inferences. Model-based cross validation assesses predictive performance while allowing for changing availability (i.e., availability is specific to each caribou) whereas map-based cross validation assesses predictive performance when binning is conducted over a larger area that is constant across caribou. Lower $\bar{r}_S$ values for model-based validation compared to map-based validation may be indicative of functional responses in resource selection (i.e., selection changes as a function of availability; Mysterud and Ims 1998).

We used RSF outputs and the most recent year of data available for each resource covariate (e.g., 2017 for fire data) to generate seasonal predictive maps of caribou habitat selection. These maps covered the entire extent of the study area (Fig. 1). For each map, we partitioned the pixels (30-m resolution) into 10 bins to improve visual interpretation of seasonal resource selection by caribou (Morris et al. 2016). Cut points between bins were delineated using an approach as was done for k-fold cross validation. Specifically, outputs from a given RSF model were used to predict values for the random locations (*n* = 40,000) sampled within the combined North and South MCPs then these locations were partitioned into decile bins (i.e., 10 bins with each bin having an equal number of points, which equates to an equal-area binning approach; Morris et al. 2016). We also computed the selection ratio for each bin, defined as the proportion of caribou GPS locations falling within a bin divided by the bin's proportion of random points. Ratios > 1 indicate areas that are relatively selected (i.e., where caribou use exceeds random expectation) while ratios < 1 indicate areas that are relatively avoided.

We also evaluated the predictive performance of each seasonal map at a finer scale by assessing how well each map predicted caribou use within each monitoring sub-region. To do so, we used r_S to assess

the correlation between bin rank and the proportional frequency of caribou locations falling within each bin. As with *k*-fold cross validation, higher r_S values indicate better predictive performance.

All statistical analyses were performed in R and the code for estimating and validating second- and third-order RSFs is contained in Appendix E.

Table 3: Explanatory (fixed-effect) variables included in seasonal models of resource selection by boreal caribou in the Northwest Territories.

Variable Category	Variable Name	Variable Type
Local land-cover[†]	Bryoids	Categorical
	Tall shrub	Categorical
	Short shrub	Categorical
	Treed wetland	Categorical
	Shrub wetland	Categorical
	Herb wetland	Categorical
	Herb	Categorical
	Open conifer forest	Categorical
	Sparse conifer forest	Categorical
	Dense broadleaf forest	Categorical
	Open broadleaf forest	Categorical
	Dense mixedwood forest	Categorical
	Open mixedwood forest	Categorical
	Water	Categorical
	Non-vegetated	Categorical
	Burned lowlands (1-10 years old)	Categorical
	Burned lowlands (11-20 years old)	Categorical
	Burned lowlands (21-30 years old)	Categorical
	Burned lowlands (31-40 years old)	Categorical
	Burned lowlands (41-60 years old)	Categorical
	Burned upland conifer (1-10 years old)	Categorical
	Burned upland conifer (11-20 years old)	Categorical
	Burned upland conifer (21-30 years old)	Categorical
	Burned upland conifer (31-40 years old)	Categorical
	Burned upland conifer (41-60 years old)	Categorical
	Burned upland broadleaf (1-10 years old)	Categorical
	Burned upland broadleaf (11-20 years old)	Categorical
	Burned upland broadleaf (21-30 years old)	Categorical
	Burned upland broadleaf (31-40 years old)	Categorical
	Burned upland broadleaf (41-60 years old)	Categorical
	Burned upland non-treed (1-10 years old)	Categorical
	Burned upland non-treed (11-20 years old)	Categorical
	Burned upland non-treed (21-30 years old)	Categorical
	Burned upland non-treed (31-40 years old)	Categorical
	Burned upland non-treed (41-60 years old)	Categorical
Landscape context	Proportion of broadleaf (1-km radius)	Continuous
	Proportion of sparse conifer forest (1-km radius)	Continuous
Anthropogenic disturbance	Linear feature density (1-km radius)	Continuous
	Distance to nearest major road	Continuous
	Distance to nearest polygonal disturbance	Continuous
	Distance to nearest settlement	Continuous

[†] For local land-cover, conifer dense is the reference category in all resource selection models. Local land-cover not designated as "burned" are areas that have not burned within the last 60 years.

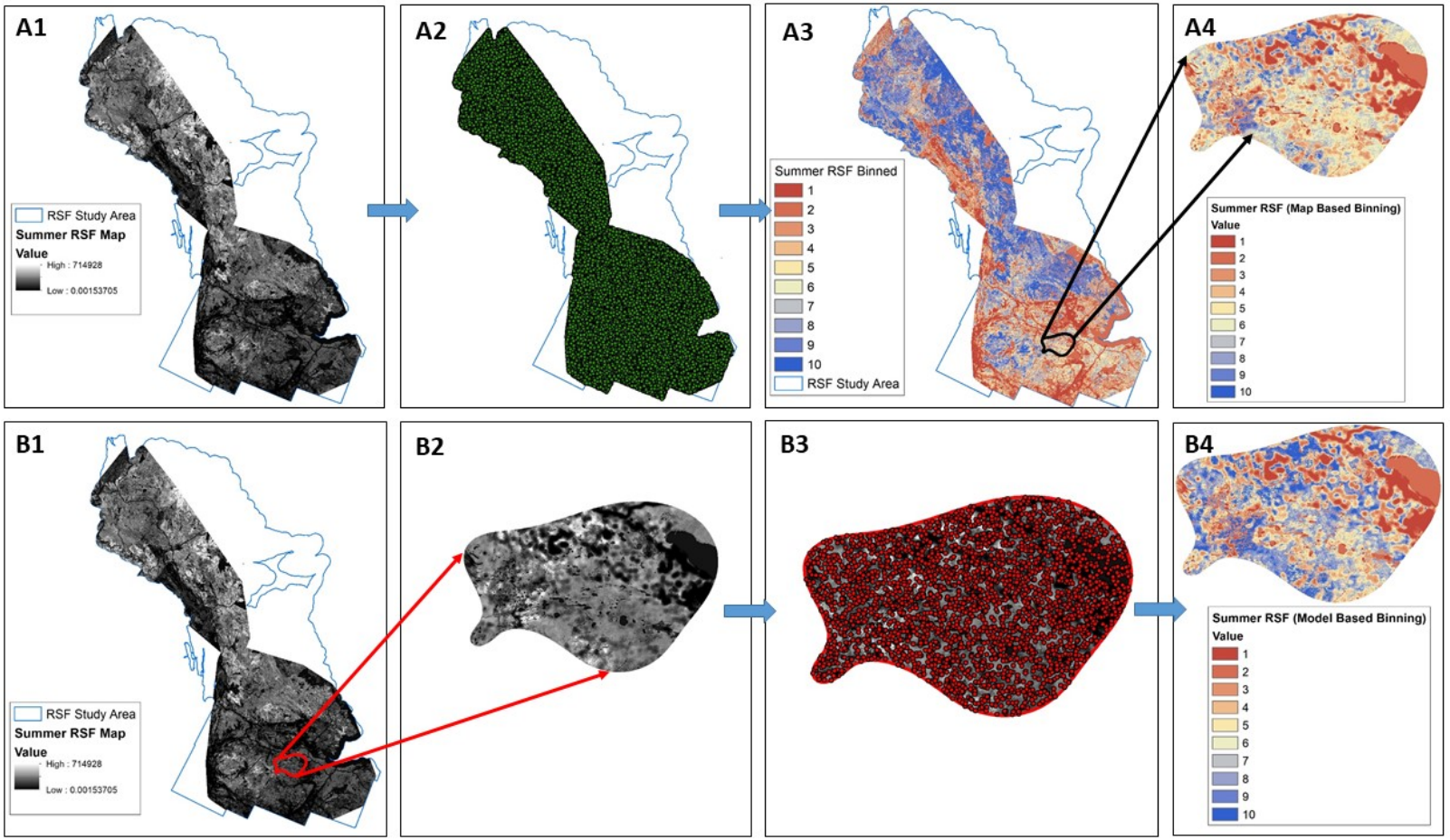

Figure 9: Schematic representation of map-based versus model-based *k*-fold cross validation at a third-order scale. In map-based validation, outputs from RSF models are used to generate predicted values of habitat selection by caribou within the MCPs of the Northern and Southern groups (A1). Random points are then used to sample these predicted values (A2). Based on these values, the random points are partitioned into decile bins and the cut points between bins are used to create a binned map (A3; i.e. 10 bins with each bin containing the same number of points. If 80,000 random points are generated, each bin would contain 8,000 points. Bin 1 would contain the points with the lowest 8,000 values; bin 10 would contain the top 8,000 values). A portion of this binned RSF map is shown clipped to the annual home range of an individual caribou (A4). In model-based validation, the unbinned RSF predictions are first clipped to the individual's home range (B1, B2). Random points are generated within the home range only (B3) and partitioned into decile bins as described above to create a binned map that is constrained to this home range (B4). Although the underlying RSF values remain the same, the two approaches differ in how these values are binned (compare B4 with A4). In both approaches, the proportional frequency of caribou locations falling within a bin is compared to bin rank.

RESULTS

Caribou Response to Local Land-cover

At both second- and third-order scales, boreal caribou demonstrated seasonal differences in resource selection. These differences were particularly evident in the responses of caribou to local land-cover (Figs. 10–17). In this section, caribou responses to burned local land-covers are presented first followed by their responses to unburned local land-covers.

Burned Local Land-cover

During the snow-free seasons (calving, summer and early fall), caribou showed relatively strong selection for burned land-covers. During calving, the five highest-ranked land-covers at the second-order scale were burns (lowland burn 1–10 years old, upland conifer burn 31–-40 years old, lowland burn 31–40 years old, non-treed burn 1–10 years old and upland broadleaf burn 31–40 years old) and four of the top six ranked land-covers at third-order scale were burns (lowland burn 1–10 years old, upland broadleaf burn 1–10 years old, non-treed burn 11–20 years old and upland conifer burn 11–20 years old).

During summer, burns remained highly selected as the six highest ranked land-covers at the second-order scale were burns, though the composition of types differed from calving with only lowland burns 1–10 years old, lowland burns 31–40 years old and upland conifer burns 31–40 years old being in the top-ranked set in both seasons. At the third-order scale during summer, burns comprised five of the eight highest ranked land-covers, with three of these burn classes being non-treed burns.

The trend of burns being highly ranked continued into early fall, though the age classes of these burns were generally older. At the second-order scale, the top three ranked land-covers were burns 31–40 years old situated in lowlands, upland conifer forest, and non-treed areas. This same age class was also represented in two of the top four ranked land-covers (non-treed and lowland burns) at the third-order scale. In late fall, caribou started to show decreasing selection for burns, particularly those of younger age classes (i.e., ≤30 years old). At the second-order scale, the top-ranked land-cover was lowland burns 31–40 years old but the next four highest-ranked were unburned classes. Burns with age classes ≤30 years old were generally ranked below the reference category (dense conifer forest), the exceptions being non-treed and lowland burns 1–10 years old. Third-order scale selection in early fall still had three of the top four ranked classes being burns but these were all >30 years old and either in lowlands or non-treed areas.

In the winter seasons, caribou selection for burns continued to weaken, particularly for burns ≤40 years old. In early winter, only one burn class—non-treed burns 41–60 years old—was among the top five ranked land-covers at the second-order scale. Two burn classes were among the top five ranked land-covers at the third-order scale but again these were burns >40 years old (lowland burns and non-treed burns 41–60 years old). In mid-winter, no burn classes were within the top five ranked land-covers at either scale as the burn class with the highest selection—41–60 years old burns in upland conifer forest— ranked eighth and ninth at the second- and third-order scales, respectively. This burn class was also the most selected burn class by caribou in late winter and was the second ranked land-cover at the second order scale.

Unburned Local Land-cover

Caribou also showed seasonal variation in the selection of non-burned land-covers (Figs. 10–17), though this variation was perhaps less pronounced than for burns. Among non-burned land-covers, bryoids, wetlands (treed, shrub, and herb) and conifer forests with minimal canopy cover (open and sparse) were generally among the top selected across all seasons and at both scales. Tall and short shrubs were also selected at rates higher than the reference class (dense conifer forest). Broadleaf forests, in contrast, were generally among the lowest ranked land-covers across all seasons and at both scales. Alongside these general trends, a few notable seasonable differences were evident. During calving and summer, caribou showed strong selection for herb and non-vegetated land-covers, particularly at the third-order scale whereas during mid- and late winter, caribou showed increasing selection for forested areas as mixedwood forests and dense conifer forest became more highly ranked.

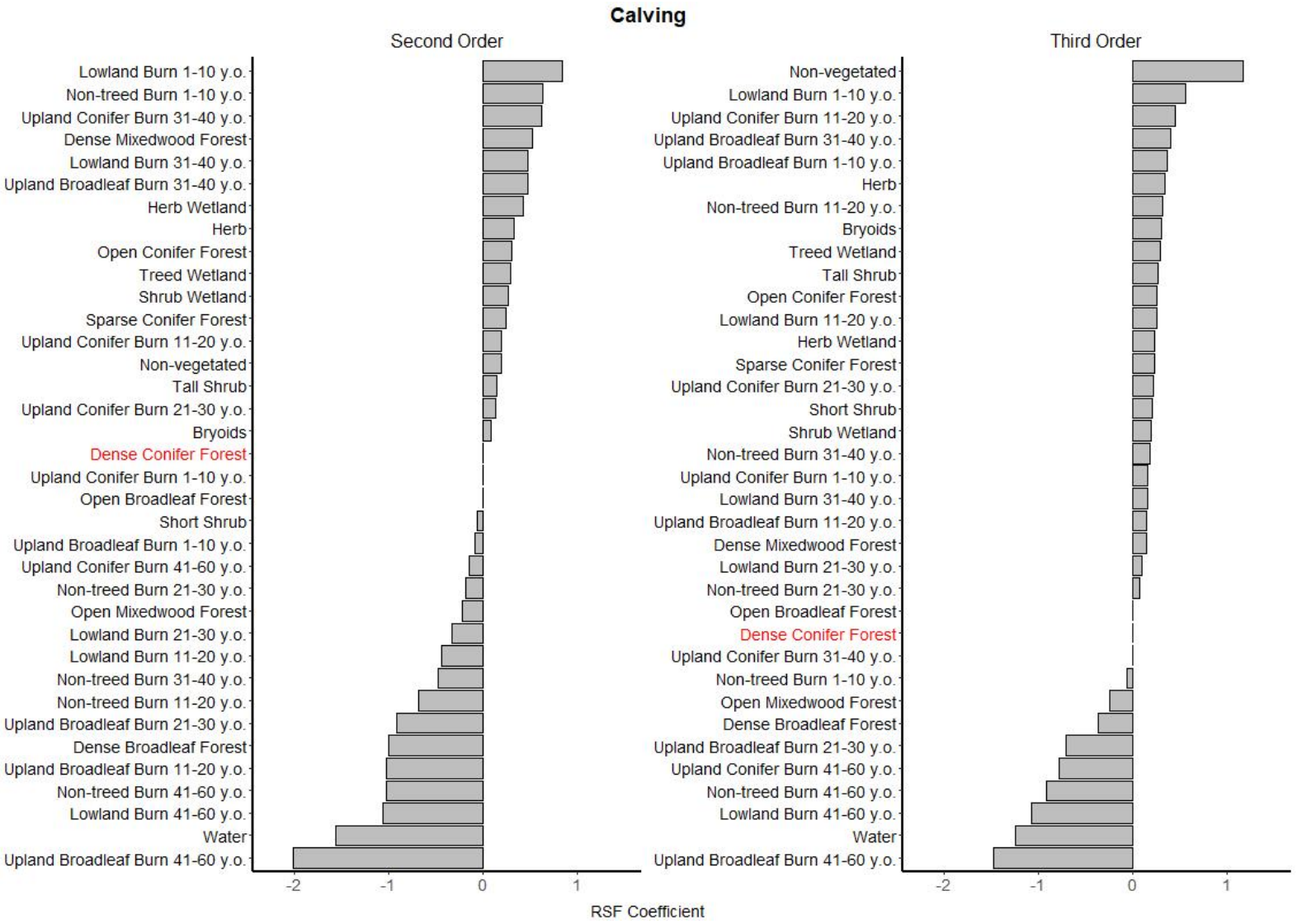

Figure 10: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the calving season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

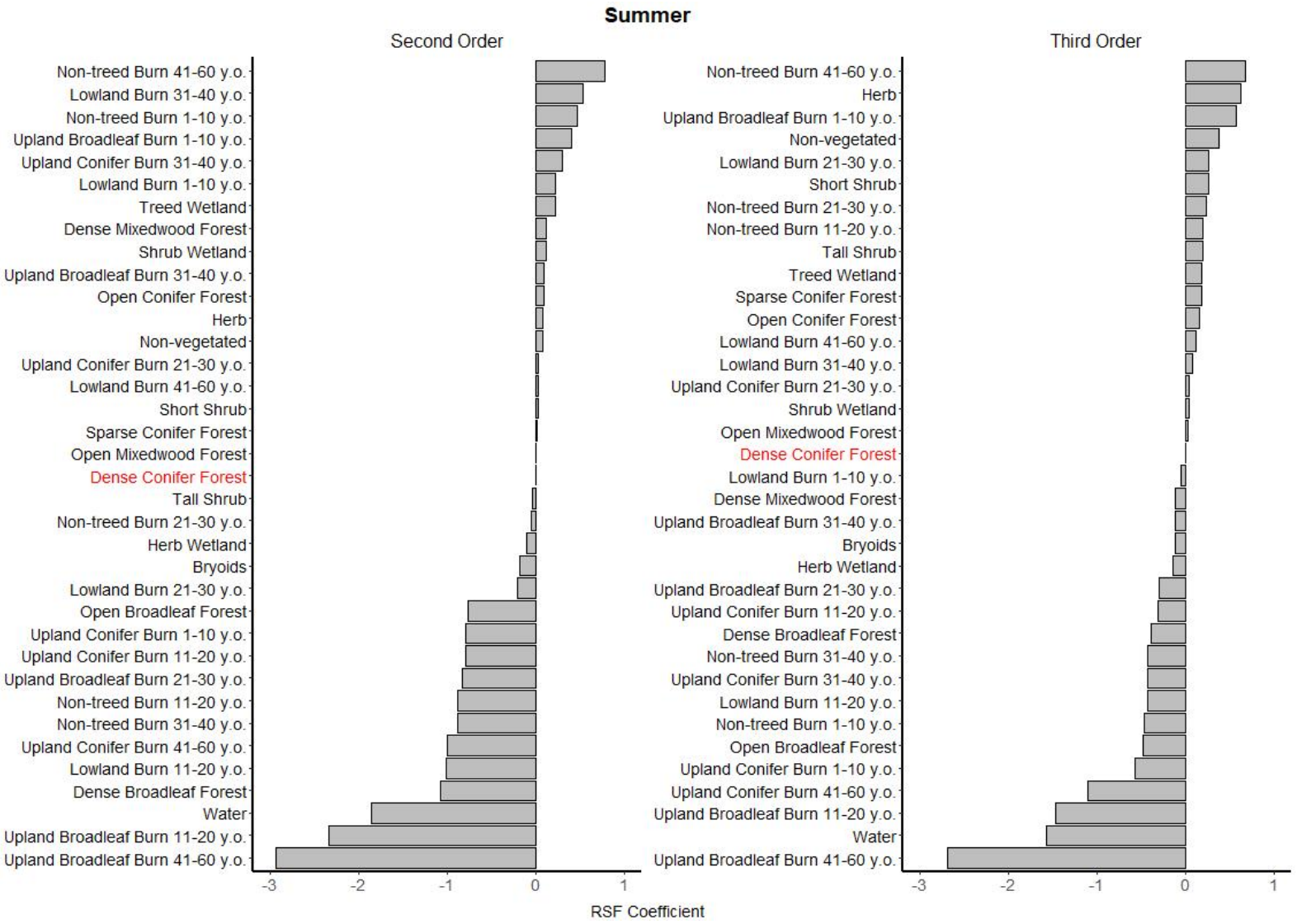

Figure 11: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the summer season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

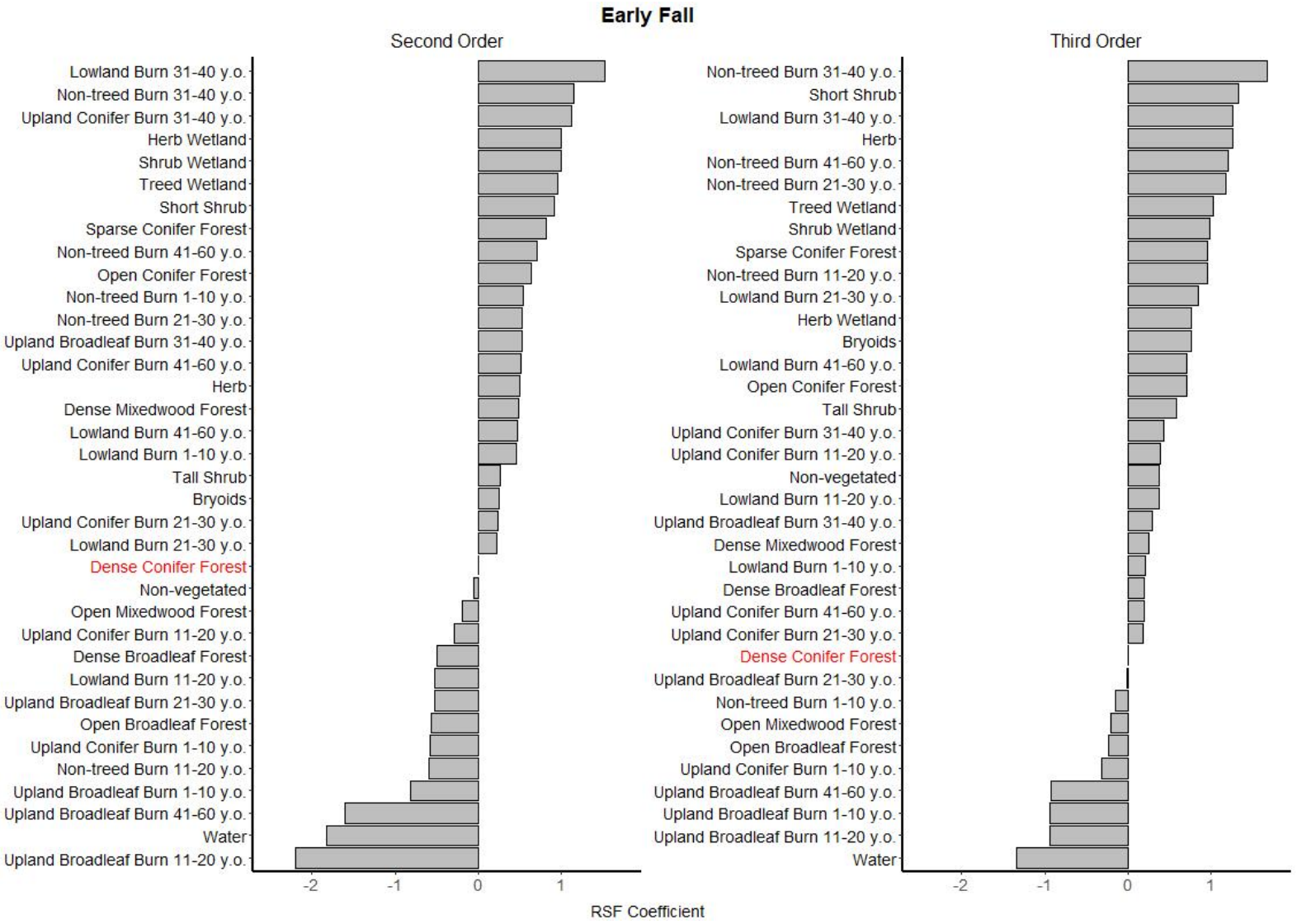

Figure 12: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the early fall season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

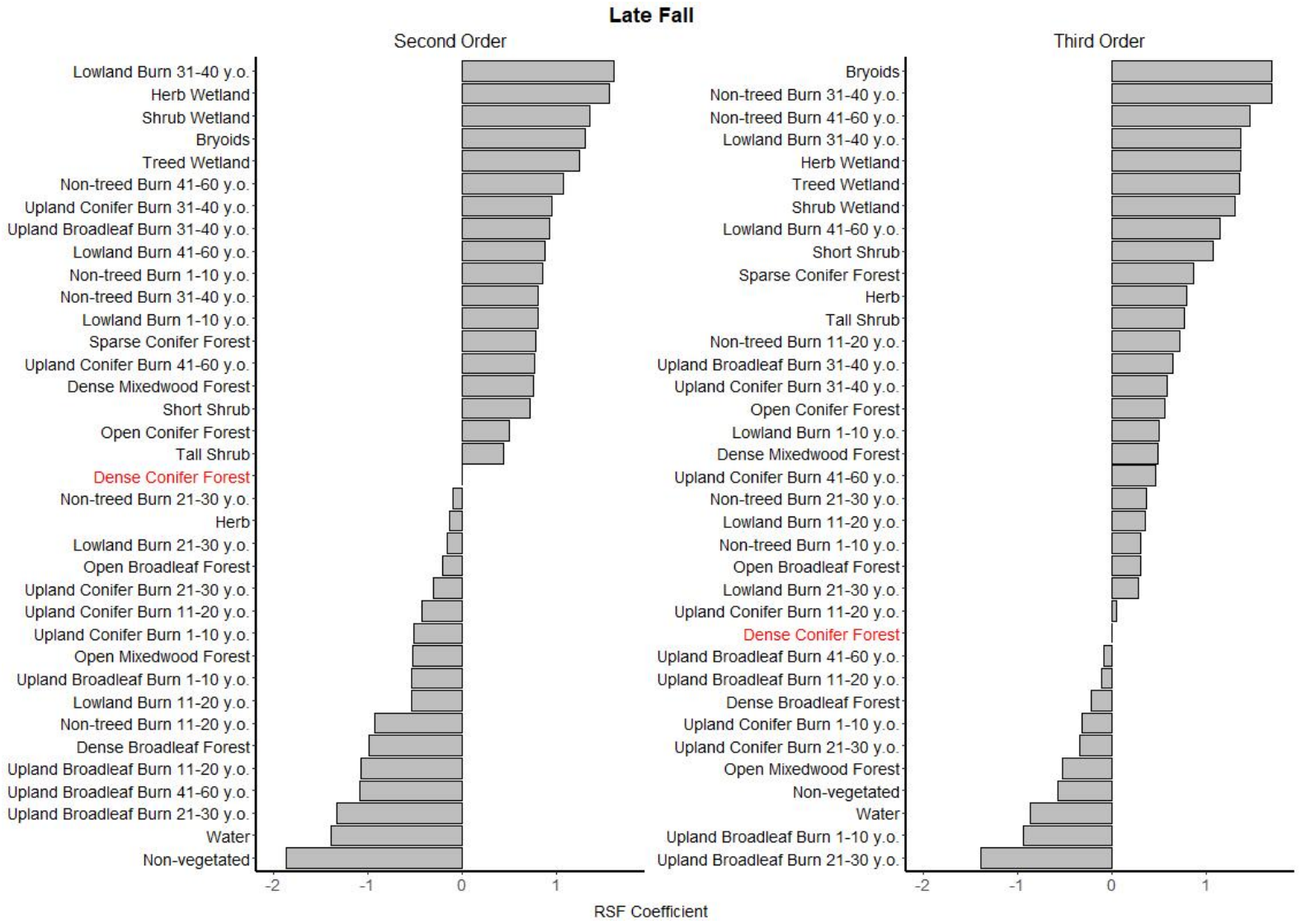

Figure 13: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the late fall season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

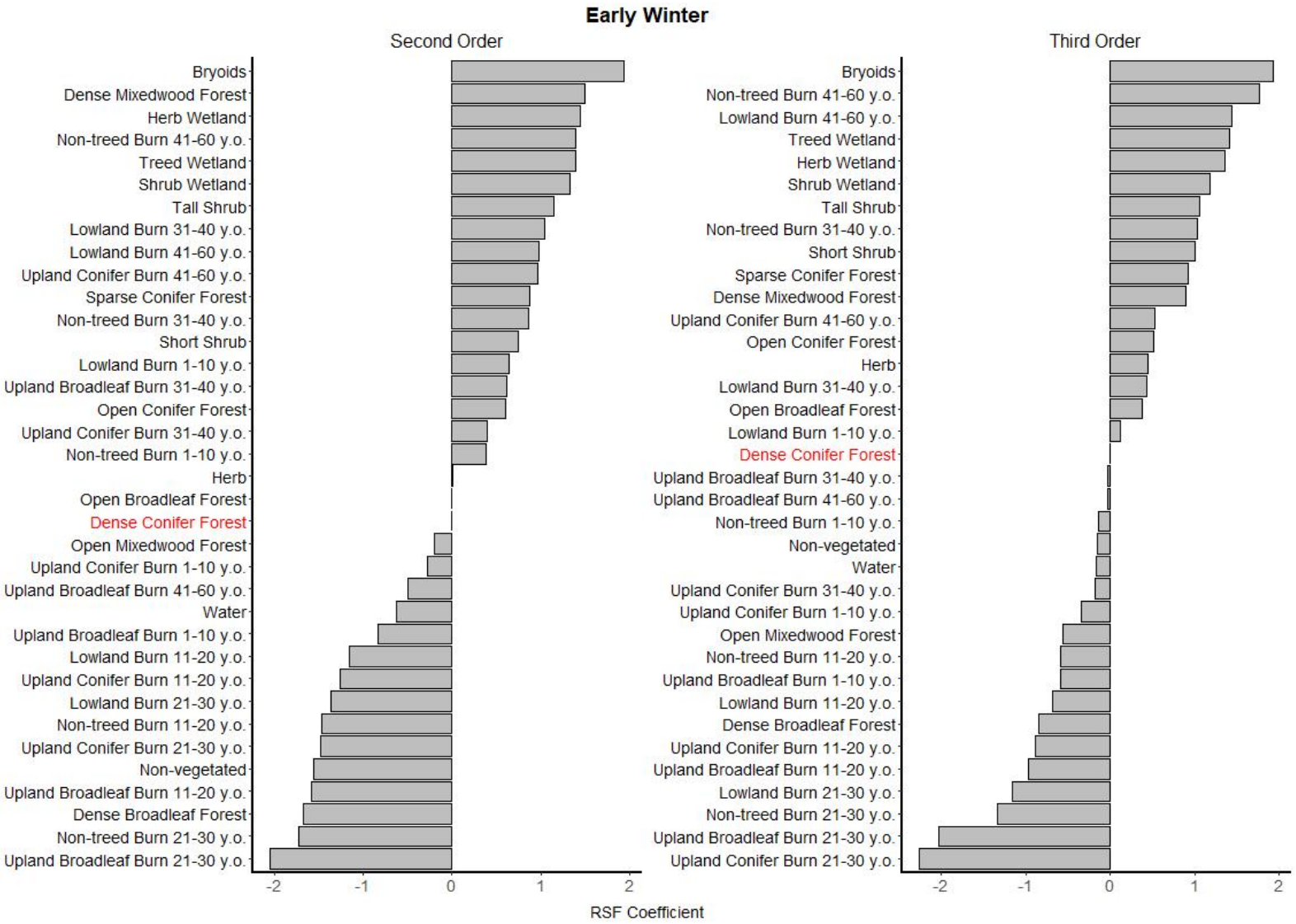

Figure 14: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the early winter season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

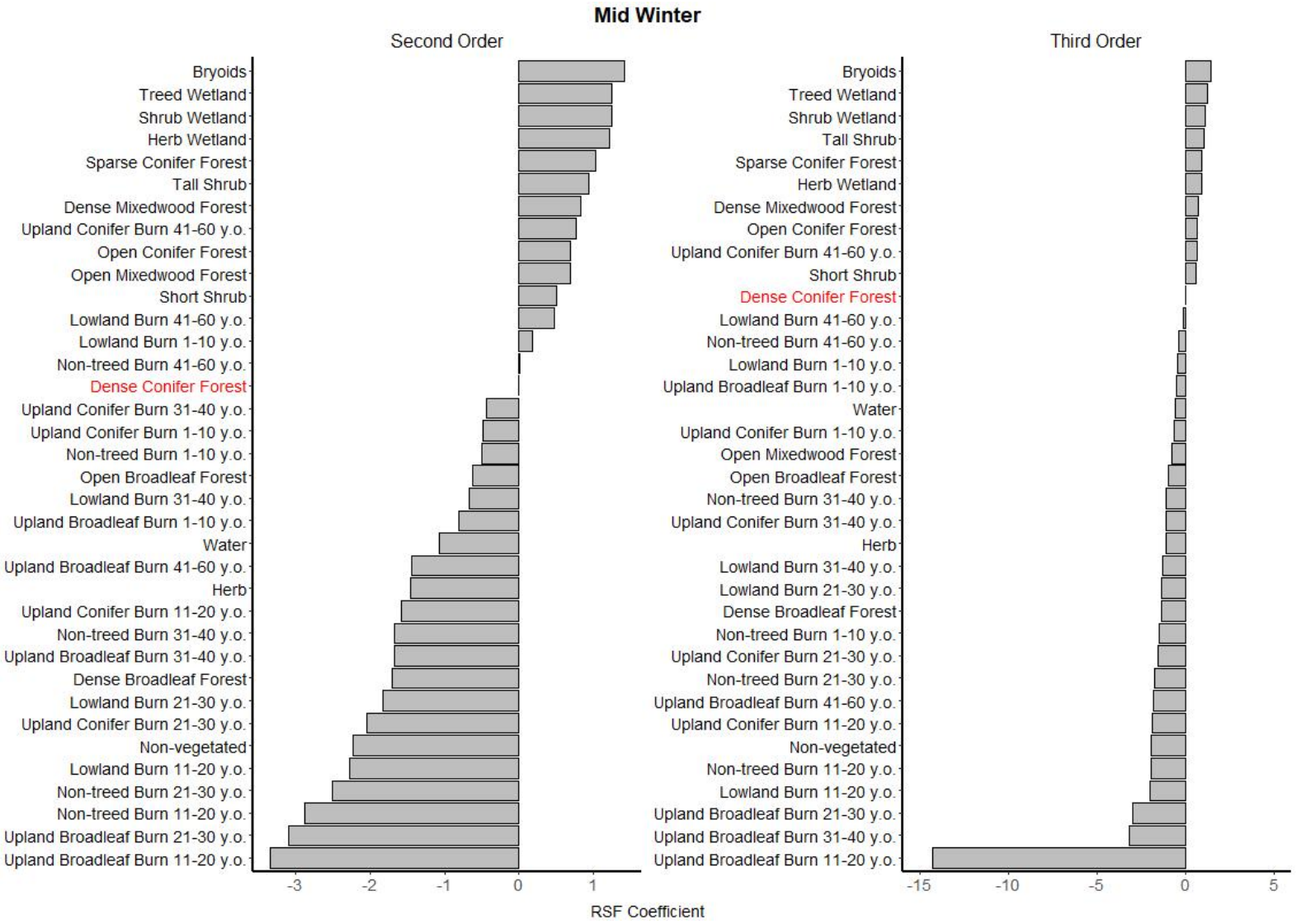

Figure 15: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the mid-winter season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red). Note that x-axis differs between second- and third-order bar charts.

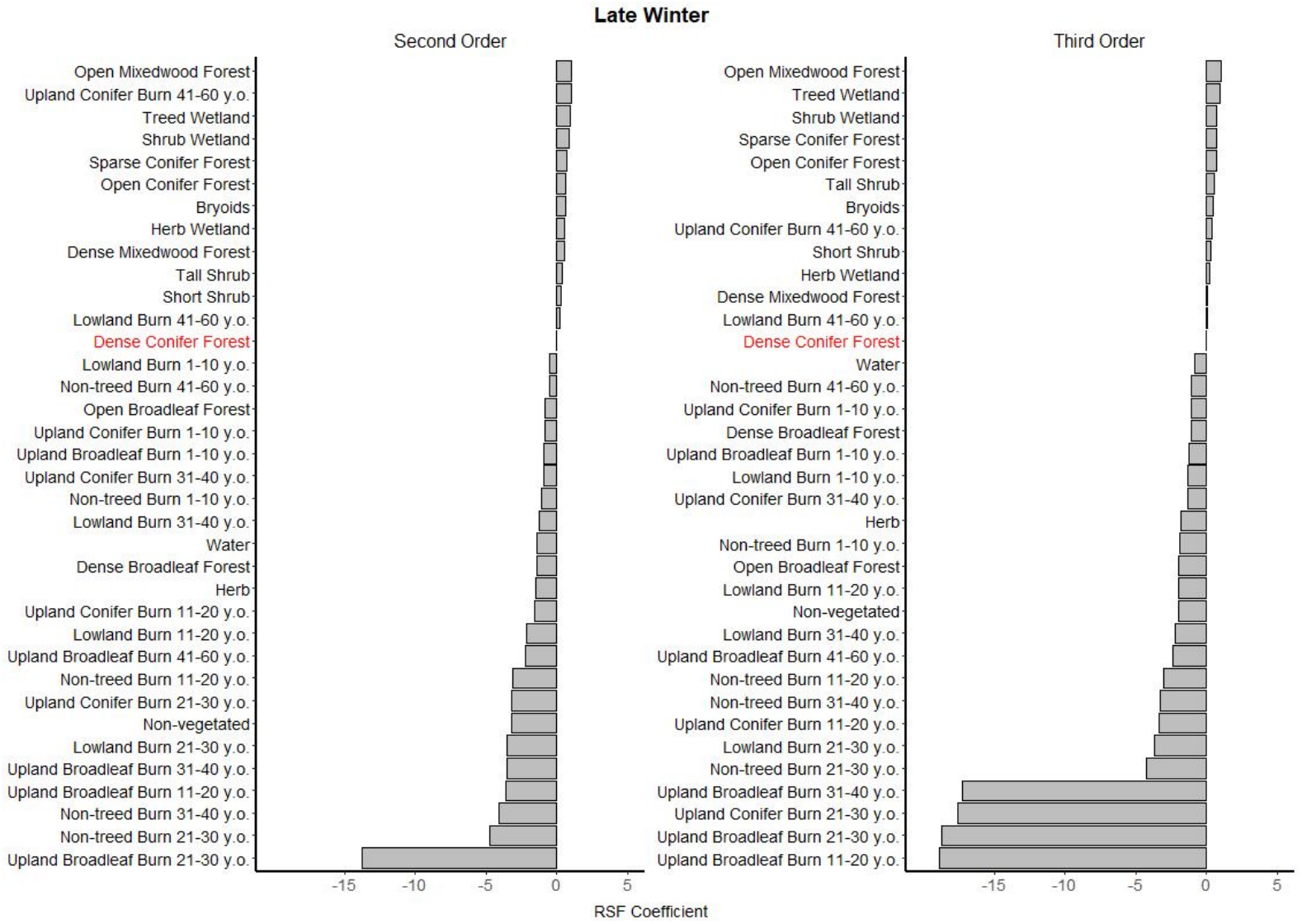

Figure 16: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales during the late winter season of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

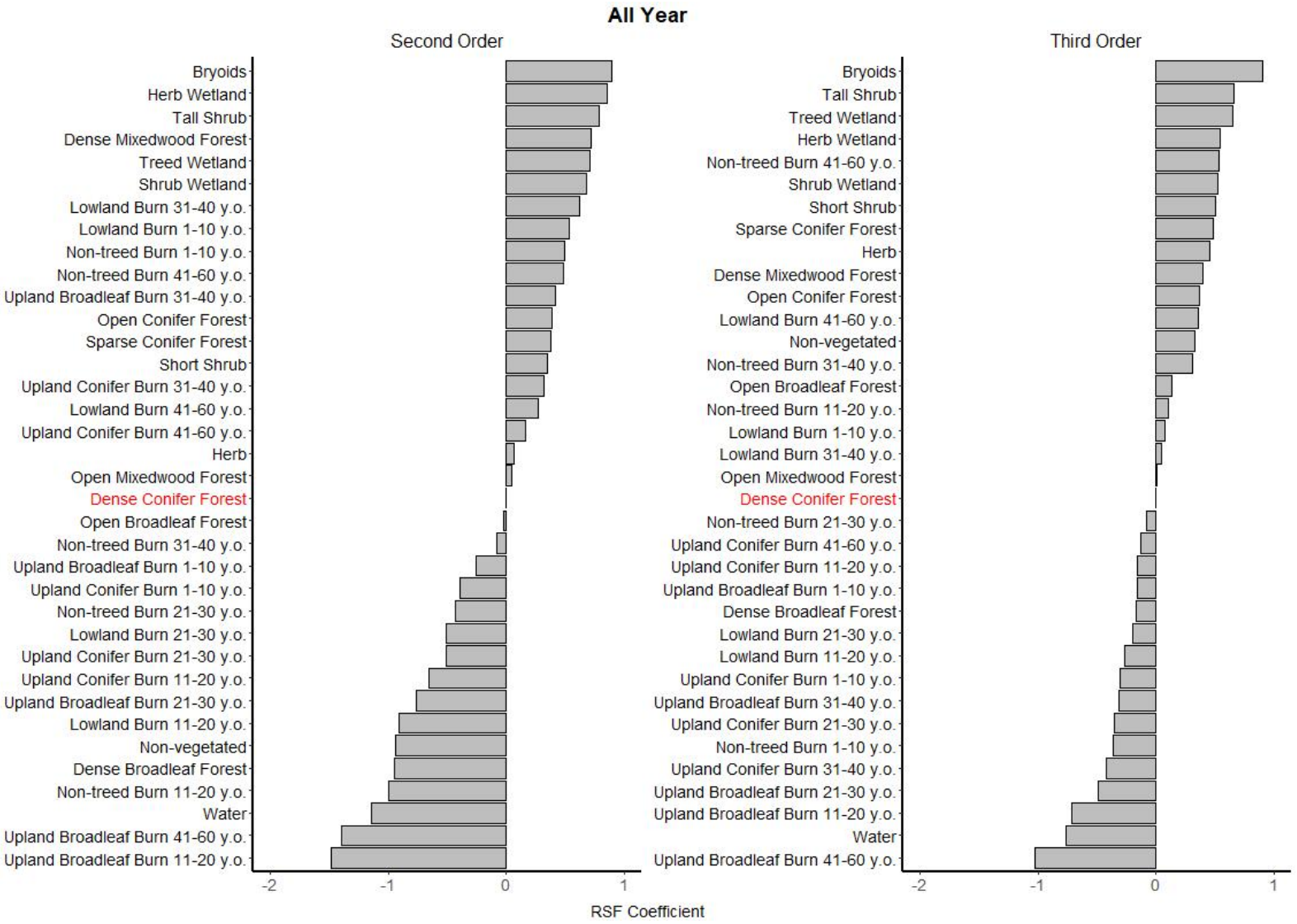

Figure 17: Model coefficients for land-cover variables (see Table 3) from resource selection functions estimated at second- and third-order scales across the entire year of boreal caribou in the Northwest Territories. Variables are ordered by their ranking relative to the reference category (dense conifer forest, shown in red).

Seasonal Trends in Caribou Response to Burns

As noted previously, caribou response to burns varied seasonally and these responses also varied by the land-cover that was burned (or the land-cover type that regenerated post-fire, if the fire predates the 2007/2010 EOSD data) and burn age (Figs. 18–21). Seasonal trends in caribou response to burns, however, were similar between the two scales of selection. In general, burn age influenced seasonal selection of burns by caribou. During calving, caribou showed stronger selection for younger burns (i.e., ≤20 years old), a response that was consistent across all burned land-covers considered (lowlands, upland conifer, upland broadleaf, and non-treed). After calving, caribou selection for burns generally declined during summer then increased during the fall. Despite this, burns still made up the top 6 land cover classes at the second-order scale, and 5 of the top 8 land cover classes at the third-order scale during the summer season. Selection for burns was generally lowest during mid- to late winter, particularly at the third-order scale where a few burn classes (e.g., upland conifer burn 21–30 years old) were perfectly avoided (i.e., no caribou GPS locations occurred within that class). One notable exception to this trend was upland conifer burns > 40 years old, which had relatively strong selection by caribou compared to other seasons. Among the four burned land-covers, caribou generally showed the weakest selection for upland broadleaf burns regardless of burn age.

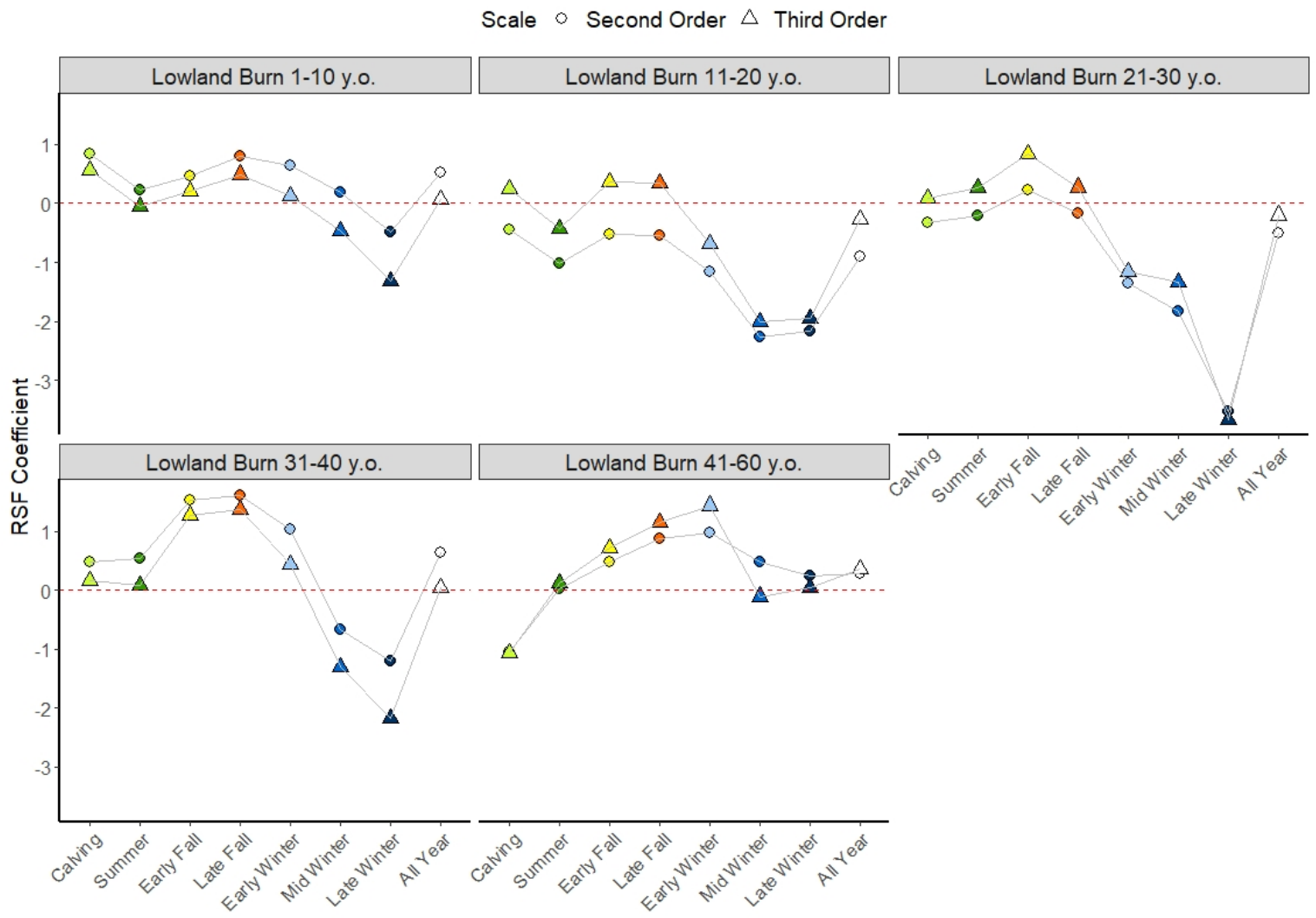

Figure 18: Seasonal trends in the response of boreal caribou to burned lowlands of various age classes (1-10 years post-fire, 11-20 years post-fire, 21-30 years post-fire, 31-40 years post-fire and 41-60 years post-fire). Coefficients >0 indicate selection for the burned land-cover type relative to dense conifer forest (the reference category) whereas coefficients <0 indicate relative avoidance. Note that season lengths differ (see Table 2).

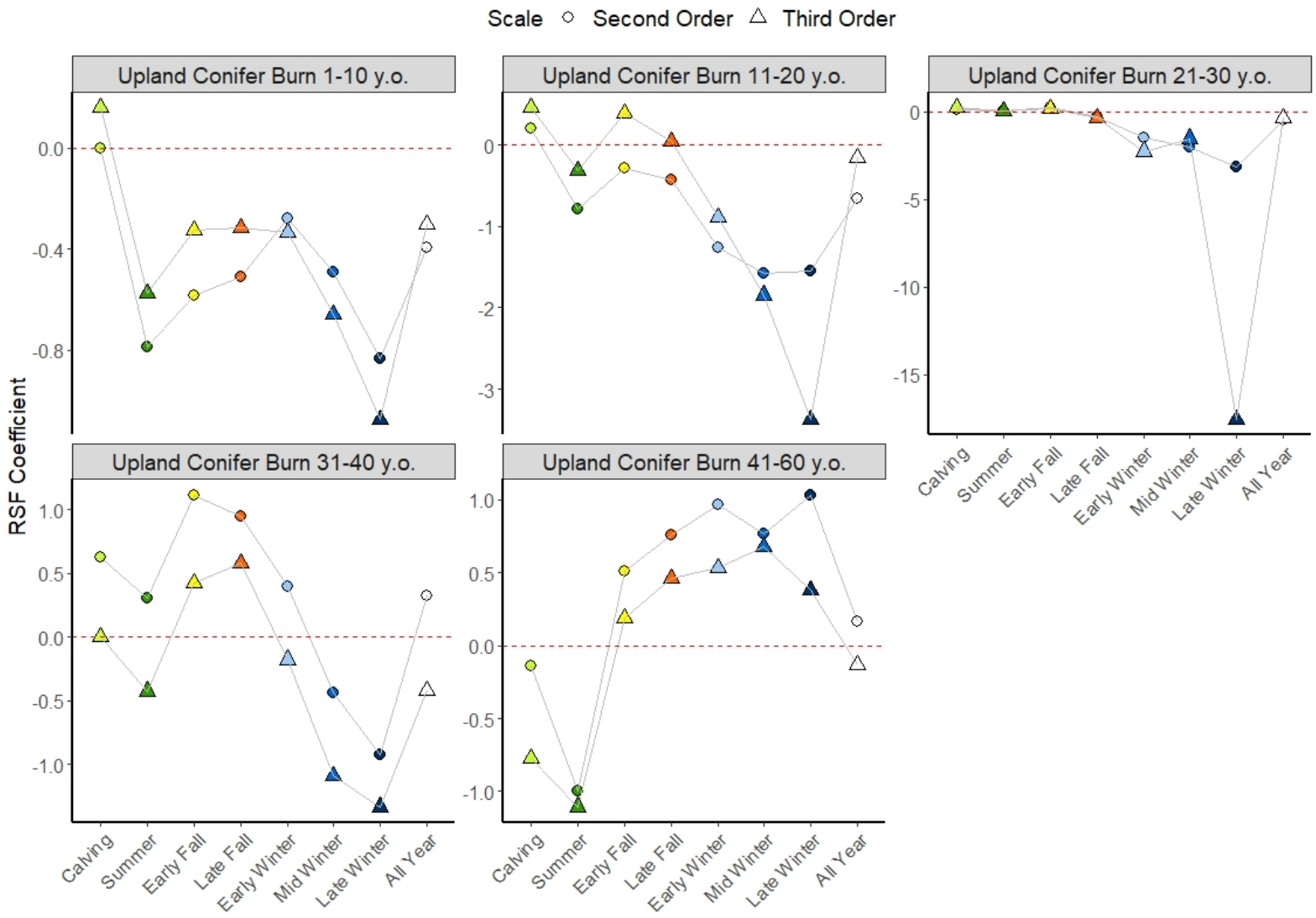

Figure 19: Seasonal trends in the response of boreal caribou to burned upland conifer forest of various age classes (1-10 years post-fire, 11-20 years post-fire, 21-30 years post-fire, 31-40 years post-fire and 41-60 years post-fire). Note that the y-axis varies among subplots and that season lengths differ (see Table 2).

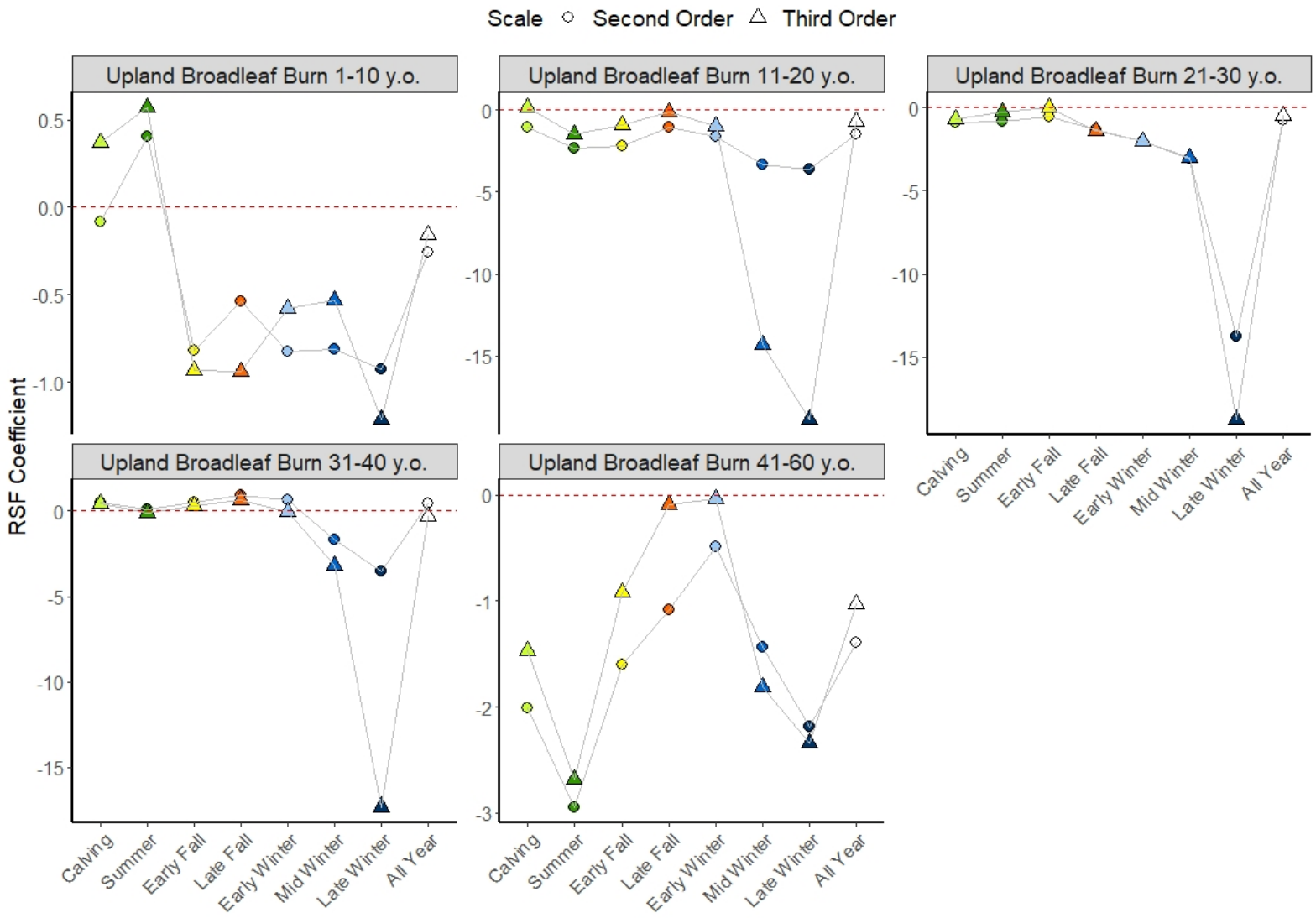

Figure 20: Seasonal trends in the response of boreal caribou to burned upland broadleaf forest of various age classes (1-10 years post-fire, 11-20 years post-fire, 21-30 years post-fire, 31-40 years post-fire and 41-60 years post-fire). Note that the y-axis varies among subplots and that season lengths differ (see Table 2).

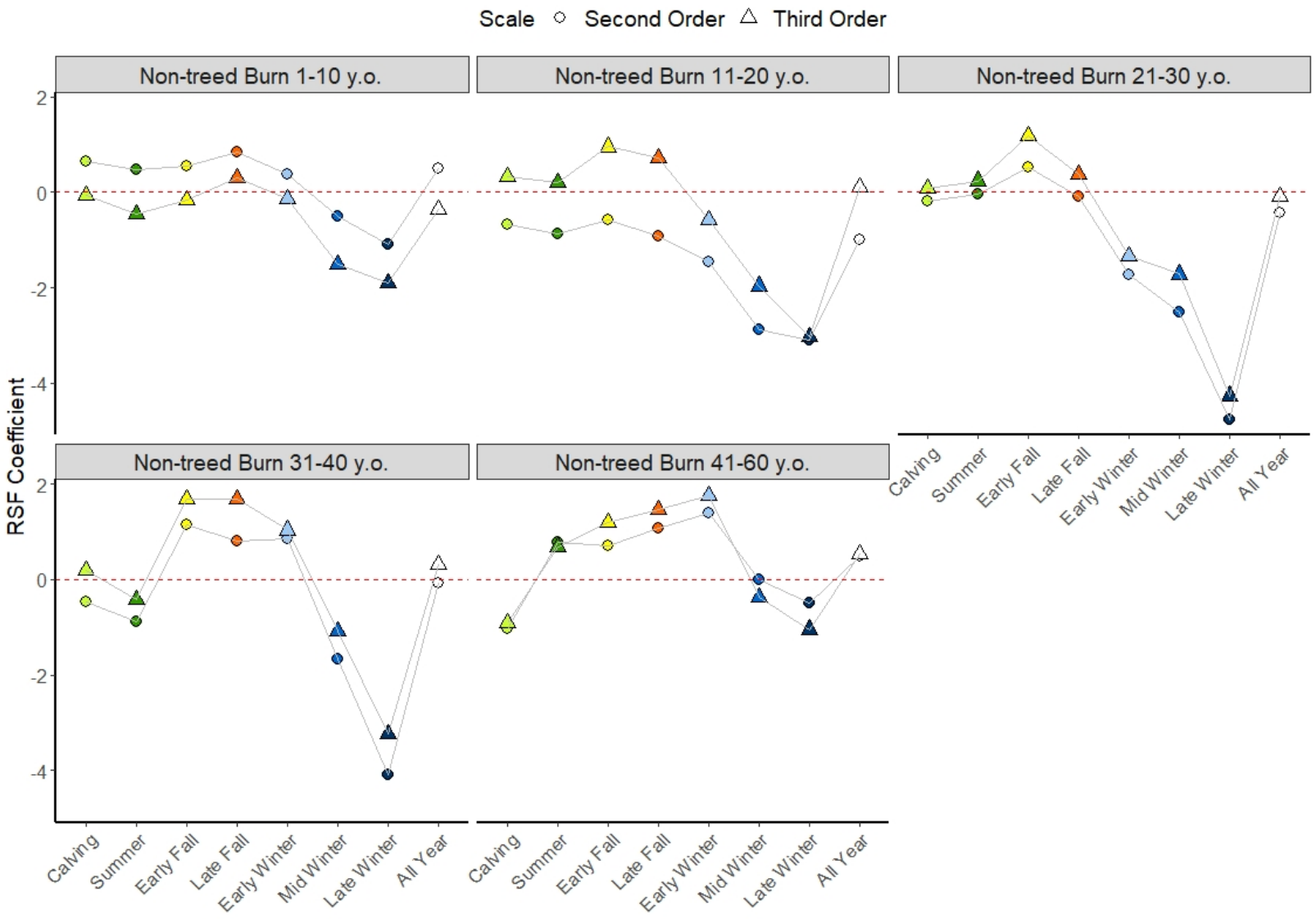

Figure 21: Seasonal trends in the response of boreal caribou to burned non-treed land-cover of various age classes (1-10 years post-fire, 11-20 years post-fire, 21-30 years post-fire, 31-40 years post-fire and 41-60 years post-fire). Note that season lengths differ (see Table 2).

Caribou Response to Landscape Context

The two landscape context variables considered—the proportion of sparse conifer forest in a 1-km radius and the proportion of broadleaf forest in a 1-km radius—had differing effects on seasonal resource selection by caribou (Fig. 22). At the third-order scale, caribou generally selected for landscapes with a higher proportion of sparse conifer forest with the strongest selection occurring in summer and early fall. However, at the second-order scale caribou seemed to be avoiding landscapes with high proportions of sparse conifer forest. Caribou response to broadleaf forest was generally more consistent as landscapes with higher densities of this forest type were avoided across all seasons and at both scales with the strongest avoidance occurring at calving.

Caribou Response to Anthropogenic Disturbances

Anthropogenic disturbances had variable effects on seasonal resource selection by caribou, though consistent trends were evident for some disturbance types (Fig. 23). Across all seasons and at both scales, caribou were generally located farther away from major roads and polygonal disturbances than would be randomly expected. For polygonal disturbances, the strength of avoidance by caribou was strongest during calving and summer then steadily diminished in the fall and into late winter. For major roads, caribou response was somewhat bimodal, with relatively strong avoidance evident in calving then diminishing in summer and early fall before increasing again during late fall and early winter and subsequently decreasing to the weakest avoidance in late winter.

The proximity of caribou to settlements varied by season and scale. Seasonally, caribou were furthest from settlements during late fall and closest during calving. At a second-order scale, caribou were generally closer to settlements than would be expected, except during late fall. In contrast, third-order selection analyses showed that caribou were generally farther from settlements when compared to the average distance of random locations sampled within their home ranges.

Caribou response to linear feature density also varied by the season. From calving to early winter, caribou generally avoided areas with high densities of linear features (as measured in a 1-km radius). From mid- to late winter, however, caribou showed increased selection of areas with higher densities of linear features, particularly at the third-order scale.

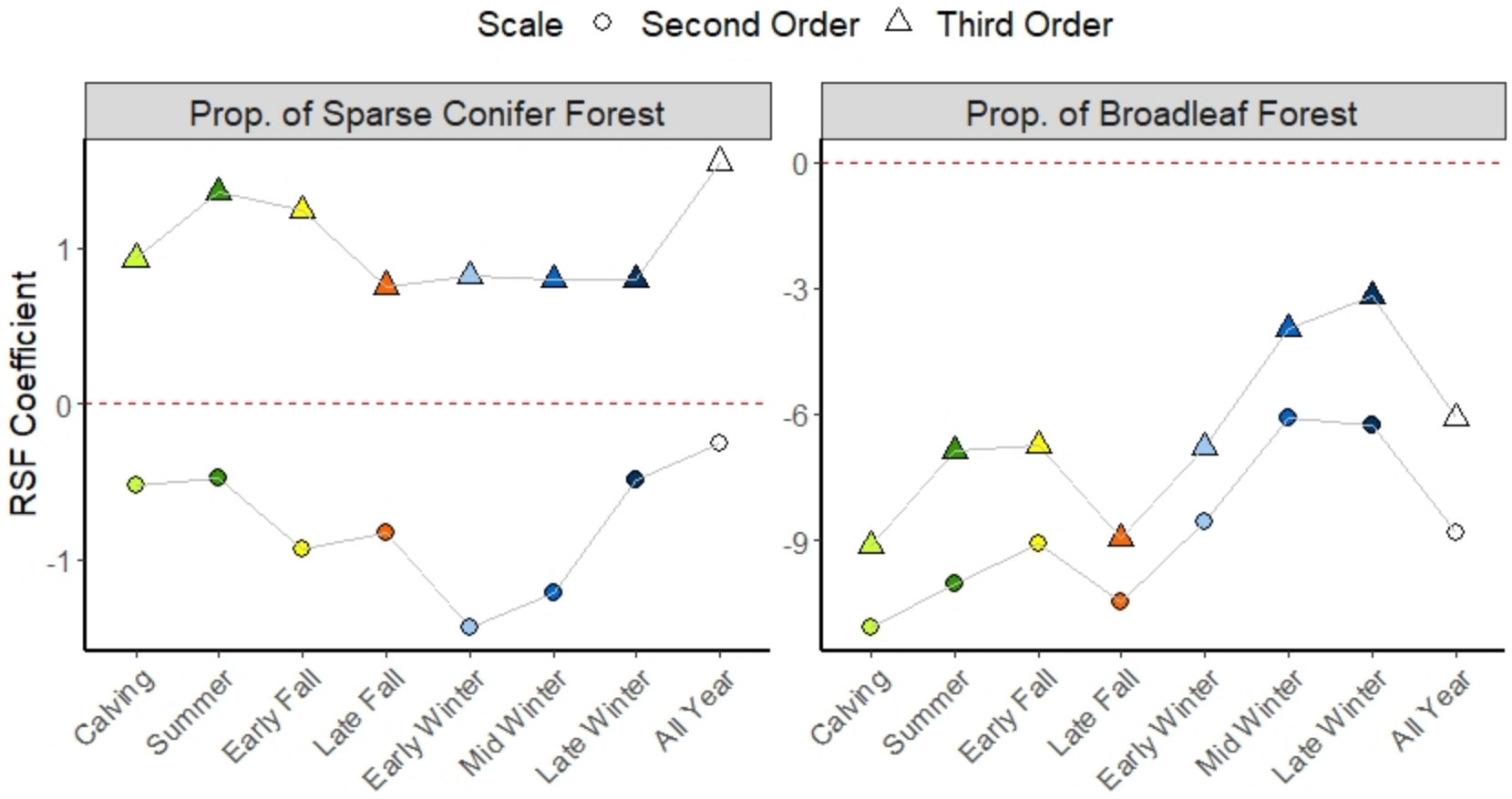

Figure 22: Seasonal responses of boreal caribou in the Northwest Territories to continuous variables describing the proportion of sparse conifer forest in a 1-km radius and the proportion of broadleaf forest in a 1-km radius. Positive RSF coefficients indicate that caribou are selecting for areas with a higher proportion of the land-cover type. Note that the y-axis differs among plots and that season lengths differ (see Table 2).

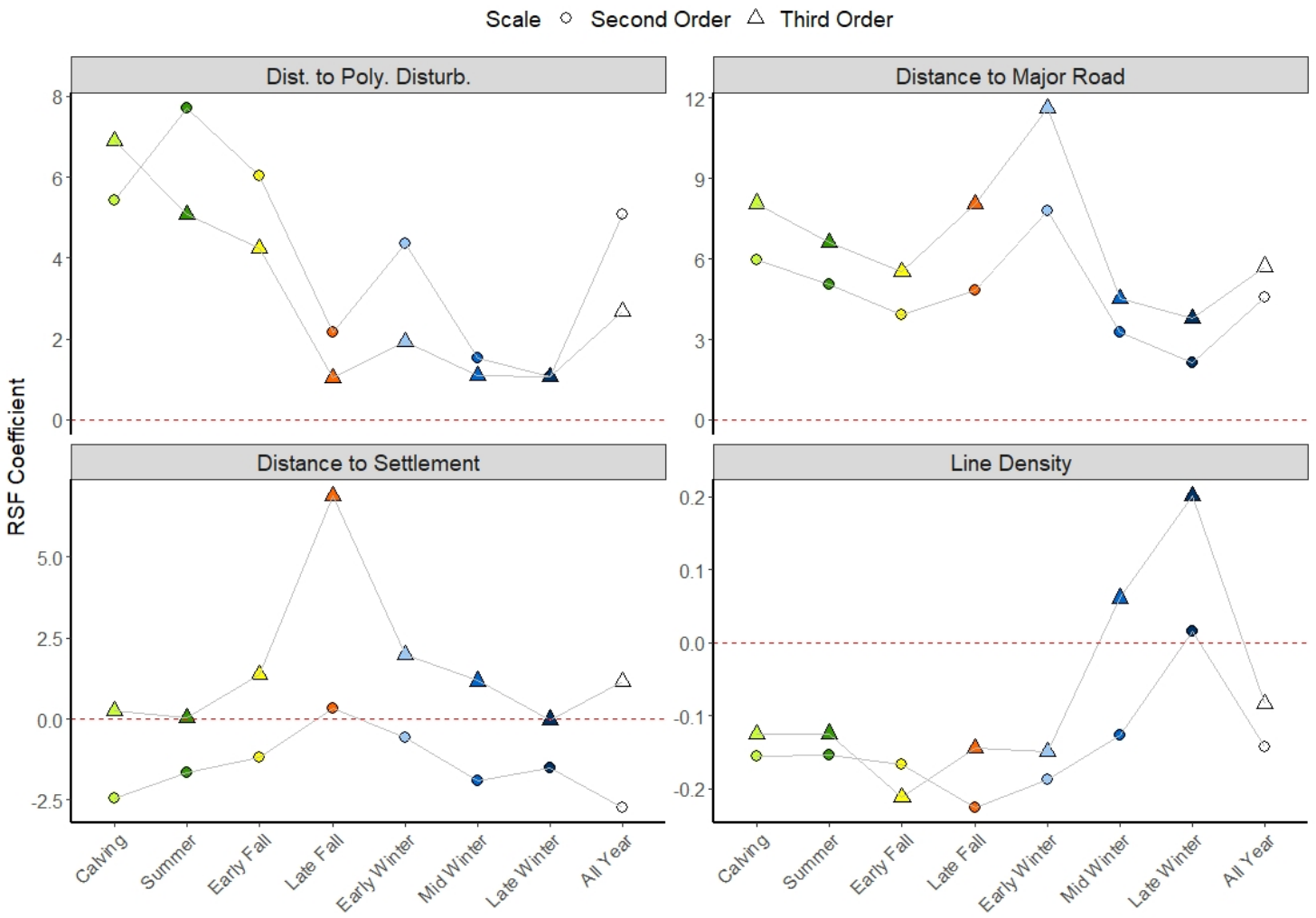

Figure 23: Seasonal responses of boreal caribou in the Northwest Territories to variables characterizing anthropogenic disturbances. All variables were included in resource selection functions estimated at second- and third-order scales. For "distance to" variables, positive RSF coefficients indicate that caribou are farther away from the feature than expected. Positive coefficients for line density indicate caribou are selecting for areas with relatively higher densities of linear features. Note that the y-axis differs among plots and that season lengths differ (see Table 2).

Predictive Performance of Seasonal RSF Models

In general, second-order RSFs had excellent predictive performance with all models having map-based $\bar{r}_s$ values exceeding 0.88 and seven of the eight models exceeding 0.94 (Table 4). Differences between map-based $\bar{r}_s$ values and model-based $\bar{r}_s$ values were also minimal (see Fig. 9 for how these approaches differ). Third-order RSFs, in contrast, had seasonal variation in their predictive performance. RSFs estimated for late fall through late winter generally had very good to excellent map-based predictive performance (all with $\bar{r}_s \geq 0.86$) whereas map-based predictive performance was low during calving, summer and early fall. Predictive performance improved when using model-based validation (all $\bar{r}_s \geq 0.93$), suggesting that functional responses in selection likely affected prediction at this scale.

Table 4: Predictive performance of seasonal models of resource selection by boreal caribou in the Northwest Territories. Models were estimated at second- and third-order scales. Predictive performance was evaluated using *k*-fold cross validation where four folds (or 80%) of the individual caribou were used for model estimation and model outputs were used to generate predictions for the GPS locations from the withheld caribou (20% of the individuals). The proportional frequency of these predictions falling within RSF bins (1–10) was compared to bin rank using Spearman's correlation coefficient ($\bar{r}_s$). Higher values of $\bar{r}_s$ equate to better predictive performance.

	Second Order $\bar{r}_s$		Third Order $\bar{r}_s$	
Season	Map	Model	Map	Model
Calving	0.97	0.98	0.66	0.95
Summer	0.88	0.93	0.46	0.93
Early Fall	0.99	0.98	0.61	0.99
Late Fall	0.99	0.99	0.91	1.00
Early Winter	0.99	0.98	0.91	0.99
Mid Winter	0.99	0.99	0.86	0.99
Late Winter	0.97	0.98	0.91	0.99
All Year	0.94	0.97	0.69	1.00

Second-order RSFs also had better predictive performance within sub-regional monitoring areas than third-order RSFs (Tables 5–6). Although prediction varied by season within sub-regions, predictive performance was generally low within the Mackenzie region across all seasons, which supports the exclusion of these caribou from RSF models. In most instances, sub-regional prediction was improved if the original RSF bins (i.e., those delineated by the full RSF model) were adjusted by their relative area within a sub-region or by re-delineating RSF bins to an equal area for each bin within a sub-region. For the former approach ("area-adjusted"), recall that RSF bins were delineated into equal areas using the entire study area as the spatial extent (i.e., RSF Bin 1 would cover an area that is equal to RSF Bin 2, etc.). If the spatial extent is narrowed to a specific sub-regional monitoring area, it is unlikely that the originally delineated RSF bins will continue to have equal area representation (i.e., in a given sub-regional monitoring area, RSF Bin 1 could cover more (or less) area than Bin 2). We can account for this unequal representation by calculating the selection ratio for a given RSF bin as

$$Selection\ ratio\ of\ RSF\ Bin_i = \frac{proportion\ of\ caribou\ GPS\ locations\ in\ bin_i}{proportional\ area\ of\ bin_i}$$

These selection ratios are then compared to bin rank using $\bar{r}_s$, as was done for all other approaches evaluating predictive performance.

Examples of predictive RSF maps at the second- and third-order scales of selection are provided in Figures 24–27 using the All Year models. A full set of predictive maps for each seasonal activity period and each scale of selection are provided in Appendix I. Figures 24 and 26 display predicted RSF values from second- and third-order models partitioned into 10 bins. Bins were specified using an "equal area" approach where the RSF predictions from random points (n = 40,000) sampled within the 2nd-order scale of availability (North and South polygons—see Figure 3) were assigned to one of 10 bins with each bin having an equal number of points. Note that extrapolating the RSF model to the full study area causes some inequality in the number of map pixels contained in each category. Figures 25 and 27 display the same predictive RSF maps focused in on the Dehcho North sub-region. The predictive RSF maps represent the relative likelihood (Bin 1 represents the weakest selection and Bin 10 represents strongest selection) that a given habitat pixel in the landscape would be selected by an "average" adult female boreal caribou moving through the landscape, based on conditions as of 2017 (i.e. including fire data up to and including 2017 and anthropogenic disturbance as measured in 2015). In general, areas falling in Bin 7 and higher are selected by boreal caribou, and areas in Bins 6 and lower are used in proportion to availability or less than expected by chance.

Table 5: Predictive performance of seasonal models of resource selection by boreal caribou within each of the 10 sub-regional monitoring areas in the Northwest Territories. Models were estimated at a second-order scale and predictive performance was measured by the strength of correlation (Spearman's correlation coefficient; r_S) between the rank of binned selection values (10 total bins) and the proportional frequency of caribou locations falling within each bin ("Full Model"). Post-hoc correlation coefficients were also estimated where the proportional frequency of caribou locations within a bin was scaled by the bin's area within a sub-region ("area-adjusted") and where bins were re-delineated into deciles of equal area within a sub-region ("equal area").

			r_S		
Season	Sub-region	No. of Caribou[2]	Full Model	Sub-region Area-adjusted	Sub-region Equal Area
Calving	Gwich'in North	17	0.94	0.85	0.81
	Gwich'in South	14	0.82	0.94	0.73
	Sahtu	12	0.89	0.95	0.93
	North Slave	19	0.85	0.90	0.84
	Mackenzie[1]	27	0.75	0.82	0.72
	Dehcho North	43	0.75	0.84	0.88
	Dehcho South	42	0.98	0.99	1.00
	Hay River Lowlands	49	0.98	1.00	1.00
	Pine Point / Buffalo Lake	25	0.99	0.92	0.88
	South Cameron	28	0.89	0.98	0.96
Summer	Gwich'in North	14	0.89	0.92	0.82
	Gwich'in South	15	0.73	0.81	0.53
	Sahtu	15	0.89	0.93	0.89
	North Slave	19	0.83	0.82	0.83
	Mackenzie[1]	27	0.52	0.44	0.54
	Dehcho North	33	0.73	0.78	0.68
	Dehcho South	38	0.76	0.99	1.00
	Hay River Lowlands	32	0.99	0.98	0.99
	Pine Point / Buffalo Lake	24	0.88	0.95	0.88
	South Cameron	21	0.62	0.78	0.94
Early Fall	Gwich'in North	12	0.94	0.88	0.65
	Gwich'in South	16	0.84	0.89	0.70
	Sahtu	11	0.78	0.79	0.68
	North Slave	14	0.88	0.85	0.83
	Mackenzie[1]	26	0.08	0.44	0.45
	Dehcho North	36	0.98	0.90	0.78
	Dehcho South	40	0.87	0.99	1.00
	Hay River Lowlands	45	0.90	1.00	0.99
	Pine Point / Buffalo Lake	22	0.99	0.98	0.82
	South Cameron	25	0.60	0.85	0.92
Late Fall	Gwich'in North	13	0.92	0.92	0.72
	Gwich'in South	14	0.71	0.85	0.70
	Sahtu	14	0.81	0.84	0.81
	North Slave	18	0.94	0.99	0.93
	Mackenzie[1]	28	0.58	0.66	0.58
	Dehcho North	37	0.99	0.88	0.89
	Dehcho South	46	0.81	1.00	1.00
	Hay River Lowlands	51	0.94	1.00	1.00
	Pine Point / Buffalo Lake	24	0.99	0.94	0.78
	South Cameron	25	0.95	0.99	0.95

(*cont'd*)

Season	Sub-region	No. of Caribou[2]	r_S Full Model	r_S Sub-region Area-adjusted	r_S Sub-region Equal Area
Early Winter	Gwich'in North	13	0.90	0.84	0.52
	Gwich'in South	16	0.83	0.96	0.94
	Sahtu	11	0.81	0.73	0.73
	North Slave	18	0.94	0.96	0.82
	Mackenzie[1]	33	0.37	0.73	0.68
	Dehcho North	38	0.96	1.00	1.00
	Dehcho South	50	0.95	1.00	1.00
	Hay River Lowlands	65	0.96	1.00	1.00
	Pine Point / Buffalo Lake	32	0.90	0.87	0.67
	South Cameron	25	0.96	0.99	0.95
Mid Winter	Gwich'in North	13	0.90	0.96	0.85
	Gwich'in South	16	0.94	0.96	0.95
	Sahtu	14	0.71	0.75	0.78
	North Slave	17	0.95	0.83	0.82
	Mackenzie[1]	33	0.38	0.62	0.44
	Dehcho North	59	0.98	1.00	1.00
	Dehcho South	72	0.99	1.00	1.00
	Hay River Lowlands	85	0.94	1.00	0.99
	Pine Point / Buffalo Lake	32	0.88	0.92	0.90
	South Cameron	32	0.98	0.99	1.00
Late Winter	Gwich'in North	16	0.87	0.85	0.82
	Gwich'in South	19	0.93	0.95	0.98
	Sahtu	16	0.71	0.72	0.67
	North Slave	24	0.93	0.94	0.95
	Mackenzie[1]	33	0.60	0.78	0.65
	Dehcho North	55	1.00	0.95	0.98
	Dehcho South	74	0.98	0.99	1.00
	Hay River Lowlands	81	0.96	0.99	0.98
	Pine Point / Buffalo Lake	34	0.81	0.84	0.88
	South Cameron	31	0.96	0.96	0.99
All Year	Gwich'in North	12	0.87	0.92	0.78
	Gwich'in South	10	0.89	0.81	0.66
	Sahtu	10	0.79	0.82	0.78
	North Slave	19	0.82	0.93	0.90
	Mackenzie[1]	31	0.76	0.99	1.00
	Dehcho North	32	0.90	0.88	0.87
	Dehcho South	18	0.65	0.85	0.90
	Hay River Lowlands	39	0.93	0.98	0.99
	Pine Point / Buffalo Lake	28	0.65	0.79	0.65
	South Cameron	23	0.92	0.85	0.68

[1] Radio-collar data from Mackenzie caribou were excluded from the data used to estimate second- and third-order RSF models.
[2] Data from all available caribou (post-data screening procedures) within a given sub-region were used in this process.

Table 6: Predictive performance of seasonal models of resource selection by boreal caribou within each of the 10 sub-regional monitoring areas in the Northwest Territories. Models were estimated at a third-order scale and predictive performance was measured by the strength of correlation (Spearman's correlation coefficient; r_S) between the rank of binned selection values (10 total bins) and the proportional frequency of caribou locations falling within each bin ("Full Model"). Post-hoc correlation coefficients were also estimated where the proportional frequency of caribou locations within a bin was scaled by the bin's area within a sub-region ("area-adjusted") and where bins were re-delineated into deciles of equal area within a sub-region ("equal area").

			r_S		
Season	Subregion	No. of Caribou[2]	Full Model	Study Area Area-adjusted	Study Area Equal Area
Calving	Gwich'in North	13	0.99	0.92	0.84
	Gwich'in South	12	0.83	0.96	0.96
	Sahtu	8	0.76	0.76	0.77
	North Slave	18	0.92	0.95	0.98
	Mackenzie[1]	27	0.90	0.89	0.88
	Dehcho North	33	0.89	0.94	0.93
	Dehcho South	34	0.55	0.92	0.99
	Hay River Lowlands	38	-0.02	0.78	0.99
	Pine Point / Buffalo Lake	23	0.49	0.92	0.96
	South Cameron	15	0.14	0.61	0.88
Summer	Gwich'in North	11	0.93	0.92	0.72
	Gwich'in South	13	0.72	0.81	0.58
	Sahtu	8	0.79	0.78	0.82
	North Slave	18	0.89	0.99	0.98
	Mackenzie[1]	27	0.25	0.41	0.53
	Dehcho North	28	0.76	0.77	0.72
	Dehcho South	30	0.35	0.83	0.90
	Hay River Lowlands	26	-0.18	0.55	0.99
	Pine Point / Buffalo Lake	24	-0.18	0.44	0.99
	South Cameron	12	0.13	0.95	0.98
Early Fall	Gwich'in North	11	0.92	0.58	0.52
	Gwich'in South	14	0.83	0.88	0.60
	Sahtu	11	0.90	0.92	0.77
	North Slave	13	0.93	0.99	0.99
	Mackenzie[1]	26	0.42	0.38	0.54
	Dehcho North	33	0.94	0.90	0.90
	Dehcho South	36	0.52	0.98	0.98
	Hay River Lowlands	41	0.42	0.95	0.99
	Pine Point / Buffalo Lake	22	0.48	0.87	0.89
	South Cameron	14	-0.45	0.88	0.94
Late Fall	Gwich'in North	10	0.93	0.82	0.52
	Gwich'in South	12	0.70	0.82	0.67
	Sahtu	13	0.88	0.88	0.82
	North Slave	17	0.90	0.98	0.97
	Mackenzie[1]	28	0.32	0.54	0.56
	Dehcho North	30	0.99	0.99	0.99
	Dehcho South	40	0.70	0.99	1.00
	Hay River Lowlands	48	0.70	1.00	1.00
	Pine Point / Buffalo Lake	24	0.87	0.96	0.99
	South Cameron	15	0.47	0.94	0.99

(*cont'd*)

Season	Subregion	No. of Caribou[2]	r_S Full Model	Study Area Area-adjusted	Study Area Equal Area
Early Winter	Gwich'in North	12	0.94	0.76	0.68
	Gwich'in South	13	0.83	0.78	0.84
	Sahtu	11	0.98	0.95	0.78
	North Slave	18	0.85	0.94	0.93
	Mackenzie[1]	28	0.36	0.56	0.50
	Dehcho North	34	0.96	1.00	0.99
	Dehcho South	47	0.79	1.00	1.00
	Hay River Lowlands	44	0.59	1.00	1.00
	Pine Point / Buffalo Lake	25	0.55	0.92	0.96
	South Cameron	21	0.54	0.99	0.99
Mid Winter	Gwich'in North	11	0.87	0.76	0.84
	Gwich'in South	11	0.81	0.98	0.80
	Sahtu	7	0.86	0.85	0.83
	North Slave	0	-	-	-
	Mackenzie[1]	23	0.47	0.52	0.42
	Dehcho North	32	0.95	1.00	1.00
	Dehcho South	51	0.87	0.99	0.99
	Hay River Lowlands	51	0.81	1.00	0.96
	Pine Point / Buffalo Lake	25	0.72	0.82	0.96
	South Cameron	21	0.67	0.96	1.00
Late Winter	Gwich'in North	13	0.87	0.77	0.78
	Gwich'in South	15	0.78	0.87	0.94
	Sahtu	8	0.89	0.89	0.93
	North Slave	18	0.95	0.98	0.94
	Mackenzie[1]	28	-0.10	0.10	0.26
	Dehcho North	39	0.98	0.99	0.98
	Dehcho South	53	0.91	0.98	0.98
	Hay River Lowlands	48	0.68	0.98	0.95
	Pine Point / Buffalo Lake	24	0.75	0.88	0.88
	South Cameron	22	0.75	0.96	0.98
All Year	Gwich'in North	12	0.92	0.88	0.82
	Gwich'in South	10	0.93	0.95	0.93
	Sahtu	10	0.96	0.94	0.93
	North Slave	19	0.98	1.00	0.99
	Mackenzie[1]	31	0.61	0.95	0.95
	Dehcho North	32	0.95	0.98	0.96
	Dehcho South	18	-0.13	0.98	1.00
	Hay River Lowlands	39	0.03	0.70	0.99
	Pine Point / Buffalo Lake	28	0.27	0.50	0.59
	South Cameron	23	-0.10	0.73	0.95

[1] Radio-collar data from Mackenzie caribou were excluded from the data used to estimate second- and third-order RSF models.
[2] Data from all available caribou (post-data screening procedures) within a given sub-region were used in this process.

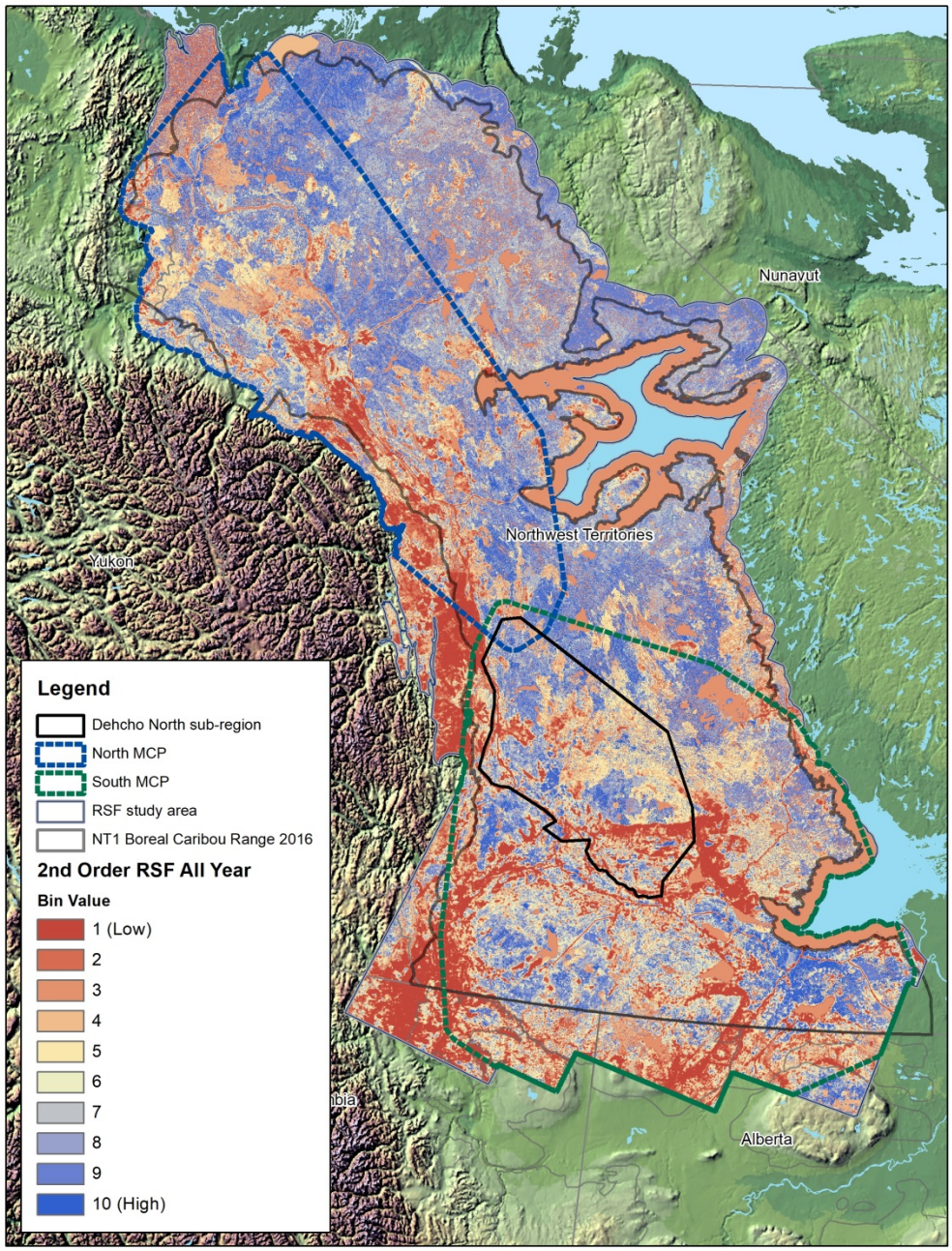

Figure 24: Predictive map of habitat selection from the 2nd-order All Year RSF model. Predicted RSF values were partitioned into 10 bins. Bins were specified using an "equal area" approach where the RSF predictions from random points (*n* = 40,000) sampled within the 2nd-order scale of availability (North and South polygons—see Figure 3) were assigned to one of 10 bins with each bin having an equal number of points. Bin 1 (dark red) represents the least selected habitat and Bin 10 (dark blue) represents the most highly selected habitat. Note that extrapolating the RSF model to the full study area causes some inequality in the number of map pixels contained in each category. Areas outside of the North and South MCP polygons represent areas where the RSF predictions have been extrapolated beyond the extent of the collar data. Predicted 2nd-order habitat selection within the Dehcho North sub-region is displayed in Figure 25.

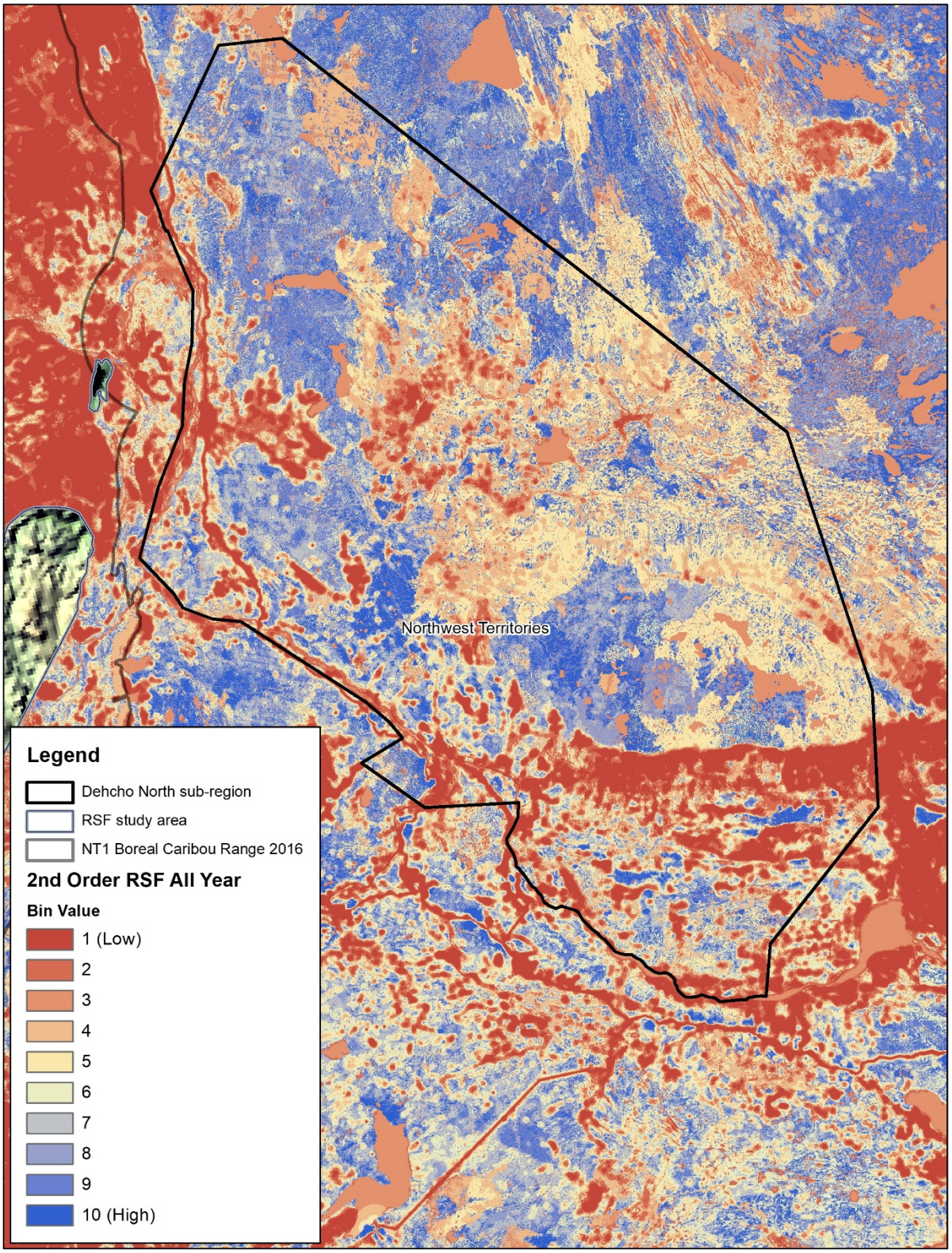

Figure 25: Predictive map of habitat selection from the 2nd-order All Year RSF model focused in on the Dehcho North sub-region.

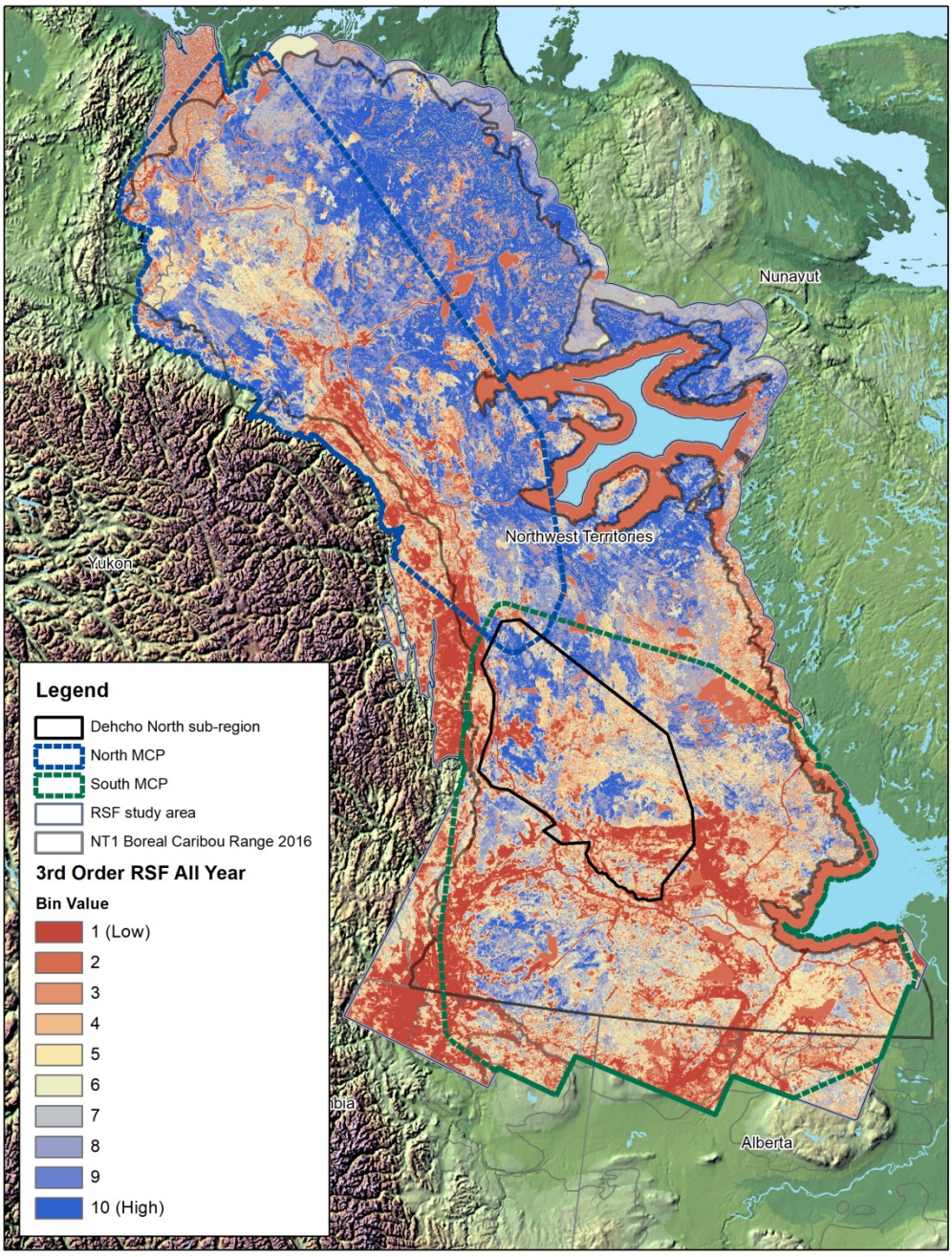

Figure 26: Predictive map of habitat selection from the 3rd-order All Year RSF model. Predicted RSF values were partitioned into 10 bins. Bins were specified using an "equal area" approach where the RSF predictions from the random points (*n* = 40,000) sampled within the North and South MCPs were assigned to one of 10 bins with each bin having an equal number of points. Bin 1 (dark red) represents the most strongly avoided habitat and Bin 10 (dark blue) represents the most highly selected habitat. Note that extrapolating the RSF model to the full study area causes some inequality in the number of map pixels contained in each category. Areas outside of the North and South MCP polygons represent areas where the RSF predictions have been extrapolated beyond the extent of the collar data. Predicted 3rd-order habitat selection within the Dehcho North sub-region is displayed in Figure 27.

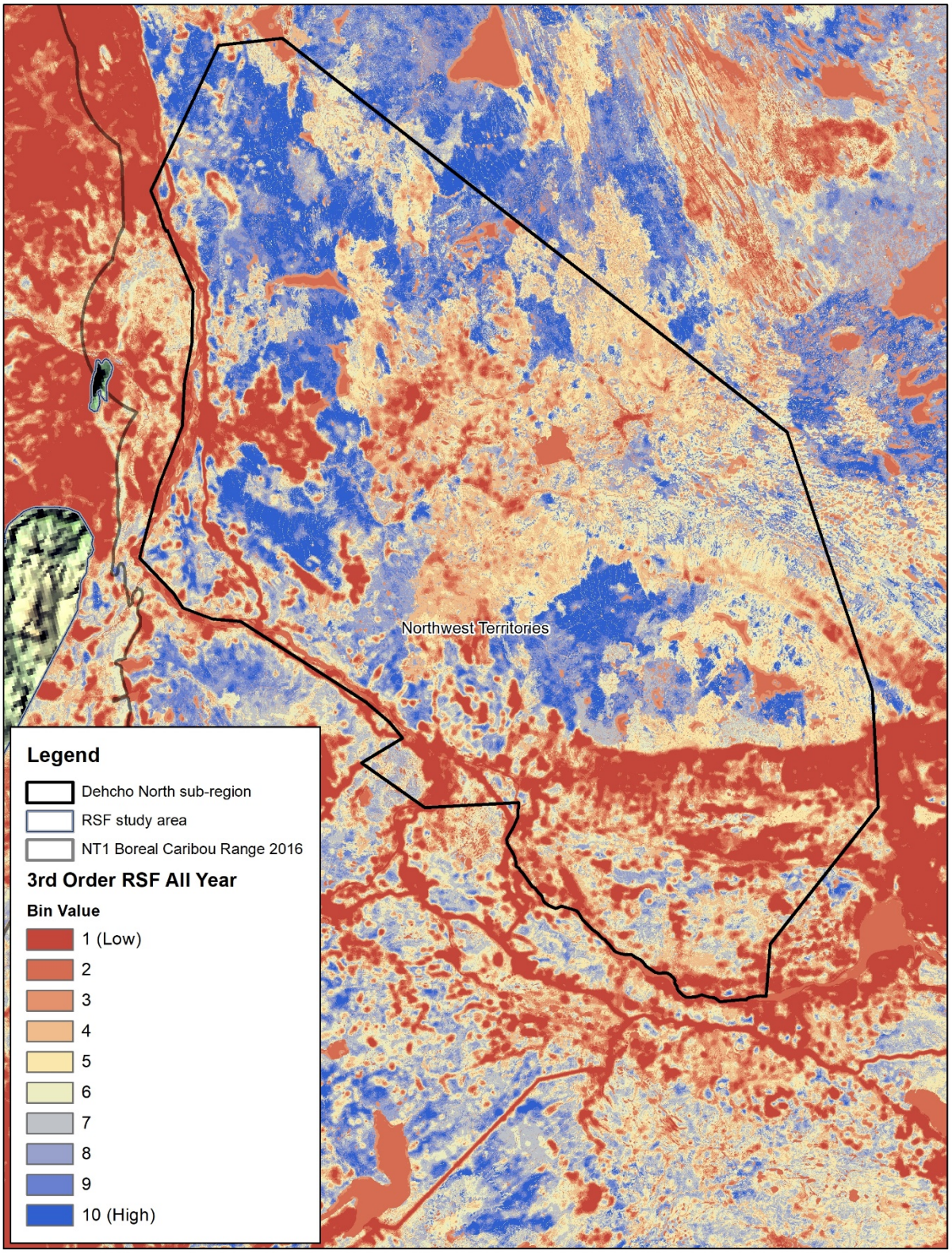

Figure 27: Predictive map of habitat selection from the 3rd-order All Year RSF model focused in on the Dehcho North sub-region.

DISCUSSION

In Canada's boreal forest, fire is the dominant form of natural disturbance and its effects influence the distribution and abundance of organisms through space and time (Sousa 1984, Fisher and Wilkinson 2005). For boreal caribou, previous literature has suggested that fire may alter their range use (Dalerum et al. 2007, Faille et al. 2010) and negatively affect their demography (Sorensen et al. 2008, Environment Canada 2011, 2012). Because of these relationships, current recovery strategies for caribou have considered fires <40 years old as a key factor in determining habitat quality at the range scale for caribou (Environment Canada 2011, 2012, Environment and Climate Change Canada 2019). Recent research, however, has questioned the relative importance of fire effects on caribou demography and distribution (Skatter et al. 2017, DeMars et al. 2019, Johnson et al. 2020). To increase our understanding of fire effects on boreal caribou, particularly for those populations occurring in the NWT, we assessed seasonal patterns of habitat selection by female boreal caribou in fire-disturbed landscapes. In general, our results did not show consistent avoidance of fires <40 years old by caribou, suggesting that these fires may have a lower effect on caribou space use than previously hypothesized. Patterns of selection for burns were also influenced by a number of factors including burn age, season, the land-cover type burned, and, to a lesser extent, by the scale of analysis.

Burn age seemed to be a key factor influencing caribou response to burns, particularly during the snow-free seasons. Caribou generally showed higher selection for younger burns (<10 years old) and older burns (>30 years old) and avoided middle-aged burns (11–30 years old). This variability in caribou response to burn age is somewhat consistent with findings from Traditional Knowledge (TK) studies conducted in the NWT. In the Gwich'in region, hunters and elders reported that boreal caribou often used burns for the first few years post-fire then avoided these areas for the next 2–4 decades (Benson 2011). Traditional knowledge from the Dehcho region also indicates that boreal caribou may use younger burns during the calving seasons, as such burns often impede predators movements, and during the summer for foraging on shrubs and morel mushrooms (Dehcho First Nations 2011, Species at Risk Committee 2012). Tlicho elders stated that boreal caribou do not return to burned areas for at least 20–30 years post-fire as it takes time for lichen to recover after fires and also time for vegetation to regrow sufficiently to provide protection from predators (Legat et al. 2019).

Compared to studies conducted in other areas of Canada, boreal caribou in the NWT showed relatively high selection for burned areas, although our findings are similar to caribou responses in nearby northeastern British Columbia (Mumma et al. 2018). In Manitoba, caribou avoided burns <10 years old, though this behaviour was only studied during the winter season (Schaefer and Pruitt Jr 1991). The proposed mechanisms underlying caribou avoidance included post-fire reductions in lichen abundance, thicker and harder snow cover in burned areas, and a lowered ease of travel due to accumulated deadfall. In Quebec, caribou also avoided disturbed landscapes, which included fire and logging effects over a 20–30 year period, during winter (Courtois et al. 2007). Caribou avoidance in the Quebec study was not attributed to food limitations as lichen biomass was found to be sufficient post-disturbance; rather, avoidance was more likely due to a higher mortality risk for caribou in disturbed landscapes. In some respects, our results mirrored the above findings as burns became increasingly avoided by caribou in the NWT during the winter months (Figs. 14–16); however, by extending our analyses to other seasonal periods, our results show that burns are not consistently avoided by caribou year-round and in certain seasons may become highly selected, at least in the NWT.

Selection for burns by caribou in the NWT appeared to be strongest during the snow-free seasons. This difference could arise for a few reasons. First, boreal caribou are known to disperse from groups just prior to calving and through the summer they remain as individuals, calf-cow pairs or in groups that are smaller in size than at other times of the year (Bergerud and Page 1987, Stuart-Smith et al. 1997, Culling et al. 2006, Benson 2011, Dehcho First Nations 2011). This behaviour is a tactic to decrease predation risk to vulnerable calves (Legat et al. 2019) and likely evolved because it increases the individual fitness of females (DeMars et al. 2016). Dispersion results in females using a larger proportion of the landscape—indeed, the spatial extent at calving is often a key factor for defining range boundaries (Schaefer et al. 2001)—and spacing away from other females may influence how a female selects habitat at this time of the year. This larger use of the landscape likely results in females using a wider variety of land-cover types, including burns. Indeed, selection coefficients for land-cover types generally have a more even distribution during calving and summer compared to the winter seasonal periods (Figs. 10–17). Specific to calving, a second reason proposed for caribou selecting relatively open areas such as recent burns and clear-cuts is that these areas provided longer sight lines that facilitate the early detection of predators (Pinard et al. 2012).

A third factor potentially influencing caribou selection for burned areas during calving and summer is the nutritional requirements of females at this time of year. For females with calves, nutritional demands increase with the onset of lactation (Parker et al. 2009) and consequently females may select habitats that optimize forage quality and/or abundance (Denryter et al. 2020). During the snow-free season, caribou switch from a lichen-dominated winter diet to a more diverse and protein-rich diet that includes deciduous shrubs, forbs and sedges (Thompson and McCourt 1981, Thompson et al. 2015, Denryter et al. 2017). These types of summer forage become highly abundant in burned areas, at least within the first 10–20 years post-fire (Schaefer and Pruitt Jr 1991). As a result, female caribou in the NWT may be selecting burns to access higher quality and/or quantities of forage to meet nutritional demands post-calving. Skatter et al. (2017) reported similar findings as caribou in Saskatchewan showed selection for more productive bogs and fens (c.f. mature forest) within burns 11–20 years old during the post-calving period. Similarly, in the Gwich'in region, hunters noted that boreal caribou may use fires for the first few years after a burn because of the rapid growth of deciduous forage species, followed by a much longer period of avoidance until lichens recover (Benson 2011). Our results further show that selection for burns continues through summer and into the fall, a pattern that likely reflects the reproductive life history strategy of caribou. As capital breeders, females rely on accumulated energy reserves from the previous growing season for reproduction (Parker et al. 2009). To accumulate sufficient reserves, females may select for areas with higher quality and/or quantities of forage, such as burns, throughout the growing season.

Seasonal changes in diet can also explain why caribou selection for burns declined during the winter. Among ungulates in the boreal forest, caribou are uniquely adapted to subsist on a lichen-dominated diet, a dietary strategy that spatially separates them from other ungulates and may have evolved to reduce predation risk (Bergerud 1974, James et al. 2004). Within the boreal forest, lichen abundance is generally higher in forests >40 years old (Dunford et al. 2006, McMullin et al. 2011) and our results suggest a correlation between winter patterns of habitat selection by caribou and land-covers predicted to have higher lichen biomass. In mid- and late-winter, caribou increased their selection for mature wetlands, sparse conifer forests and upland conifer burns 41–60 years old and these land-covers generally have higher lichen biomass than younger forests (Schaefer and Pruitt Jr 1991, McMullin et al.

2011). The increased selection for older upland conifer forests and lowered selection for burns during mid- and late-winter is also consistent with TK, which suggests that caribou favor these older forests for their increased lichen availability and shallower snow conditions that increase mobility (Dehcho First Nations 2011, Species at Risk Committee 2012).

During the snow-free seasons, caribou in the NWT selected for burns occurring in all four broadly-defined land-cover classes (lowlands, upland conifer, upland broadleaf, and non-treed). The selection for burns in broadleaf land-covers is somewhat surprising given previous research showing that caribou generally avoid these types of forests because of their increased predation risk (James et al. 2004, McLoughlin et al. 2005, Peters et al. 2013). Much of this research, however, was conducted in caribou ranges highly disturbed by anthropogenic activities and with high densities of predators and alternate prey (Latham 2009, Latham et al. 2011b, Hervieux et al. 2014). In the NWT, where anthropogenic impacts and densities of predators and alternate prey are much lower (Serrouya et al. 2016), the relative risk of broadleaf land-covers to caribou may be considerably lower. Consequently, females in the NWT may select these high quality foraging areas because the trade-off has lower predation risk than it does for females in southern ranges. This reasoning does not imply that females in the NWT are able to forage relatively risk-free. During calving and summer, females generally selected young broadleaf burns (i.e., <10 years old) and, to a lesser extent, burns 31–40 years old and avoided broadleaf burns 11–20 years old. This selectivity to burn age suggests predation-sensitive foraging as this pattern is in direct contrast to the post-fire responses attributed to moose (e.g. avoidance of young burns and selection for middle-aged burns; Maier et al. 2005, Street et al. 2015, DeMars et al. 2019) and presumably their generalist predators (Robinson et al. 2012).

In addition to fires, anthropogenic disturbances influenced seasonal habitat selection by caribou in the NWT. In general, caribou were further away from polygonal disturbances (e.g. cutblocks, well pads) than expected across all seasons, a finding consistent with other studies conducted on populations of boreal caribou across Canada (Rettie and Messier 2000, Smith et al. 2000, Courbin et al. 2013, Mumma et al. 2018). Because polygonal disturbances are selected by moose (Rempel et al. 1997, Mumma et al. 2018), the avoidance of these features by caribou is thought to be a behaviour to reduce predation risk. This proposed mechanism is further supported by the seasonal variation in the strength of avoidance as the strongest avoidance occurred during calving and summer when many females are accompanied by vulnerable young calves.

Caribou were also further away from major roads than expected, a finding that is again consistent with caribou responses in other areas of Canada (Dyer et al. 2001, 2002, Leblond et al. 2013, Mumma et al. 2017). Proposed mechanisms for this response include avoiding areas with high human activity (Dyer et al. 2001, Leblond et al. 2013) and to reduce predation risk as roads may be used as travel corridors by predators (Dickie et al. 2017b, Mumma et al. 2017). Compared to these other studies, the density of major roads in the NWT is relatively low, especially in the northern half of the study area. As a result, during all seasons caribou were on average at least 15-km from the nearest major road (Appendix H). Because the potential zone of influence from roads is unlikely to extend this far (Polfus et al. 2011, Leblond et al. 2013), changes in the strength of avoidance seasonally likely do not reflect a biological mechanism and are more likely statistical artefacts attributable to seasonal changes in the spatial distribution of caribou (i.e. moving to late-winter areas that may be closer to roads than calving areas). Nevertheless, the raw distance-to data (e.g. Appendix H) suggests that caribou do not spend a lot of time in close proximity to roads.

A similar explanation likely applies to caribou response to settlements. On average, caribou were >20-km away from settlements during any given season (Appendix H), which likely exceeds the potential zone of influence (Polfus et al. 2011, Boulanger et al. 2012). Settlements are rare and widely spaced in the NWT, yet caribou at times may appear to be closer to settlements than expected because on average, random locations at the second-order scale were ~50-km away from settlements (random locations at the third order scale were ~35-km away on average). The relative 'closeness' of caribou to settlements compared to random expectation may be an artefact of how caribou are captured and radio-collared (second-order scale) or because of differences in seasonal intensities of use within their home range (third-order scale). Because of the vastness of the study area and the rarity of settlements, radio-collars were likely not deployed at random; rather, because capture crews necessarily base out of settlements, radio-collars were likely deployed closer to settlements than what would be randomly expected within the study area. In this project, we transformed distance-to measures to place more emphasis on locations actually occurring close enough to the feature to have a hypothesized biological effect (Nielsen et al. 2009). From a mapping perspective, this transformation improves the generality of the resulting maps (i.e., reduces 'over-fitting') but may limit quantifying the actual response of caribou to the feature of interest. If a better understanding of caribou response to settlements is a management objective (e.g. estimating a potential zone of influence), then transforming distance-to variables to a series of binary variables with different distances thresholds may be a preferable approach (e.g., Leblond et al. 2011).

Linear feature density seemed to have a relatively small effect on the seasonal selection of habitat by caribou, although a more robust comparison of the actual effect sizes among these variables requires transforming the variables to a common scale. Understanding caribou responses to linear features has garnered considerable research interest because of the ubiquity of linear features within many caribou ranges and their perceived negative effects on caribou demography (McKenzie et al. 2012, DeMars and Boutin 2018, Mumma et al. 2018). For the most part, the prevailing literature suggests that caribou avoid linear features in terms of proximity (e.g., Dyer et al. 2001, Nagy 2011, Leblond et al. 2011, DeMars and Boutin 2018) but it is unclear as to whether they can perceive and respond to linear feature density (DeMars and Boutin 2018, Mumma et al. 2019). For the few studies that reported caribou avoidance of areas with high linear feature density, the scale of density measurement was so small that the observed response was more likely avoidance by proximity than a response to linear feature density *per se* (e.g., 70-m radius, DeCesare et al. 2012). In our project, we elected to assess caribou response to linear feature density within a radius of 1-km because such scales are necessary to capture meaningful variation in density as the spacing of seismic lines can vary from 50-m to >2-km apart (Boyce 2006, Lankau 2014). Moreover, these larger scales are likely more meaningful to the management of wide-ranging species such as caribou (Boyce 2006). In general, caribou in the NWT appeared to avoid areas with high linear feature density during the snow-free season but this trend appeared to reverse during mid- to late winter, especially at a second-order scale (Fig. 23). These seasonal contrasts could reflect temporal changes in predation risk as predators have been shown to increase their selection of linear features during the snow-free season compared to the winter (Latham et al. 2011a, Dickie et al. 2017b). Univariate comparisons by region suggested that most of the avoidance behaviour was driven by the Dehcho and the North Slave regions, the latter of which had no GPS locations falling within areas containing linear features from calving through early winter (Appendix H, Figs. H40–H48). Caribou in the other three regions, in contrast, were largely ambivalent to variation in linear feature density, although this ambivalence could be masking caribou responses that could vary among sub-regional monitoring

areas. The varied seasonal responses also highlight an additional confounding factor that could influence inferences on caribou response to linear feature density: if linear feature densities vary by land-cover type, then disentangling the separate effects of land-cover and linear feature density can be problematic. For example, if linear features are more abundant in lichen-dominated mature forests, then caribou may appear to be selecting areas with high linear feature density in winter and avoiding them in the snow-free period, a response that may be driven by seasonal changes in diet more than a direct response to linear features *per se*. Currently, linear feature densities are relatively low in the NWT and their effect on caribou habitat selection appears small; however, if their densities continue to rise within caribou range, further research investigating caribou response to these features may be warranted, including whether they cause home range shifts as has been reported elsewhere for southern mountain caribou (MacNearney et al. 2016).

Patterns of habitat selection by caribou were generally similar for the second- and third-scales of analysis, although some key differences did emerge, perhaps in part due to differences in the selection processes evaluated by each scale. An example of these differences is the scale-dependent responses of caribou to middle-aged burns (i.e., 11–30 years old). Caribou appeared to avoid these burns at the second-order scale but weakly selected for them at the third-order scale, except for those in broadleaf forests (Figs. 18–21). These responses suggest that caribou were generally selecting home ranges that had lower densities of these burns compared to the study area at large but still occasionally used these burns when encountered, resulting in weak selection at the third-order scale. Avoidance of these burns at the second-order scale is consistent with habitat selection theory, which predicts that the coarsest scales of selection should be largely influenced by a species' primary limiting factors (Rettie and Messier 2000). For caribou, predation is a primary limiting factor (Bergerud 1996, Wittmer et al. 2005) and, as previously mentioned, middle-aged burns are associated with increased predation risk because they are selected by moose and their generalist predators (Maier et al. 2005, Robinson et al. 2012, Street et al. 2015). At finer spatial scales (e.g. third-order), selection is more likely to be influenced by multiple factors and, as such, can result in more individual variation in selection (Rettie and Messier 2000). Scale-dependent differences in selection also occurred for sparse conifer forest. Caribou did not appear to be situating their home ranges in landscapes with high densities of sparse conifer forest when compared to the larger area of availability that defines the second-order scale. Yet, sparse conifer forest was one of the most highly-used land-cover types across all seasons (Appendix H), resulting in its selection at a third-order scale. These examples illustrate the hierarchical nature of habitat selection and underscore the necessity of evaluating selection at multiple spatial scales (McGarigal et al. 2016).

Management Implications

A key component to the federal recovery strategy for boreal caribou is the recommendation to maintain or reduce the cumulative extent of disturbances to <35% of caribou range (Environment Canada 2012, Environment and Climate Change Canada 2019). Currently, the extent of fires <40 years old is included in the calculation of disturbance impacts. A primary mechanism linking fires to caribou population declines is that fires increase the extent of young forests that are favorable to moose, which leads to increased moose populations and subsequently increased predator populations that incidentally predate caribou at unsustainable rates. Recently, this mechanism has been questioned as fires of this age did not seem to facilitate population increases of moose in boreal forests of western Canada (DeMars et al. 2019) and these fires had a much smaller effect on survival of adult female caribou than anthropogenic disturbances (Johnson et al. 2020). Although our project did not directly test the

disturbance-mediated apparent competition hypothesis or directly link fires to caribou demography, our results still yield inferences on caribou-fire relationships and dynamics. In natural landscapes, patterns of resource selection should reflect individual fitness; that is, resources that are highly selected should be those that have a positive influence on survival and reproduction (Boyce and McDonald 1999). Within the boreal forest, caribou have evolved with fire and therefore caribou would not be selecting burned areas if they had a negative effect on fitness (i.e., 'natural' ecological traps do not occur; Schlaepfer et al. 2002). Our results showed that younger and older burns are selected by boreal caribou in the NWT, suggesting that these areas are not necessarily detrimental to individual fitness and, by extension, caribou demography. Our results, combined with those of DeMars et al. (2019) and Johnson et al. (2020), suggest that different disturbance types have differing effects on caribou distribution and demography. Further, the magnitude of disturbance effects may be context-specific, which may diminish the efficacy of management strategies that are broadly applied across the wide and geographically varied distribution of boreal caribou (Whittingham et al. 2007, Rudolph et al. 2017). Within the NWT, this context-specificity likely applies to caribou in the Mackenzie sub-regional monitoring area, which were excluded from RSF analyses because of the high availability of recent burns in this area. RSF models at both scales generally had poor predictive power when applied to the Mackenzie sub-region (Tables 5–6), suggesting that further research may be required to understand how caribou responses to burns change when the extent of burns is high.

We evaluated habitat selection by caribou at two spatial scales and each has direct links to management and the federal recovery strategy. At the broad scale, second-order selection analyses can inform delineations of critical habitat for caribou in the NWT. In the federal recovery strategy, the scale of measurement for critical habitat is a population's range (Environment Canada 2011, Environment and Climate Change Canada 2019), yet ranges and populations are coarsely defined in the NWT. Because second-order analyses evaluate how caribou select areas within a large spatial extent, results at this scale are useful for distinguishing between caribou habitat and other areas that may be suboptimal. From a range-planning perspective, these larger-scale inferences are most appropriate for updating and mapping the estimated distribution of caribou within the NWT (Boyce 2006). At a finer spatial scale, third-order analyses are useful for identifying potentially important areas within caribou range. While evidence is limited as to whether managing habitat below the range scale can positively impact caribou demography, the federal recovery strategy does stipulate that ranges need to contain the biophysical attributes necessary for caribou to complete life processes (Environment and Climate Change Canada 2019). Such attributes are best identified by assessing how an animal uses and selects habitat within its home range (Boyce 2006).

The usefulness of the scale-specific maps to guide management decisions depends somewhat on their predictive ability. For this project, second-order maps had consistently higher predictive power than those derived from third-order analyses. This difference is likely attributable to how availability was defined for each scale and how it varied within each scale. For second-order analyses, availability was the same for large groups of caribou (i.e., the North and South groups) and held constant across years. For third-order analyses, availability was unique to each caribou-year. This changing availability likely impacted predictive power because selection can change as a function of availability (i.e., a functional response in selection, Mysterud and Ims 1998), which is a well-known potential confounding factor with RSFs (Beyer et al. 2010). In our analyses, functional responses in selection were likely the reason why prediction was lowest for third-order maps during calving and summer as these seasons are when

caribou are most widely distributed, creating more variability in habitat use. Changing availability also likely influenced the decrease in predictive power when RSF maps were applied to the finer-scale sub-regional monitoring areas (Table 6). Although the loss of predictive power at these finer-scales of selection may be initially problematic from a management perspective, our map validation approach revealed that predictive power could be improved in most cases by re-delineating RSF map bins based on the actual availabilities of the scale of interest (rather than setting RSF bin thresholds based on availability of the larger study area). This approach may be more efficient than estimating new RSF models and maps for each region and sub-region of interest.

In recent years, a number of different modelling approaches have been proposed to improve prediction when functional responses are evident. These approaches include: *i*) using random-slope GLMMs that interact use with availability, the latter of which is constrained and contingent upon each time step (Moreau et al. 2012); and, *ii*) interacting each environmental attribute with its mean value calculated over the spatial scale of interest (generalized functional response models, (Matthiopoulos et al. 2011). For the former, computing limitations restricted the use of random-slope GLMMs because of the large number of covariates included in our models. Moreover, such fine-scale interactions of use and availability can place increased selective importance on environmental attributes when they are within a small spatial context, which may diminish prediction over large spatial scales. The other approach, generalized functional response models, is more appropriate for models primarily using continuous variables and, given our objectives of assessing caribou response to burn-by-land-cover interactions, we elected to use a high number of categorical variables. If generating maps that explicitly account for functional responses becomes a future management objective, then an alternative modelling framework may be to transform all categorical variables into continuous ones, perhaps by calculating proportions within a biologically meaningful radius.

Habitat selection is known to vary seasonally for many species and understanding such variation can be important for developing effective management strategies (Boyce 2006). For boreal caribou in the NWT, we developed maps of habitat selection for seven seasons as well as maps that predicted space use on a year-round basis. These seasonal RSF models and maps revealed seasonal differences in habitat selection by caribou, particularly in their response to burns, but we caution against assigning more importance to one season over another in terms of management implications. Assigning importance would require demographic models that identify those seasons with high influence on population dynamics (Crouse et al. 1987) and/or explicitly linking individual fitness to habitat selection (e.g., Nielsen et al. 2010, DeCesare et al. 2014). In the absence of such information, year-round RSF maps showed good predictive performance, indicating that they were able to capture meaningful variation in seasonable space use by caribou.

RSF maps represent a static 'snapshot' of predicted space use based on the most current year of the explanatory data (e.g., land-cover type, fire age and distribution, linear feature density, etc.). Because of this, the predictive power of RSF maps generally decreases through time (Beyer et al. 2010). To maintain their usefulness for management, the seasonal maps of habitat selection by caribou will need to be updated on a regular basis as new data become available. These updates will be particularly necessary if human-caused disturbances continue to increase in caribou ranges. Such disturbances can create evolutionarily novel disturbances (i.e., features that an organism has not experienced in its evolutionary past), which can cause distributional changes and/or create ecological traps when an organism does not recognize cues associated with such features that negatively impact fitness (Schlaepfer et al. 2002, Sih et

al. 2011). This latter reason has increasingly led to recommendations that habitat selection be linked to fitness or demography to better inform management in human-modified landscapes. With the rich data set of caribou radio-collar data in the NWT, such analyses should be considered as a next step to build upon the RSF modelling completed to date.

Caveats / Limitations to Interpretation and Use of Predictive RSF Maps

The predictive performance and utility of the seasonal RSF maps are contingent on the accuracy and reliability of their input variables. In many RSF studies, the primary limitation is usually a small sample size of individuals within the population of interest. For this project, our data set of caribou GPS locations was a key strength as these data were collected from individuals sampled over a large portion of the NT1 range and each seasonal RSF analysis used a minimum of 194 caribou, many of which had data spanning multiple years. These data allowed for a detailed assessment of caribou response to burns over multiple seasons and at two spatial scales. Importantly, these data provided the ability to perform the first detailed evaluation of how caribou response to burns was shaped by interactions of burn-age with land-cover.

The utility of RSF maps are also frequently dependent on the accuracy, reliability and assumptions of their spatial covariate data. In our analyses, a primary input was the EOSD land-cover data, which had issues with accuracy. Also, these data were based on 2007 and 2010 remote imagery, a time frame that only coincides with a small portion of the caribou radio-collar data. By using the EOSD data, our analyses implicitly relied on two assumptions: *i*) that a pixel assigned a land-cover type remained unchanged over the course of the study unless it burned (e.g., a pixel classified as 'tall shrub' remained 'tall shrub'); and *ii*) that the post-fire trajectory for each pixel was a return to its pre-fire land-cover type, which is generally true but may be changing as the climate warms globally (Johnstone et al. 2010). Similar assumptions applied to the anthropogenic disturbance data; for example, polygonal and linear feature disturbances were treated as static and our models did not account for the age of disturbance nor the state of its regeneration (van Rensen et al. 2015, Dickie et al. 2017a). For fires, we modeled fire age as a series of categorical variables, using age delineations primarily taken from existing literature on moose-fire relationships (e.g., Maier et al. 2005, Street et al. 2015, DeMars et al. 2019). We assumed these delineations were biologically relevant to caribou—they did perform better than treating fire as a continuous variable—, but future modelling might consider alternate age class delineations. We also note that our analyses were restricted to fires <60 years old because this time frame was the limit of historical fire data. Our analyses therefore exclude inferences on potential variation in caribou response to burns as these areas age beyond sixty years old.

We further note that our inferences on caribou response to a given environmental attribute should be viewed cautiously at the population-level as our modelling framework did not allow for estimates of variability that maintained individual caribou as the sampling unit (see Data Analysis; Arnqvist 2020). Nevertheless, our analyses still yielded a relative ranking of land-cover variables, including those representing burn-age-by-land-cover interactions, and we are confident that these rankings would remain similar if alternative modeling approaches (e.g., random-slope GLMMs) could have been used. In addition, we used a model validation approach that explicitly tested predictions on a sample of withheld caribou. Predictive power was generally good to excellent, particularly at the second-order scale, suggesting that outputs based on the entire model were able to capture and account for individual variation within the NWT population of boreal caribou.

Finally, we highlight that habitat selection is not the sole metric for evaluating a species' habitat requirements. Selection analyses typically evaluate an organism's habitat requirements by comparing the environmental attributes (or "resources") used by the organism to the availability of these attributes in the spatial scale of interest, which is generally defined by the researcher (Manly et al. 2002). Because of this scaling of use by availability, selection does not necessarily equate to the intensity of use of a given resource. For example, caribou in the Inuvik region spent the highest amount of time in sparse conifer forest, but because this land-cover was also the most abundant type, selection for sparse conifer forest was relatively weak (Appendix H, Fig. H2). In contrast, selection for herb land-cover by Inuvik caribou was relatively strong during summer even though they spent comparatively little time in this land-cover type, a result that occurred because herb land-cover was relatively rare at the second-order scale of availability. This example illustrates that using only selection coefficients to infer the relative importance of environmental attributes is problematic. To assist in the interpretation of our selection analyses, use-versus-availability graphs for all resources used in RSF models at a second-order scale are provided in Appendix H.

Below are further caveats and limitations to the interpretation of the seasonal RSF maps:

- Extrapolating RSF predictions beyond the extent of the radio-collar data (i.e., outside of the North and South availability polygons defined at the second-order scale) should be done cautiously as RSF predictive performance may change as the relative availability of environmental attributes changes through space (Beyer et al. 2010).

- Predictive maps represent a continuum of relative habitat suitability. They do not represent the absolute probability that a caribou will occur at a given location.

- Even in areas with apparently high suitability, the actual probability of caribou occurrence will be relatively low because boreal caribou normally occur at low densities throughout their range (e.g. ~ 3 caribou / 100 km^2).

- Caribou can – and probably do – occur in areas with relatively low suitability. Female caribou can show considerable individual variation in how they select habitat, particularly during calving and summer, and this variation is difficult to depict visually on a map.

- In intact natural landscapes, patterns of habitat selection likely reflect relative effects on individual fitness (Boyce and McDonald 1999); that is, highly selected habitats should equate to individuals within these areas having higher probabilities of surviving and reproducing, all else being equal. This assumption, however, may not hold in landscapes disturbed by human activities. Such disturbances can result in the creation of evolutionarily novel features (i.e., an organism has not interacted with these features in its evolutionary past) that may impact an individual's fitness, yet the individual may be behaviorally naïve to the cues associated with such impacts (Schlaepfer et al. 2002, Sih et al. 2011). Consequently, in these disturbed landscapes, an increase in habitat suitability does not necessarily equate to an increase in the probability of caribou survival. Other factors, such as predator space use, the number of predators, and disease, can influence caribou survival in addition to habitat suitability.

- The predictive maps do not yield inferences on the spatial requirements of caribou during a given season. For example, during calving females use space to distance themselves from

predators and other ungulate species (e.g. moose) and therefore space likely interacts with habitat to influence predation risk. The amount of space – or the areal extent of habitat with high suitability – required by females to effectively reduce predation risk is not currently known.

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APPENDIX A: DATA SCREENING AND RADIO-COLLAR PERFORMANCE

To model seasonal resource selection by boreal caribou in the Northwest Territories, we accessed caribou spatial data from the Movebank data repository (https://www.movebank.org/). These data consisted of GPS locations collected from 435 radio-collared boreal caribou captured in the Northwest Territories and monitored for various periods between May 2002 and March 2018. Within Movebank, the data were subjected to a number of screening procedures (Davidson 2018). First, locations recorded by the radio-collar prior to its deployment on an animal or after its removal were removed. Second, duplicate records (i.e., those with identical time stamps) were removed. Third, outlying locations beyond the range of biologically plausible movement were identified and removed. Potential outliers were flagged by a speed filtering algorithm (>0.5 m/s) then visually inspected prior to their removal to confirm the record's status as a true outlier.

Prior to seasonal analyses of resource selection, we applied further screening procedures to the Movebank data. First, we excluded all locations falling outside of the study area. Next, we calculated the monitoring interval for each individual caribou within a given season and excluded those individuals that were not monitored for at least one of the seasonal period within a given year (see *Defining Seasons* in the main report) to limit potential spatiotemporal bias. For analyses using data across the entire year, we included only those individuals monitored for ≥231 days, a threshold where estimated sizes of annual home ranges reached an asymptote (see *Evaluating Resource Selection: General Framework* in the main report).

We also screened data based on radio-collar performance, specifically the mean rate of successfully acquiring a GPS location. Among individual caribou, the sampling interval for acquiring GPS locations (i.e., the fix-rate) differed due to differences in collar make, model and programming. For all collars, the programming schedule was unknown. Using the R code described later (see *R Code for Determining Collar Fix Rates*), we determined the fix rate of individual collars within a given season then created a 'regular' movement trajectory, which is a time-series of data where there is a constant time lag between each row (or entry) of data. The majority of data rows were associated with a GPS location acquired by the radio-collar. For time-steps removed by the Movebank screening procedures or when the radio-collar missed acquiring a GPS location, a row containing 'NA' values was inserted. For individual time-series where the fix rate varied within a season, we subsampled the data to the coarsest fix rate to ensure a consistent sampling interval. We then calculated the fix success rate for each caribou-season by dividing the number of rows with a successful GPS fix by the total number of rows in the time-series. Because fix success rates <90% can bias inferences on resource selection (Frair et al. 2010), we excluded caribou-seasons falling below this threshold from resource selection analyses.

After these screening procedures, the final data set consisted of 480 caribou-seasons for calving (n = 276 caribou), 371 caribou-seasons for summer (n = 238 caribou), 396 caribou-seasons for early fall (n = 247 caribou), 446 caribou-seasons for late fall (n = 270 caribou), 478 caribou-seasons for early winter (n = 301 caribou), 677 caribou-seasons for mid-winter (n = 373 caribou), 718 caribou-seasons for late winter (n = 383 caribou) and 338 caribou-years (n = 222 caribou) for analyses using data across the entire year. Note that these numbers include caribou in the Mackenzie sub-region, which were subsequently excluded from RSF analyses (see main report for details). The distribution of these caribou-seasons varied regionally with the Dehcho and South Slave regions having the highest representation (Fig. A 1).

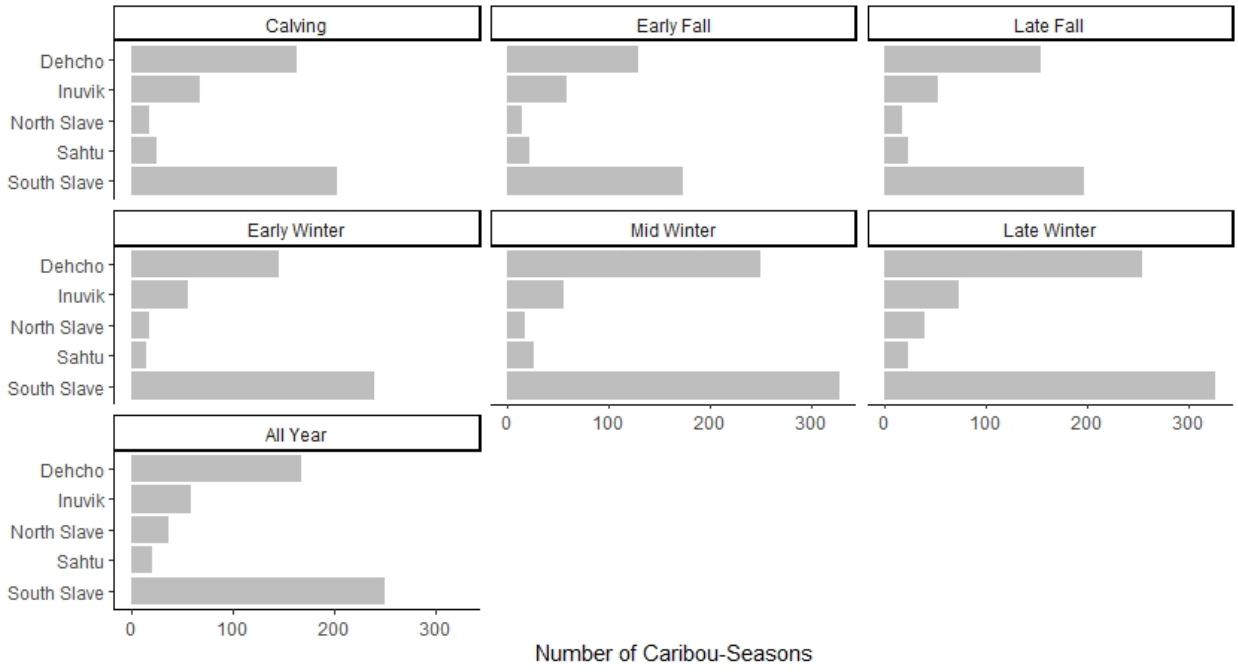


Figure A 1: The number of caribou-seasons by region used in seasonal analyses of resource selection by boreal caribou in the Northwest Territories from May 2002–March 2018.

To evaluate for potential biases in collar performance, we assessed for differences in fix success rate by year, region and among collar brands and models. For these analyses, we used all the Movebank location data including those locations falling outside of the RSF study area. Across the 15 years of monitoring (2002–2017), there was no evidence of a trend in fix success rates (p = 0.48, R^2 = 0.04, Fig. A 2). Six of the 15 years had mean rates >90% and only two years—2003 and 2004—had mean rates <70% (Table A 1). Fix success rates did vary by region and across seasons within regions (Table A 2). The North Slave region had the highest mean rate of fix success. Because all North Slave collars were deployed in 2017, this result may indicate better performance of newer collars, though the monitoring intervals for these collars were shorter compared to those in other regions (Figs. A 3-7). Comparisons of fix success rates among collar brands and models, however, also suggests better performance of newer collar models, such as those associated with Iridium satellite technology, which all had mean rates of fix success ≥97% (Table A 3).

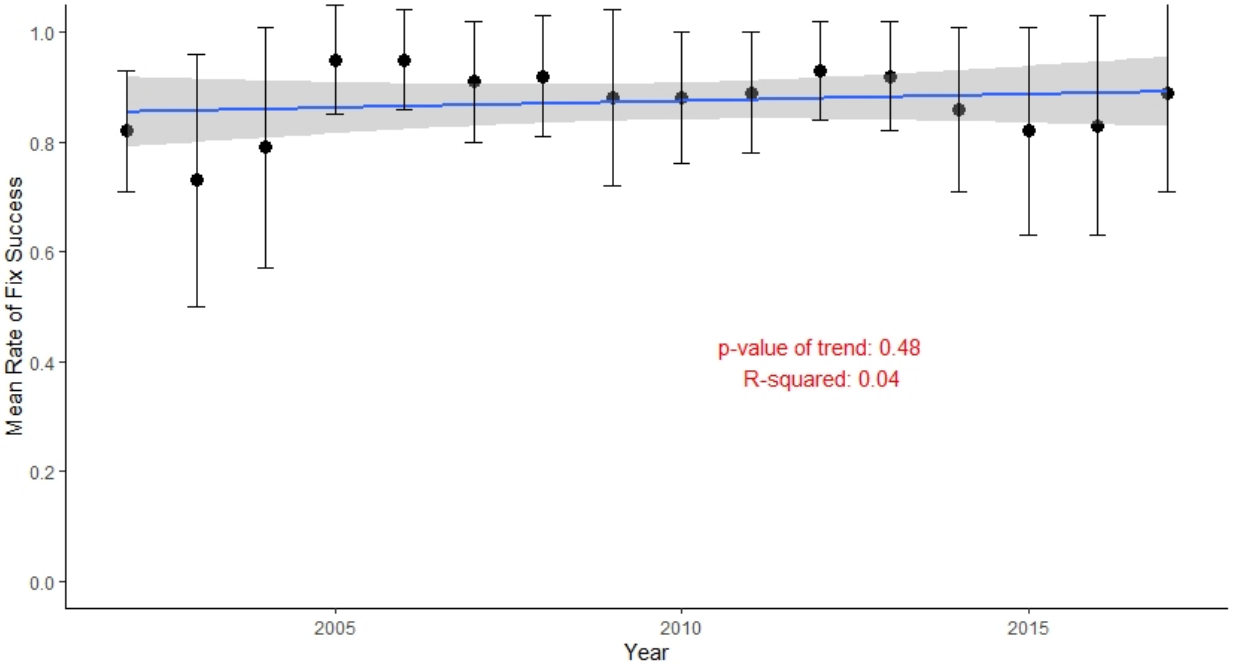


Figure A 2: The mean rates of fix success (with standard deviation bars) by year from radio-collars deployed on boreal caribou in the Northwest Territories between May 2002 and March 2018. Statistical evidence for a potential temporal trend in fix success rate was not significant.

Table A 1: The mean rate of fix success ($\bar{x}$ with standard deviation [SD]) by year among radio-collared boreal caribou (*n* = caribou-years) monitored in the Northwest Territories between May 2002 and March 2018.

	Fix Success Rate		
Year	$\bar{x}$	SD	*n*
2002	0.82	0.11	8
2003	0.73	0.23	44
2004	0.79	0.22	50
2005	0.95	0.10	212
2006	0.95	0.09	328
2007	0.91	0.11	437
2008	0.92	0.11	537
2009	0.88	0.16	460
2010	0.88	0.12	349
2011	0.89	0.11	200
2012	0.93	0.09	181
2013	0.92	0.10	311
2014	0.86	0.15	359
2015	0.82	0.19	457
2016	0.83	0.20	530
2017	0.89	0.18	806

Table A 2: The mean rates of fix success ($\overline{FSR}$ with standard deviation in brackets) from radio-collars deployed on boreal caribou in five regional study areas in the Northwest Territories. The number of caribou-seasons (n) used to calculate $\overline{FSR}$ per region is also listed.

		Season						
Region		Calving	Summer	Early Fall	Late Fall	Early Winter	Mid Winter	Late Winter
Dehcho	$\overline{\text{FSR}}$	0.87	0.83	0.86	0.90	0.88	0.90	0.91
		(0.14)	(0.15)	(0.18)	(0.14)	(0.15)	(0.15)	(0.18)
	n	328	273	252	238	359	344	285
Inuvik	$\overline{\text{FSR}}$	0.88	0.92	0.90	0.89	0.88	0.90	0.90
		(0.15)	(0.13)	(0.19)	(0.18)	(0.15)	(0.14)	(0.13)
	n	103	85	78	79	102	77	86
North Slave	$\overline{\text{FSR}}$	0.99	0.97	0.95	0.98	0.98	0.99	0.99
		(0.02)	(0.06)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)
	n	20	20	19	20	42	18	20
Sahtu	$\overline{\text{FSR}}$	0.88	0.86	0.89	0.85	0.73	0.88	0.82
		(0.08)	(0.19)	(0.28)	(0.18)	(0.21)	(0.17)	(0.15)
	n	57	39	45	47	38	44	52
South Slave	$\overline{\text{FSR}}$	0.88	0.84	0.89	0.91	0.90	0.92	0.92
		(0.15)	(0.14)	(0.15)	(0.14)	(0.14)	(0.15)	(0.18)
	n	365	302	350	300	458	439	317

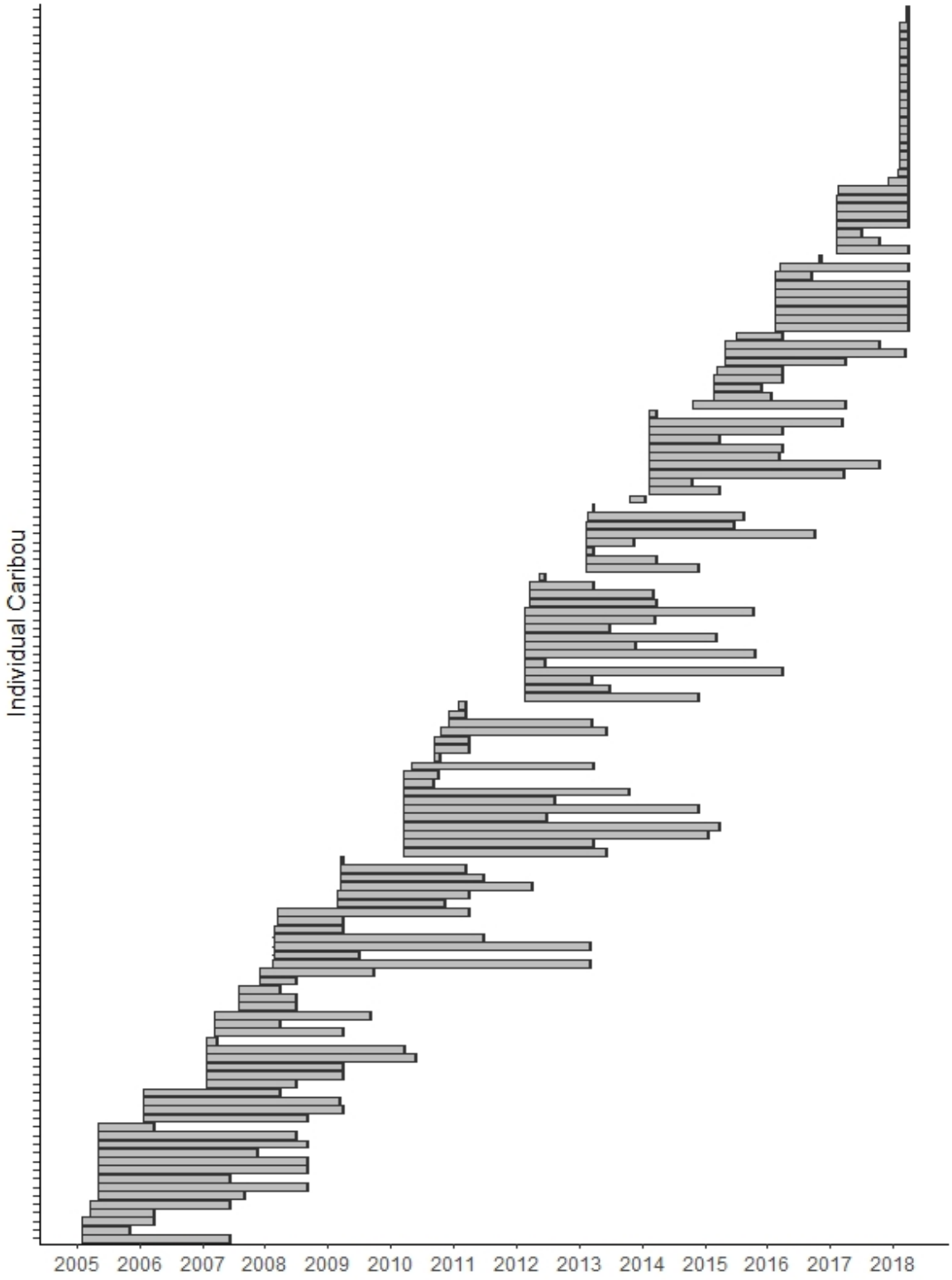


Figure A 3: The monitoring intervals for radio-collared boreal caribou in the Dehcho region of the Northwest Territories. Data from these individuals were included in analyses to infer seasonal resource selection by boreal caribou.

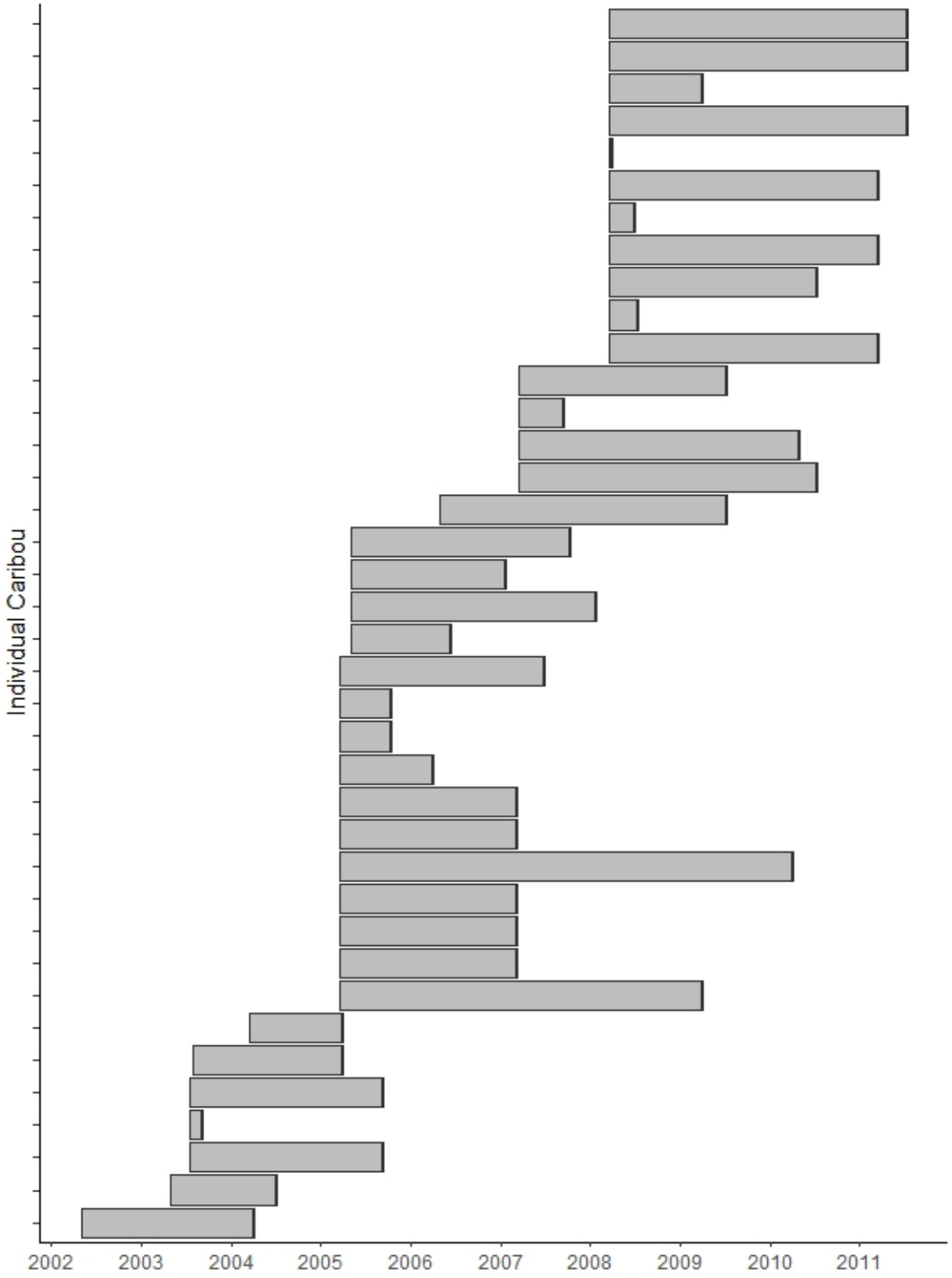


Figure A 4: The monitoring intervals for radio-collared boreal caribou in the Inuvik region of the Northwest Territories. Data from these individuals were included in analyses to infer seasonal resource selection by boreal caribou.

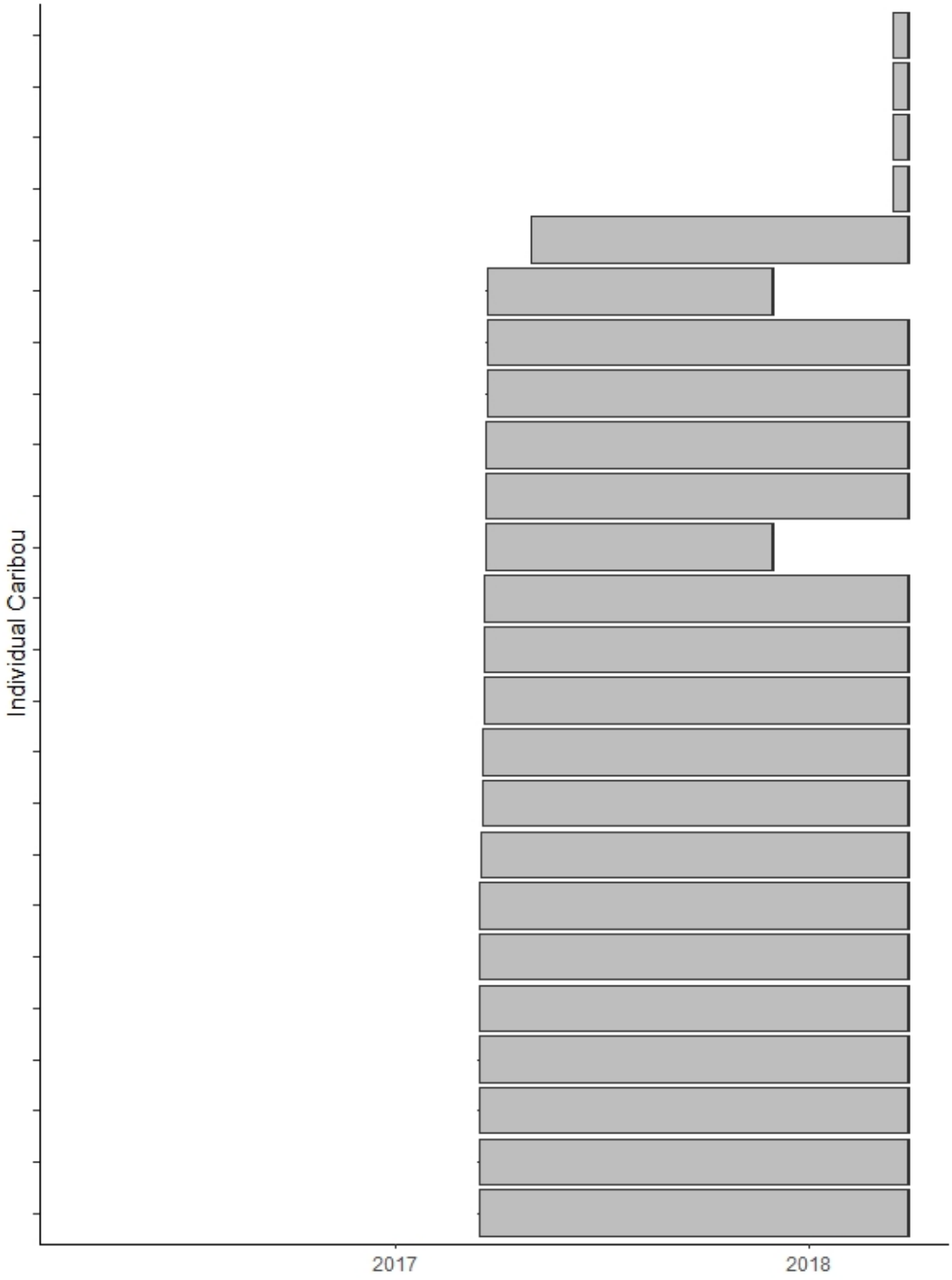


Figure A 5: The monitoring intervals for radio-collared boreal caribou in the North Slave region of the Northwest Territories. Data from these individuals were included in analyses to infer seasonal resource selection by boreal caribou.

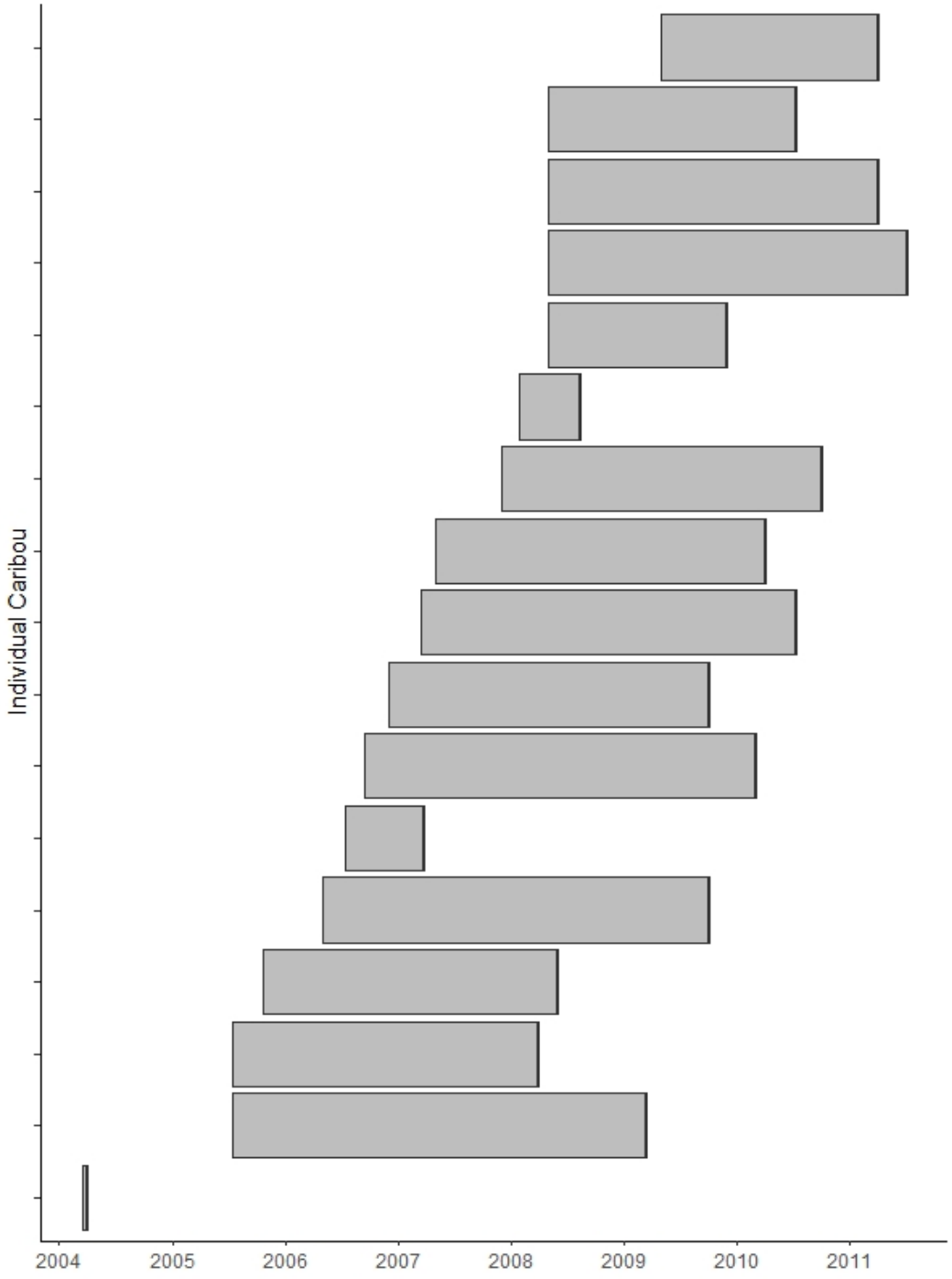


Figure A 6: The monitoring intervals for radio-collared boreal caribou in the Sahtu region of the Northwest Territories. Data from these individuals were included in analyses to infer seasonal resource selection by boreal caribou.

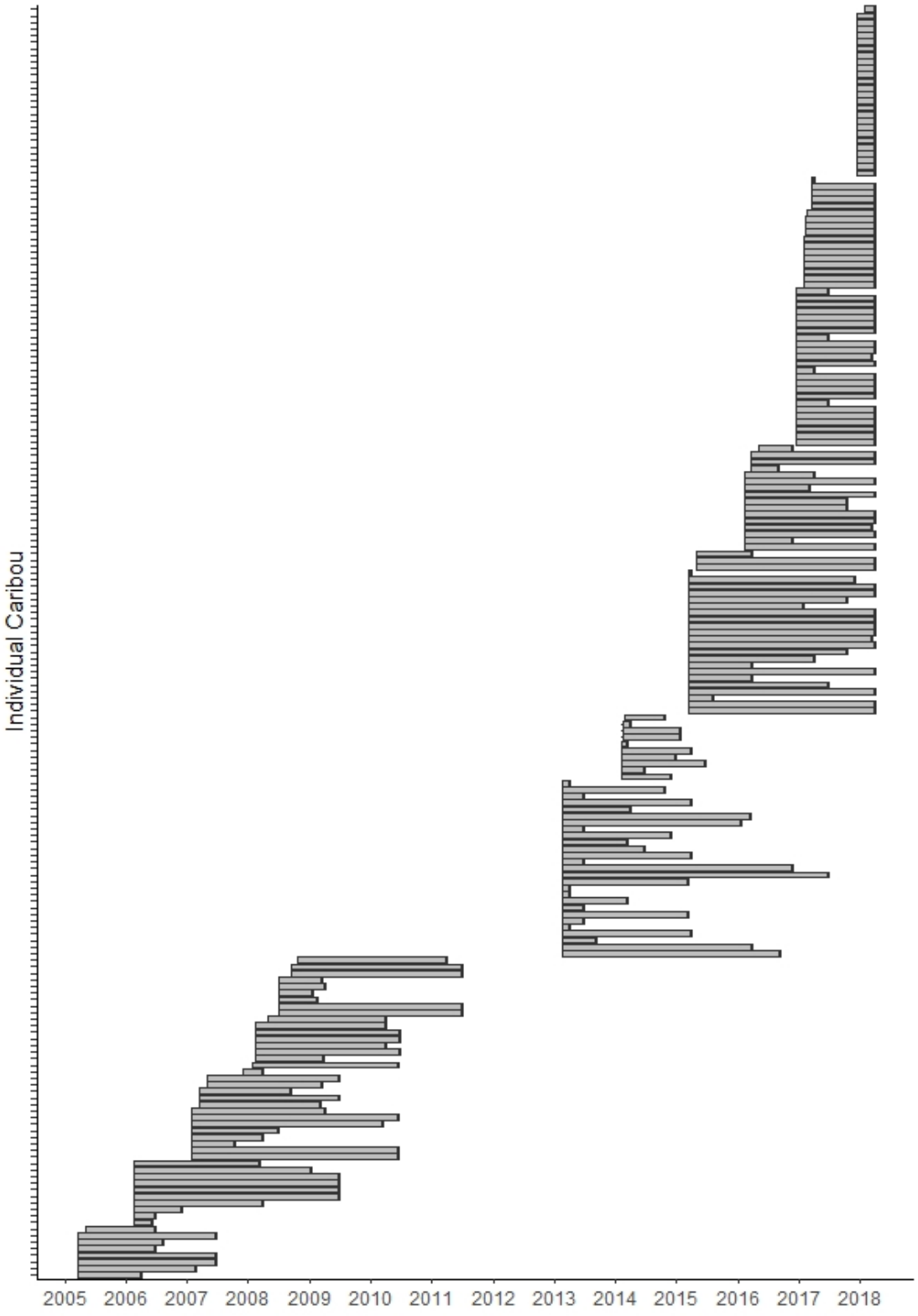


Figure A 7: The monitoring intervals for radio-collared boreal caribou in the South Slave region of the Northwest Territories. Data from these individuals were included in analyses to infer seasonal resource selection by boreal caribou.

Table A 3: The mean rate of fix success ($\overline{FSR}$ with standard deviation [SD]) by brand and model of radio-collars deployed on boreal caribou *(n* = caribou-years) in the Northwest Territories between May 2002 and March 2018.

		FSR		
Collar Brand	Model	$\bar{x}$	SD	*n*
Telonics	Argos	0.97	0.09	210
Telonics	GPS	0.90	0.07	559
Telonics	GPS Iridium	1.00	0.01	123
Telonics	GPS/Argos	0.87	0.16	1920
Telonics	GPS/Argos GPS4	0.81	0.19	937
Telonics	GPS/GlobalStar	0.86	0.13	55
Telonics	GPS/Iridium	0.98	0.05	631
Telonics	GPS/Iridium TGW-4677-4	0.98	0.04	159
Telonics	GPS/Iridium/Argos	0.97	0.08	135
Telonics	ST-10	0.92	0.11	65
Telonics	ST-14	0.94	0.12	84
Telonics	TGW-3680	0.88	0.16	467
Vectronic	GPS Plus 2	0.99	0.01	50
unknown	*n/a*	0.85	0.19	323

R Code for Determining Collar Fix Rates

The following code is used to determine the fix rate from GPS radio-collar data when the programmed fix rate for the collar is unknown. A key component of the code is the 'mk_track' function from the R package 'amt'.

```
#Load required packages
pcks <- c("move", "plyr", "tidyverse", "amt", "lme4", "adehabitatLT", "sp")
sapply(pcks, require, character = TRUE)
```

The first step is to import the Movebank data. The code for this step is not shown here.

To illustrate how fix rates are determined, data from the summer season are used as an example.

```
#Import Movebank data
#all.dat <- read.csv("your_directory\\Movebank_data.csv") #NOT RUN. Load data
from your directory

#Display the first two rows of data
head(all.dat, 2)
```

```
##   X   trackId individual_id local_identifier nick_name           timestamp
## 1 1 BWCA17600     469002982        BWCA17600   NS17600 2017-03-22 04:00:00
## 2 2 BWCA17600     469002982        BWCA17600   NS17600 2017-03-22 08:00:00
##       habitat Region location_long location_lat
## 1 North Slave nslave     -218717.7      2481535
## 2 North Slave nslave     -218707.8      2481526
```

```
#Transform into same projection as EOSD land cover data
lc.prj <- "+proj=aea +lat_1=50 +lat_2=70 +lat_0=40 +lon_0=-112 +x_0=0 +y_0=0
+ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_defs"
coordinates(all.dat) <- c("location_long", "location_lat")
#These lines were not run as the Movebank data stored for this analysis have
already been transformed. If the data is directly imported from Movebank, the
n run these next two lines.
#proj4string(all.dat) <- CRS("+init=epsg:4326") #This is WGS84
#all.dat <- spTransform(all.dat, CRS(lc.prj))
proj4string(all.dat) <- CRS(lc.prj)


#Display the first two rows of data
head(all.dat, 2)
```

```
##   X   trackId individual_id local_identifier nick_name           timestamp
## 1 1 BWCA17600     469002982        BWCA17600   NS17600 2017-03-22 04:00:00
## 2 2 BWCA17600     469002982        BWCA17600   NS17600 2017-03-22 08:00:00
```

```
##       habitat Region
## 1 North Slave nslave
## 2 North Slave nslave
```

```
#Read in study area shapefile
studyarea <- st_read("I:\\Contract_Work\\ABMI\\NWT_RSF\\GIS_Data\\StudyArea\\
RSF_study_area_EOSD_update_extent_hand_edit_eosd_prj.shp")

#Ensure it is in the same projection as the EOSD data
studyarea <- st_transform(studyarea, crs = lc.prj)
studyarea <- sf::as_Spatial(studyarea)

#Select only those locations occurring in the study area

all.dat <- all.dat[studyarea,]
plot(studyarea, col='transparent')
plot(all.dat, add=TRUE)
```

```
all.dat <- as.data.frame(all.dat)

#Extract summer season data
northbou <- all.dat[all.dat$Region=="inuvik" | all.dat$Region=="sahtu", ]
southbou <- all.dat[all.dat$Region=="dehcho" | all.dat$Region=="nslave" | all
.dat$Region=="sslave", ]

#Because the dates of the summer season differ between the North and South re
```

```
gions, the data first need to be split.

#First, north caribou
summer.n <- data.frame()
for(i in 2002:2017){
  sumdat <- northbou[northbou$timestamp >= as.POSIXct(paste0(i, "-07-13 00:00
:00"), tz = "America/Edmonton") & northbou$timestamp <= as.POSIXct(paste0(i,
"-09-08 23:59:59"), tz = "America/Edmonton"),]
  summer.n <- rbind.data.frame(summer.n, sumdat)
}

summer.n$Yr <- as.numeric(strftime(summer.n$timestamp, format ="%Y"))
summer.n$AIDYr <- paste0(summer.n$nick_name, ".", summer.n$Yr) #creates a car
ibou-year identifier

#Assess monitoring times per caribou-season in North
mt1 <- ddply(summer.n, .(AIDYr), summarise, Start = timestamp[1], End = tail(
timestamp,1), N= n())
mt1$MT <- difftime(mt1$End, mt1$Start, units = "days")
head(mt1)

##         AIDYr               Start                 End   N            MT
## 1 IN0701.2007 2007-07-13 07:58:05 2007-09-09 00:00:00 163 57.66800 days
## 2 IN0701.2008 2008-07-13 08:03:42 2008-09-08 16:01:55 166 57.33209 days
## 3 IN0701.2009 2009-07-13 08:03:42 2009-09-09 00:00:00 159 57.66410 days
## 4 IN0701.2010 2010-07-13 08:03:42 2010-08-01 16:01:55  53 19.33209 days
## 5 IN0704.2007 2007-07-13 07:58:05 2007-09-09 00:00:00 168 57.66800 days
## 6 IN0704.2008 2008-07-13 08:03:42 2008-09-08 16:01:55 161 57.33209 days

nrow(mt1) #154

## [1] 154

#Get rid of those bou with less than 29 days of monitoring time (1/2 of total
monitoring period)
sboun <- mt1[mt1$MT > 29,]
sbounID <- unique(sboun$AIDYr)
length(sbounID) #133 bou-years

## [1] 133

summer.s <- data.frame()
for(i in 2002:2017){
  sumdat <- southbou[southbou$timestamp >= as.POSIXct(paste0(i, "-07-01 00:00
:00"), tz = "America/Edmonton") & southbou$timestamp <= as.POSIXct(paste0(i,
"-09-12 23:59:59"), tz = "America/Edmonton"),]
  summer.s <- rbind.data.frame(summer.s, sumdat)
}

summer.s$Yr <- as.numeric(strftime(summer.s$timestamp, format ="%Y"))
summer.s$AIDYr <- paste0(summer.s$nick_name, ".", summer.s$Yr) #creates a car
```

```
ibou-year identifier

#Assess monitoring times per caribou-season in the South
mt2 <- ddply(summer.s, .(AIDYr), summarise, Start = timestamp[1], End = tail(
timestamp,1), N= n())
mt2$MT <- difftime(mt2$End, mt2$Start, units = "days")
head(mt2)

##        AIDYr               Start                 End   N            MT
## 1 BI318.2013 2013-07-01 08:00:00 2013-09-13 00:00:00 214 73.66667 days
## 2 BI318.2014 2014-07-01 08:00:00 2014-09-13 00:01:00 184 73.66736 days
## 3 BI318.2015 2015-07-01 16:00:00 2015-08-23 00:01:00 126 52.33403 days
## 4 BI319.2013 2013-07-01 08:00:00 2013-09-13 00:00:00 184 73.66667 days
## 5 BI319.2014 2014-07-03 00:00:00 2014-09-11 00:00:00 134 70.00000 days
## 6 BI319.2015 2015-07-01 08:00:00 2015-09-13 00:00:00 131 73.66667 days

nrow(mt2) #673

## [1] 673

#Get rid of those bou with less than 37 days of monitoring time (1/2 of total
monitoring period)
sbous <- mt2[mt2$MT > 37,]
sbousID <- unique(sbous$AIDYr)
length(sbousID) #604 bou-years

## [1] 604

summer <- rbind.data.frame(summer.n, summer.s)
rm(summer.n, summer.s)

sbouID <- c(sbounID, sbousID)
length(sbouID) #737

## [1] 737

#Use 'mk_track' function from package 'amt' to get fix rate intervals for eac
h caribou-year.  It requires a data frame with XY coordinates and a coordinat
e reference system (CRS).

sumres <- data.frame()
for(i in sbouID){
  sdat <- summer[summer$AIDYr==i,]
  sdat <- sdat[complete.cases(sdat[, 8:9]),]
  tdat <- data.frame(x = sdat$location_long, y = sdat$location_lat, ts = sdat
$timestamp)
  tdat <- tdat[!duplicated(tdat$ts),]
  yrtrack <- mk_track(tdat, x, y, ts, crs = sp::CRS(lc.prj))
  df <- as.data.frame(summarize_sampling_rate(yrtrack, time_unit="hour"))
  df$AIDYr <- i
  df$AID <- str_sub(df$AIDYr, 1, str_length(df$AIDYr)-5)
  df$nrow <- nrow(sdat)
```

```
  df$Start.Date <- sdat$timestamp[1]
  df$End.Date <- tail(sdat$timestamp,1)

  sumres <- rbind.data.frame(sumres, df)
}
head(sumres)
```

```
##        min       q1   median     mean       q3      max       sd   n unit
## 1 7.968056 7.968056 7.970278 8.543407 8.061667 24.00000 2.213799 162 hour
## 2 7.968056 7.968056 7.970278 8.339214 8.061667 24.00000 1.840158 165 hour
## 3 7.968056 7.968056 7.970278 8.759103 8.061667 24.00000 2.515430 158 hour
## 4 7.874444 7.968056 7.970278 8.287616 8.061667 16.03194 1.490988 167 hour
## 5 7.968056 7.968056 7.970278 8.599814 8.062222 16.03194 2.111837 160 hour
## 6 7.968056 7.968056 7.968056 8.237728 8.061667 24.00000 1.623790 168 hour
##         AIDYr    AID nrow          Start.Date            End.Date
## 1 IN0701.2007 IN0701  163 2007-07-13 07:58:05 2007-09-09 00:00:00
## 2 IN0701.2008 IN0701  166 2008-07-13 08:03:42 2008-09-08 16:01:55
## 3 IN0701.2009 IN0701  159 2009-07-13 08:03:42 2009-09-09 00:00:00
## 4 IN0704.2007 IN0704  168 2007-07-13 07:58:05 2007-09-09 00:00:00
## 5 IN0704.2008 IN0704  161 2008-07-13 08:03:42 2008-09-08 16:01:55
## 6 IN0709.2007 IN0709  169 2007-07-13 08:03:42 2007-09-09 00:00:00
```

The median time difference between successive GPS locations identifies the likely programmed fix rate of the collar during the season. The summary below gives the number of caribou-years for some given fix rates.

```
sumres$roundMedian <- round(sumres$median, 0)

nrow(sumres)

## [1] 737

nrow(sumres[sumres$roundMedian==24,])

## [1] 71

nrow(sumres[sumres$roundMedian==12,])

## [1] 0

nrow(sumres[sumres$roundMedian==8,])

## [1] 459

nrow(sumres[sumres$roundMedian==6,])

## [1] 0

nrow(sumres[sumres$roundMedian==4,])
```

```
## [1] 25

nrow(sumres[sumres$roundMedian==2,])

## [1] 14
```

Identifying the fix rate allows for the creation of a regular movement trajectory. 'Regular' means that within an individual's time-series of data there is a row for every time step as specified by the fix rate. The majority of these rows will be associated with an actual GPS location. For steps where the collar did not record a GPS location or the location was removed by our data screening procedures, values within the row—other than the timestamp—are assigned a value of 'NA'. The fix success rate can then be calculated by dividing the number of rows having a GPS location by the total number of rows in the time-series. The R package 'adehabitatLT' is used to create the regular movement trajectory. The following code demonstrates how to create a regular trajectory for caribou with a 2-hour fix rate then calculates the fix success rate for each caribou-season.

```
#Extract caribou with 2-hour fix rates
fr2 <- sumres[sumres$roundMedian ==2,]
u2 <- unique(fr2$AIDYr)
length(u2)

## [1] 14

#Calculate fix rates and remove time-abherrant fixes.
traj2 <- data.frame()
bou2.dat <- data.frame()
for(i in u2){
  dat2 <- summer[summer$AIDYr==i,]
  dat2$AIDYr <- droplevels(dat2)$AIDYr

  #This section removes time-abherrant fixes, i.e. those that fall well beyon
d the 2-hr fix rate
  timediff <- as.numeric(diff(dat2$timestamp), units = "secs") #get time diff
erences between successive steps
  dat2$dt <- NA
  dat2$dt[2:length(dat2$dt)] <- as.numeric(abs(timediff))
  dat2$dt[1] <- as.numeric(difftime(dat2$timestamp[2], dat2$timestamp[1], uni
ts="secs"))
  dat2$dt2 <- dat2$dt %% 7200 #7200 is 2 hours (in seconds)
  dat2 <- filter(dat2, dt2 <= 1800 | dt2 >= 5401 & dt2 <= 8999) #keep those w
ithin 30 minutes of the 2-hr fix rate
  dat2 <- dat2[!(dat2$dt < 5400),]

  #This section creates the movement trajectory
  lt <- as.ltraj(dat2[,9:10], dat2$timestamp, id=dat2$AIDYr, proj4string = sp
::CRS(lc.prj))
  lt <- setNA(lt, dat2$timestamp[2], 2*60*60, tol=1800) #this function places
```

```
NA rows where fixes were missed or removed
  lt <- sett0(lt, dat2$timestamp[2], 2*60*60, tol=1800)
  df <- as.data.frame(summary(lt)) #store the summary of the movement traject
ory in a data frame
  df$Yr <- as.numeric(format(df$date.begin, "%Y"))

  #This section saves and formats the regular time-series of data
  ltdf <- as.data.frame(lt[[1]])
  ltdf <- ltdf[!is.na(ltdf$x),]
  ltdf$AIDYr <- i
  ltdf$AID <- str_sub(ltdf$AIDYr, 1, str_length(ltdf$AIDYr)-5)
  ltdf$Yr <- as.numeric(format(ltdf$date, "%Y"))
  ltdf$Month <- as.numeric(format(ltdf$date, "%m"))
  ltdf$Day <- as.numeric(format(ltdf$date, "%d"))
  ltdf$Hr <- as.numeric(format(ltdf$date, "%H"))
  ltdf$Min <- as.numeric(format(ltdf$date, "%M"))

  traj2<- rbind.data.frame(traj2, df)
  bou2.dat <- rbind.data.frame(bou2.dat, ltdf)
}
head(traj2)
```

```
##           id      burst nb.reloc NAs          date.begin            date.e
nd
## 1 MK709.2017 MK709.2017      888  10 2017-07-01 06:00:00 2017-09-13 04:00:
00
## 2 MK710.2017 MK710.2017      888  41 2017-07-01 06:00:00 2017-09-13 04:00:
00
## 3 MK711.2017 MK711.2017      888   1 2017-07-01 06:00:00 2017-09-13 04:00:
00
## 4 MK713.2017 MK713.2017      888  35 2017-07-01 06:00:00 2017-09-13 04:00:
00
## 5 MK714.2017 MK714.2017      888   7 2017-07-01 06:01:00 2017-09-13 04:01:
00
## 6 MK715.2017 MK715.2017      888  19 2017-07-01 06:00:00 2017-09-13 04:00:
00
##     Yr
## 1 2017
## 2 2017
## 3 2017
## 4 2017
## 5 2017
## 6 2017
```

```
head(bou2.dat)
```

```
##           x       y                date          dx          dy       dist
dt
## 1 -225775.0 2421877 2017-07-01 06:00:00    97.07548  289.337877  305.18856
7200
```

```
## 2 -225677.9 2422167 2017-07-01 08:00:00   611.85278 -684.258283  917.91788
7200
## 3 -225066.0 2421482 2017-07-01 10:00:00   -76.31866  -54.722501   93.91001
7200
## 4 -225142.3 2421428 2017-07-01 12:00:00 -1639.41353 -520.383083 1720.02188
7200
## 5 -226781.8 2420907 2017-07-01 14:00:00  -445.51405  183.414094  481.79196
7200
## 6 -227227.3 2421091 2017-07-01 16:00:00    10.66194    9.058112   13.99022
7200
##          R2n  abs.angle  rel.angle      AIDYr   AID   Yr Month Day Hr Min
## 1       0.00  1.2470889         NA MK709.2017 MK709 2017     7   1  6   0
## 2   93140.06 -0.8412038 -2.0882927 MK709.2017 MK709 2017     7   1  8   0
## 3  658541.41 -2.5195307 -1.6783269 MK709.2017 MK709 2017     7   1 10   0
## 4  602373.66 -2.8342316 -0.3147009 MK709.2017 MK709 2017     7   1 12   0
## 5 1954604.57  2.7510487 -0.6979051 MK709.2017 MK709 2017     7   1 14   0
## 6 2727985.76  0.7042470 -2.0468017 MK709.2017 MK709 2017     7   1 16   0
```

```
#Fix success rates by caribou-season
AIDYr.fr2 <- data.frame()
uidyr <- unique(traj2$id)
for(i in uidyr){
  bou <- traj2[traj2$id==i,]
  frdf <- data.frame(AIDYr = i, nb.reloc = bou$nb.reloc, NAs = bou$NAs, Fix.R
ate = (bou$nb.reloc - bou$NAs)/ bou$nb.reloc)
  AIDYr.fr2 <- rbind.data.frame(AIDYr.fr2, frdf)
}
head(AIDYr.fr2)
```

```
##        AIDYr nb.reloc NAs  Fix.Rate
## 1 MK709.2017      888  10 0.9887387
## 2 MK710.2017      888  41 0.9538288
## 3 MK711.2017      888   1 0.9988739
## 4 MK713.2017      888  35 0.9605856
## 5 MK714.2017      888   7 0.9921171
## 6 MK715.2017      888  19 0.9786036
```

```
nrow(AIDYr.fr2) #14
```

```
## [1] 14
```

```
nrow(AIDYr.fr2[AIDYr.fr2$Fix.Rate >= 0.9,])
```

```
## [1] 14
```

Literature Cited

Davidson, S. 2018. Notes on organizing GNWT boreal caribou telemetry datasets in Movebank. Movebank, Max Planck Institute of Animal Behaviour, Konstanz, Germany.

Frair, J. L., J. Fieberg, M. Hebblewhite, F. Cagnacci, N. J. DeCesare, and L. Pedrotti. 2010. Resolving issues of imprecise and habitat-biased locations in ecological analyses using GPS telemetry data. Philosophical Transactions of the Royal Society B: Biological Sciences 365:2187–2200.

APPENDIX B: DEFINING AVAILABILITY FOR RESOURCE SELECTION FUNCTIONS

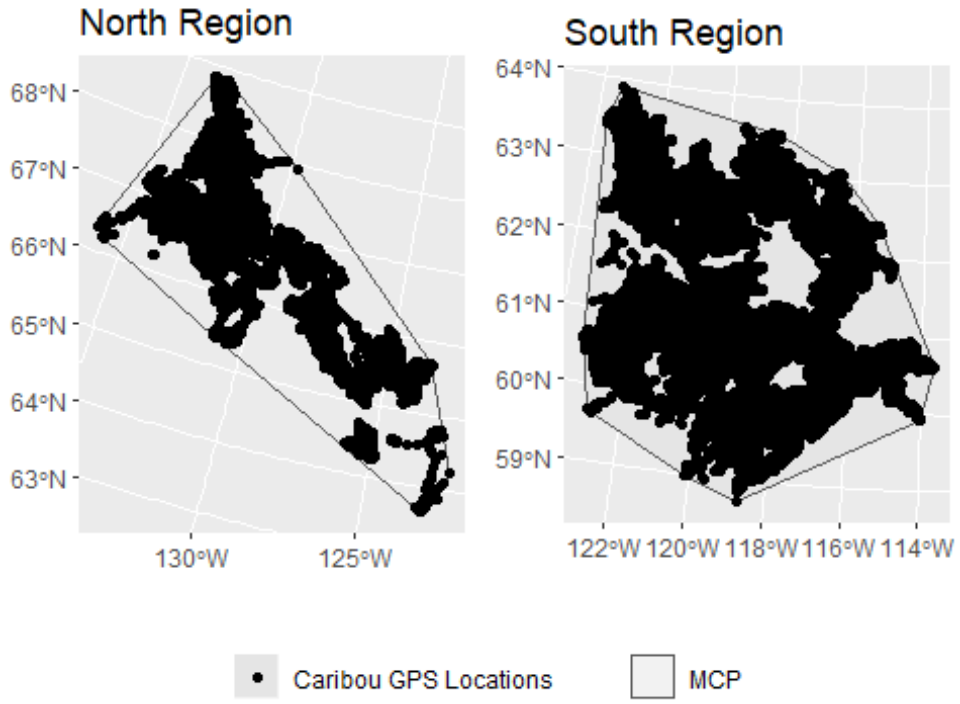
Resource selection is a hierarchical process (Rettie and Messier 2000, Boyce 2006) and an integral component to evaluating resource selection is identifying the area that is available to an individual animal. Differences in availability inform the spatial scales of resource selection (Boyce 2006). Here, we outline how availability was defined and sampled at the two scales used to assess seasonal selection of resources by boreal caribou in the Northwest Territories. R code is provided for all steps in this process.

SECOND-ORDER AVAILABILITY

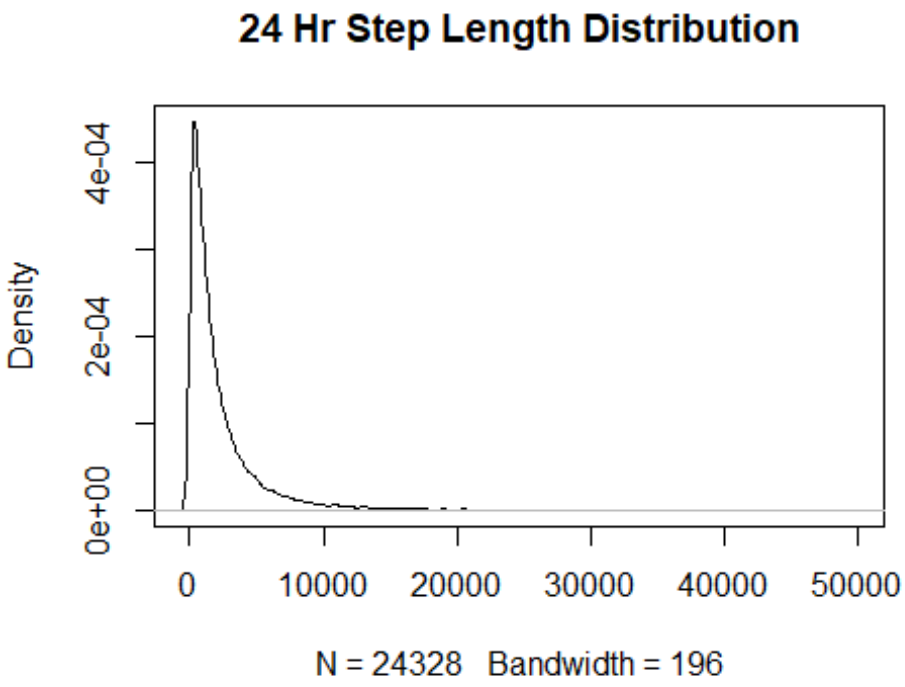
For analyses evaluating resource selection at a second-order scale, availability is typically defined as regions containing populations of the species of interest (Meyer and Thuiller 2006). Spatial delineations of boreal caribou populations in the Northwest Territories are not well defined; therefore, we defined availability at this scale by examining movement patterns among radio-collared caribou across the study area and considering expert input from regional government biologists. This process yielded two regions of availability: a North region containing caribou radio-collared in the Inuvik and Sahtu regional study areas and a South region containing caribou radio-collared in the Dehcho, North Slave, and South Slave regional study areas. We spatially delineated these regions by first fitting 100% minimum convex polygons (MCPs) around all available GPS locations within each region. The following code was used to generate the MCPs. The first step, which is not shown, was to import the screened radio-collar data into R (see Appendix A).

```
#Load required R libraries

pcks <- c("move", "tidyverse", "sf", "sp", "lwgeom", "ggpubr")
sapply(pcks, require, character = TRUE)

#All modelling was done using the same projection as the EOSD land cover data

lc.prj <- "+proj=aea +lat_1=50 +lat_2=70 +lat_0=40 +lon_0=-112 +x_0=0 +y_0=0
+ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_defs"



#Import screened radio-collar data

#all.dat <- read.csv("your_directory\\NWT_caribou_screened_GPS_data.csv")

#Display the first two rows of data
head(all.dat, 2)

##     trackId individual_id local_identifier nick_name location_lat location
_long
## 1 BWCA17600     469002982        BWCA17600   NS17600     62.25693     -116
.2770
## 2 BWCA17600     469002982        BWCA17600   NS17600     62.25686     -116
.2768
##             timestamp     habitat Region
```

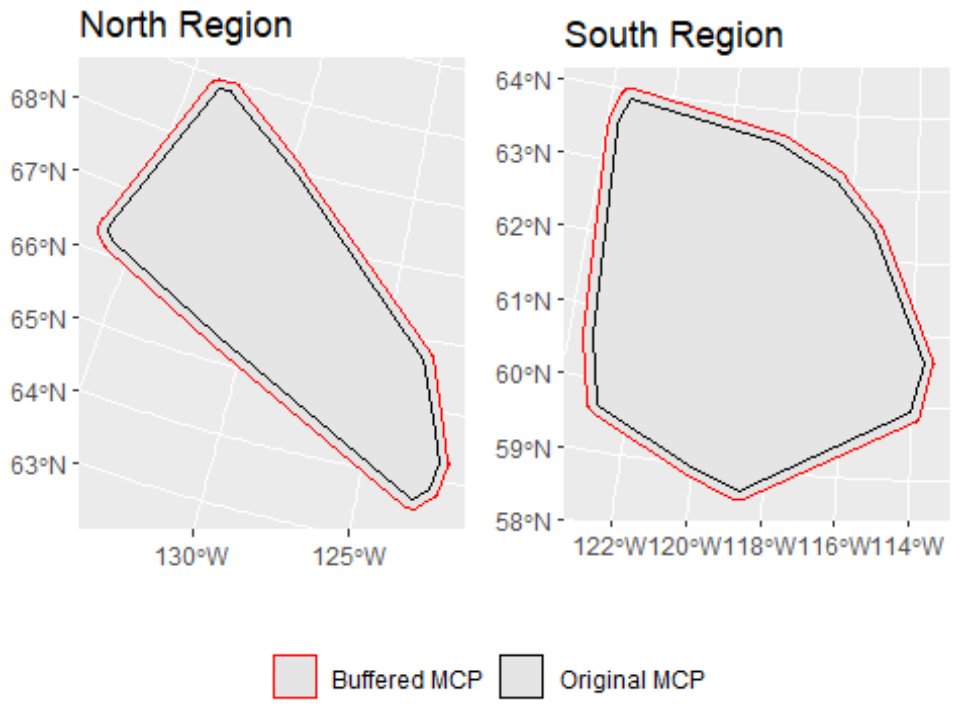
```
## 1 2017-03-22 04:00:00 North Slave nslave
## 2 2017-03-22 08:00:00 North Slave nslave

#Re-project into same projection as EOSD data. First create a SpatialPointsDa
taFrame.
coordinates(all.dat) <- c("location_long", "location_lat")
proj4string(all.dat) <- CRS("+init=epsg:4326") #this is the projection of WGS
84
all.dat <- as.data.frame(spTransform(all.dat, CRS(lc.prj)))
all.dat <- all.dat[all.dat$timestamp <= as.POSIXct("2018-03-31 23:59:59"),]

#Extract regional data
northbou <- all.dat[all.dat$Region=="inuvik" | all.dat$Region=="sahtu", ]
southbou <- all.dat[all.dat$Region=="dehcho" | all.dat$Region=="nslave" | all
.dat$Region=="sslave", ]

#Create 100% MCPs
npts <- st_as_sf(northbou, coords = c("location_long", "location_lat"), crs =
lc.prj)
nmcp <- st_convex_hull(st_union(npts)) #to create one MCP

#Plot
colors <- c("Caribou GPS Locations" = "black")
f <- c("MCP" = NA)

n.plot <- ggplot() + geom_sf(data=nmcp, aes(fill = "MCP"), show.legend = "pol
ygon") + geom_sf(data=npts, aes(color="Caribou GPS Locations"), show.legend =
"point") + scale_color_manual(values = colors, guide = guide_legend(override.
aes = list(linetype = "blank"))) + scale_fill_manual(values = f, guide = guid
e_legend(override.aes = list(shape = NA)))+ theme(legend.position="bottom", l
egend.title = element_blank()) + labs(title="North Region")

spts <- st_as_sf(southbou, coords = c("location_long", "location_lat"), crs =
lc.prj)
smcp <- st_convex_hull(st_union(spts)) #to create one MCP

s.plot <- ggplot() + geom_sf(data=smcp) + geom_sf(data=spts) + labs(title="So
uth Region")

ggarrange(n.plot, s.plot, ncol=2, common.legend = TRUE, legend="bottom")
```



Because the borders of the above MCPs are defined by the outermost GPS locations, availability becomes increasingly constrained at the outer edges of the MCP. To create a more biologically reasonable border, we buffered each MCP by an estimate of the maximum distance caribou moved in a 24-hr period. We estimated this buffer by evaluating the distribution of step lengths (i.e., the distance moved between successive GPS locations) from radio-collar data having a 24-hr fix rate, then used the 99% quantile of this distribution as the buffer distance. The following code outlines this analysis.

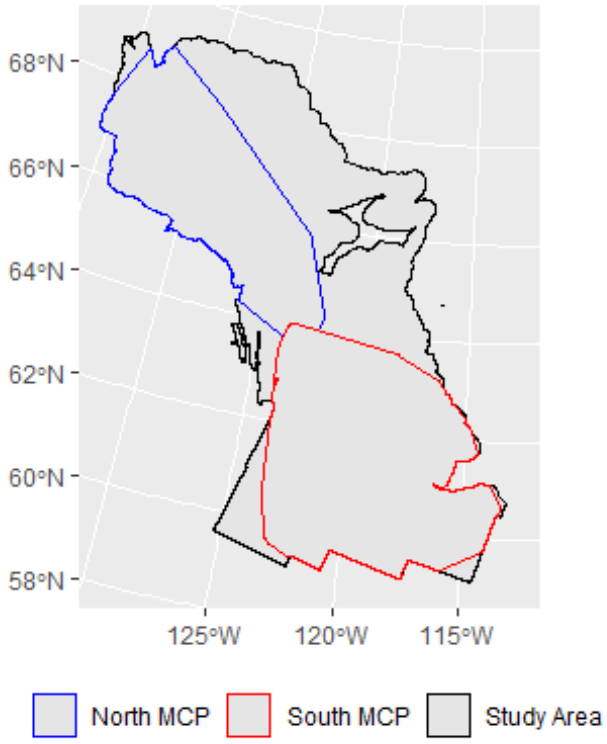



```
#Get 99% quantile of this distribution
quantile(d, probs=0.99, na.rm=TRUE)

##      99%
## 15124.71 # ~15-km


#Add 15-km buffer to MCPs
buff.cols <- c("Original MCP" = "black", "Buffered MCP" = "red")
nmcp.buff <- st_buffer(nmcp, dist=15000)
n.buff <- ggplot() + geom_sf(data=nmcp.buff, aes(color="Buffered MCP")) + geo
m_sf(data=nmcp, aes(color="Original MCP")) + labs(title="North Region") + sca
le_color_manual(values = buff.cols) + theme(legend.position="bottom", legend.
title = element_blank())

smcp.buff <- st_buffer(smcp, dist=15000)
s.buff <- ggplot() + geom_sf(data=smcp.buff, color = "red") + geom_sf(data=sm
cp, color="black") + labs(title="South Region")

ggarrange(n.buff, s.buff, ncol=2, common.legend = TRUE, legend="bottom")
```



As a final step, the buffered MCPs were clipped to the boundaries of study area.

```
#Read in study area shapefile
sa <- st_read("I:\\Contract_Work\\ABMI\\NWT_RSF\\GIS_Data\\StudyArea\\RSF_study_area_EOSD_update_extent_hand_edit.shp")

#transform to EOSD projection
sa <- st_transform(sa, crs = lc.prj)

#Intersect buffered MCPs and study area
nmcp.buff <- st_intersection(nmcp.buff, sa)
smcp.buff <- st_intersection(smcp.buff, sa)
mcp.cols2 <- c("Study Area" = "black", "North MCP" = "blue", "South MCP" = "red")

#Plot
ggplot() + geom_sf(data=sa, aes(color="Study Area")) + geom_sf(data=nmcp.buff, aes(color="North MCP")) + geom_sf(data=smcp.buff, aes(color="South MCP")) + scale_color_manual(values = mcp.cols2) + theme(legend.position="bottom", legend.title = element_blank())
```

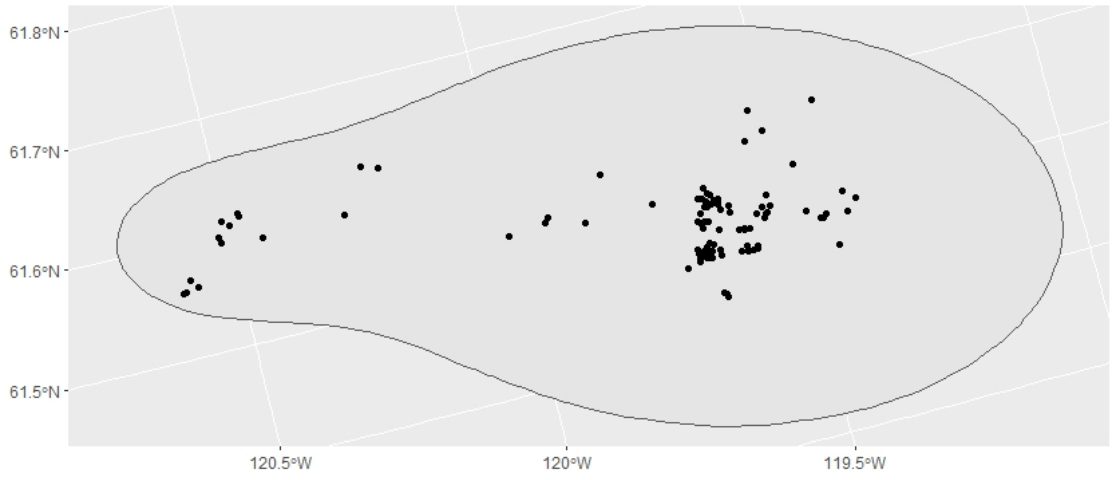


THIRD-ORDER AVAILABILITY

Third-order selection evaluates how animals select resources within their home ranges (Johnson 1980, Meyer and Thuiller 2006). For our analyses, we estimated home ranges annually, which meant that seasonal GPS locations within a given year were compared to random locations sampled within the home range of that same year. Annual home ranges for each individual caribou were estimated using all GPS locations collected from 1 May–30 April, a biological year with a start date that corresponds to the onset of the calving season. We characterized home ranges using kernel density estimates (KDEs), which represent a probability surface of an animal's space use (i.e., the probability of relocating an animal at a given spatial coordinate; Worton 1989). Compared to MCPs, KDEs provide more robust estimates of home ranges as they are less sensitive to fix rate and do not make assumptions of uniform space use (White and Garrott 1990, Börger et al. 2006). Because of these properties, KDEs were estimated using all of the MoveBank data and were not restricted to individual data sets with fix success rates > 90%. We estimated KDEs using recently developed methods that account for autocorrelation in GPS location data (Fleming et al. 2015). We used the 95% isopleth of the KDE to define the spatial boundaries of the annual home range. KDEs that partially extended beyond the study area were clipped to the study area boundary. The following code demonstrates home range estimation for an individual caribou.

```
#Load required packages
```

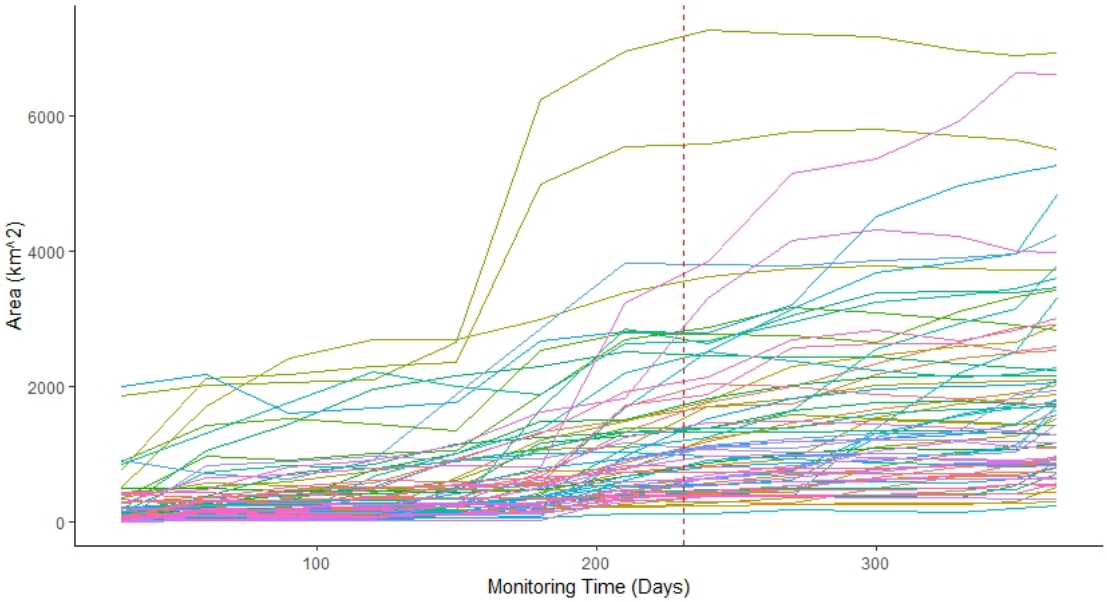
```
pcks <- c("move", "sf", "ggplot2", "ctmm") # 'ctmm' estimates KDEs
sapply(pcks, require, character = TRUE)

#Load Movebank data.  Accessing data from Movebank is not shown.

#dat <- read.csv("your_directory\\NWT_caribou_Movebank_GPS_data.csv")

#Select an individual caribou
bou <- dat[dat$local_identifier == "DN131" & dat$timestamp >= as.POSIXct("200
7-05-01 00:00:00", tz="UTC") & dat$timestamp <= as.POSIXct("2007-05-01 00:00:
00", tz="UTC") + (3600*24*365), ]
bou.pts <- st_as_sf(bou, coords = c("location_long", "location_lat"), crs = "
+init=epsg:4326")


bou$local_identifier <- droplevels(bou)$local_identifier
bou <- as.telemetry(bou) #transforms to a telemetery object
GUESS <- ctmm.guess(bou,interactive=FALSE)
control <- list(method='pNewton') #this is a better optimizer than the defaul
t
FIT <- try(ctmm.fit(bou,GUESS, control = control), TRUE)
#Compute akde object
UD.bou <- akde(bou,FIT)
udbou <- SpatialPolygonsDataFrame.UD(UD.bou) #transform AKDE into SPDF
udbou <- st_as_sf(udbou) #then into an sf object
udbou <- udbou[2,2]

ggplot(data = udbou) + geom_sf() + geom_sf(data=bou.pts)
```



Although KDEs are relatively robust to variation in fix rate, they can be sensitive to the monitoring interval (i.e., the total time an animal is monitored; Börger et al. 2006). For example, a KDE estimated using three months of data may substantially differ from one estimated using 12 months of data. We therefore conducted a sensitivity analysis to identify the minimum monitoring interval necessary to adequately estimate the annual home range. To do so, we used only those caribou that were monitored for at least 350 days and iteratively compared the area of KDEs estimated for each caribou as the length of monitoring time was increased from 30 days to 365 days. We used a mixed-effects piecewise regression approach to identify the minimum monitoring time after which the area of KDEs stabilized. This analysis suggested that the estimated area of annual KDEs stabilized after 231 days. The following code details this sensitivity analysis and produces a plot to illustrate the relationship between KDE size and monitoring time.

```
#Use 2009 as example
yr09 <- dat90[dat90$timestamp >= as.POSIXct("2009-05-01 00:00:00", tz="UTC")
& dat90$timestamp <= as.POSIXct("2009-05-01 00:00:00", tz="UTC") + (3600*24*3
65), ] #start year on May 1, start of calving season
yr09 <- arrange(yr09, local_identifier, timestamp)

mt <- ddply(yr09, .(local_identifier), summarise, St.date = timestamp[1], End
.date = tail(timestamp,1)) #assess monitoring times for each caribou
mt$MT <- difftime(mt$End.date, mt$St.date, unit = "days")
for.yr <- mt[mt$MT >=350,] #select only those monitored for >= 350 days
yrID <- unique(for.yr$local_identifier)

sensdat <- yr09[yr09$local_identifier %in% yrID,]
sensdat$local_identifier <- droplevels(sensdat)$local_identifier

#Run through bou with at least one year of monitoring
sensres <- data.frame()

for(i in c(30, 60, 90, 120, 150, 180, 210, 240, 270, 300, 330, 350, 365)){
  subdat <- sensdat[sensdat$timestamp <= as.POSIXct("2009-05-01 00:00:00", tz
="UTC") + (3600*24*i), ]

  subres <- data.frame()
  for(j in yrID){
    bou <- subdat[subdat$local_identifier==j,]
    bou$local_identifier <- droplevels(bou)$local_identifier
    bou <- as.telemetry(bou) #transforms to a telemetery object
    GUESS <- ctmm.guess(bou,interactive=FALSE)
    control <- list(method='pNewton') #this is a better optimizer than the de
fault
    FIT <- try(ctmm.fit(bou,GUESS, control = control), TRUE)
    #Compute akde object
    UD.bou <- akde(bou,FIT)
    udbou <- SpatialPolygonsDataFrame.UD(UD.bou) #transform AKDE into SPDF
```

```
    udbou <- st_as_sf(udbou) #then into an sf object
    a <- st_area(udbou[[2]][1]) %>% set_units(km^2) %>% as.vector()
    df <- data.frame(AID = j, Area = a, MT = i)
    subres <- rbind.data.frame(subres, df)
  }
 sensres <- rbind.data.frame(sensres, subres)
}

##Plot##
p <- ggplot(sensres, aes(x = MT, y = Area, color = AID)) + geom_line() + them
e_classic() + theme(legend.position = "none") + xlab("Monitoring Time (Days)"
) + ylab("Area (km^2)")

##Assess for breakpoint using a mixed-effects approach. See this webpage for
code: https://stats.stackexchange.com/questions/19772/estimating-the-break-po
int-in-a-broken-stick-piecewise-linear-model-with-rando

#Basis functions
bp = 250
b1 <- function(x, bp) ifelse(x < bp, bp - x, 0)
b2 <- function(x, bp) ifelse(x < bp, 0, x - bp)

#Wrapper for Mixed effects model with variable break point
foo <- function(bp)
{
  mod <- lmer(Area ~ b1(MT, bp) + b2(MT, bp) + (b1(MT, bp) + b2(MT, bp) | AID
), data = sensres)
  deviance(mod)
}

search.range <- c(min(sensres$MT)+0.5,max(sensres$MT)-0.5)
foo.opt <- optimize(foo, interval = search.range)
bp <- foo.opt$minimum

#add to plot
p <- p + geom_vline(xintercept = bp, lty = "dashed", color = "red")
p
```


6000
4000
2000
0
Area (km^2)
100
200
300
Monitoring Time (Days)

APPENDIX C: RANDOM POINT SENSITIVITY ANALYSES

To evaluate the seasonal selection of habitat by boreal caribou in the Northwest Territories, we estimated resource selection functions (RSFs) at second- and third-order scales. RSFs compare the environmental attributes associated with caribou GPS locations to those associated with random points sampled within each scale's area of availability. Determining the number of random points to sample is critical to RSFs as insufficient sampling can bias inferences whereas over-sampling can lead to protracted computing times, particularly when using large data sets (Benson 2013, Northrup et al. 2013). Here, we outline the sensitivity analyses used to determine the number of random points required to adequately characterize availability at each scale. Example R code is also provided.

For second-order RSFs, availability was defined by creating two buffered minimum convex polygons (MCPs): one around all caribou GPS locations from a north "population" (caribou in the Sahtu and Inuvik regional study areas) and one around all caribou GPS locations from a south "population" (caribou in the Dehcho, North Slave and South Slave regional study areas; see Appendix B). To identify the minimum number of random points required to adequately sample each MCP, we conducted repeated RSFs, varying the number of random points used, then determining the sample size of random points at which RSF coefficients stabilized. We considered a minimum sample size of 500 random points then progressively increased the sample size up to 5000. We also evaluated a sampling ratio where one random point was generated for every GPS location. At each sample size, we iteratively estimated the same RSF model 30 times, using a unique set of random points on each iteration, then estimated the mean and standard deviation of each RSF coefficient. This sensitivity analysis used data from the summer season (see main text for seasonal delineations) but inferences should apply across all seasons as availability remains constant across all seasonal analyses. Also, in contrast to the RSF analyses described in the main text, we used simplified burn variables where burned land covers were grouped together by burn age and not separated by land cover type.

Results from this second-order sensitivity analysis suggested that continuous variables such as "distance-to-nearest-settlement" required 3000 random points for their RSF coefficient to stabilize, although most other RSF coefficients stabilized prior to this sample size (~ 2000 random points; Figs. C 1). We therefore used 3000 random points sampled within each population-level MCP for all second-order RSF analyses.

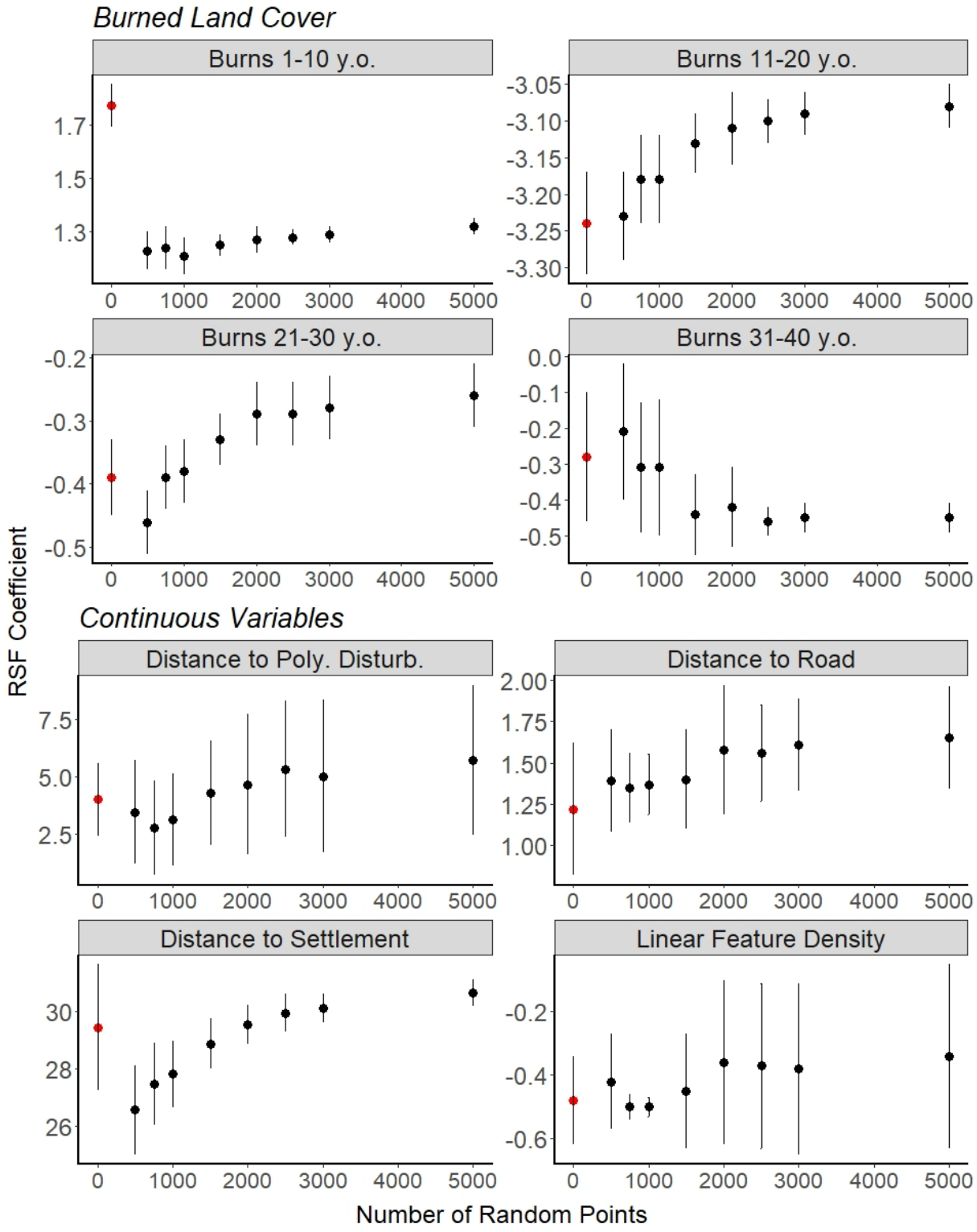


Figure C 1: Sensitivity analysis to determine the minimum sample size of random points required to achieve stable coefficients (mean value with standard deviation bars) for second-order resource selection functions. Sample sizes ranged from 500–5000 random points. A sampling regime where one random point was generated for every caribou GPS location was also considered (red point).

We followed the same process to determine the minimum number of random points required for third-order RSF analyses. At this scale, availability is defined as the annual home range for each individual caribou (see Appendix B). Results from this analysis suggested that RSF coefficients stabilized at a sample size of ~3000 random points (Fig. C 2). We therefore used 3000 random points sampled within each annual home range for all third-order RSF analyses.

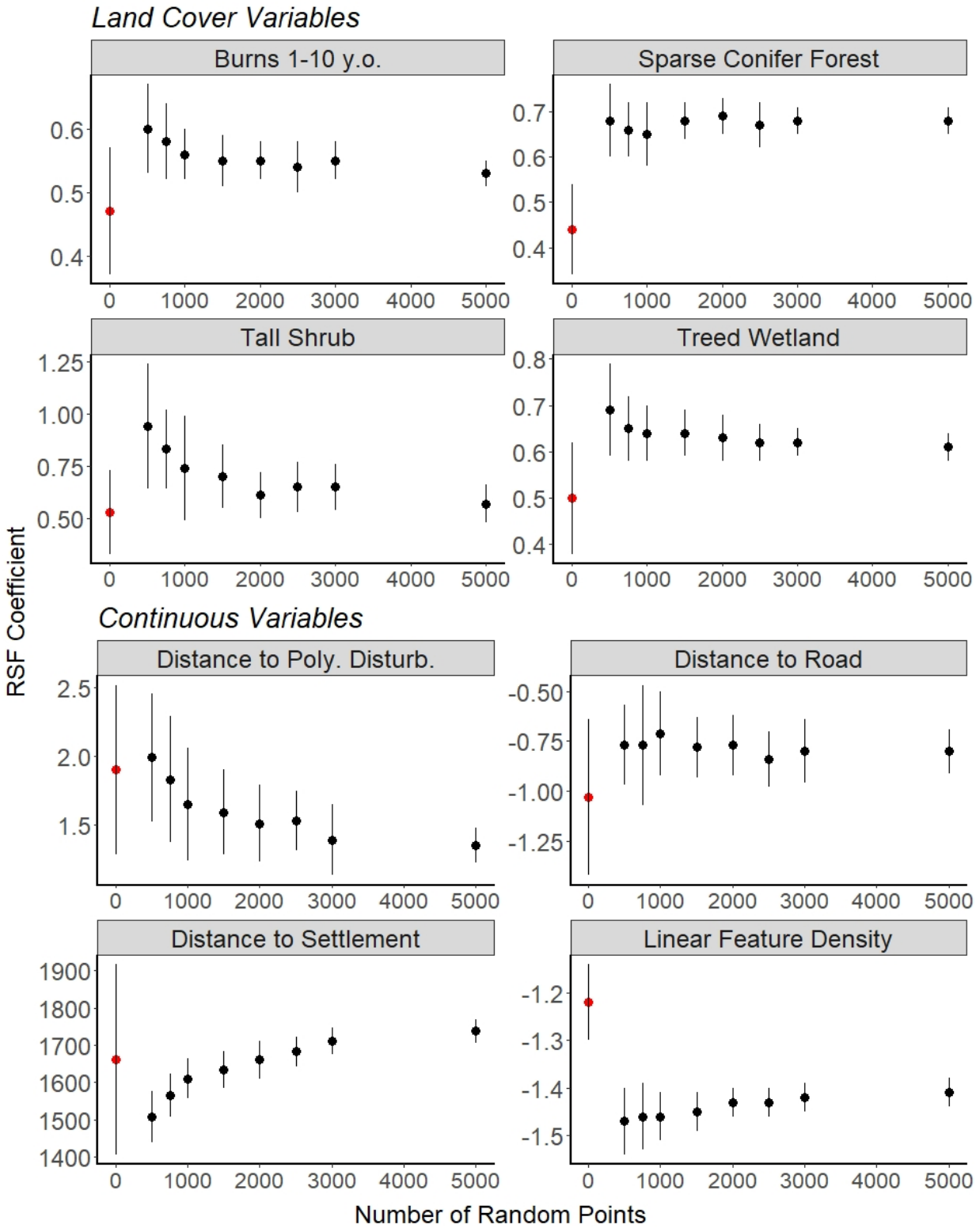


Figure C 2: Sensitivity analysis to determine the minimum sample size of random points required to achieve stable coefficients (mean value with standard deviation bars) for third-order resource selection functions. Sample sizes ranged from 500–5000 random points. A sampling regime where one random point was generated for every caribou GPS location was also considered (red point).

R Code for Random Point Sensitivity Analyses

The following R code outlines the steps used to conduct a sensitivity analysis to determine the minimum number of random points required for RSF coefficients to stabilize. The code uses data for second-order RSF analyses. Code for third-order analyses is not shown as these analyses used a similar process.

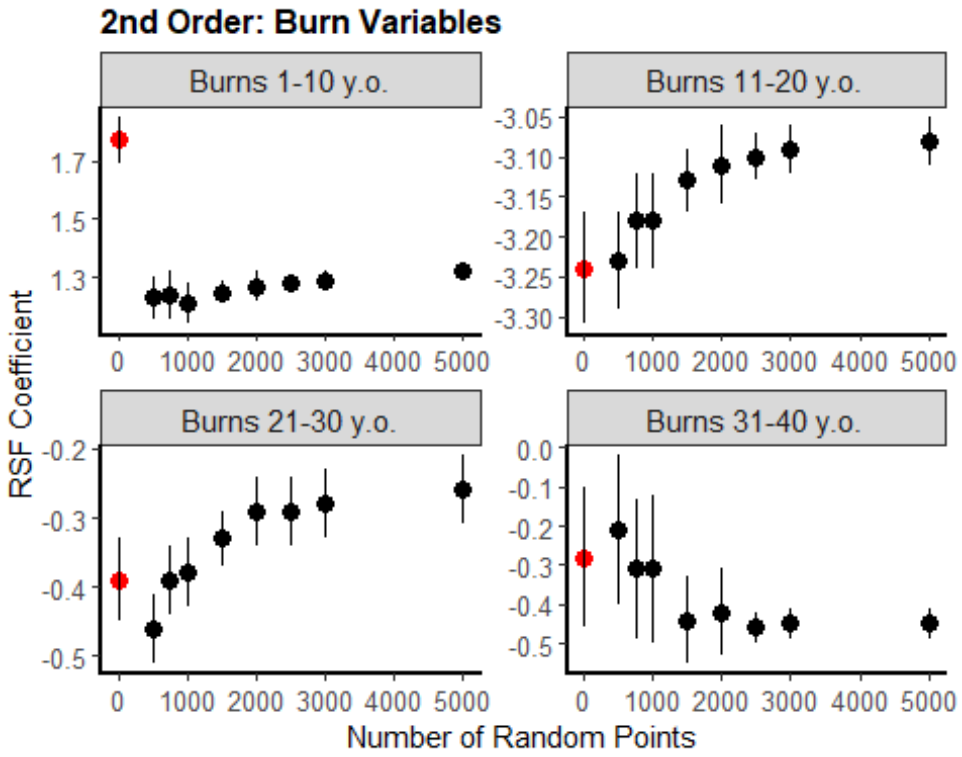
```
#Load packages
pcks <- c("tidyverse", "sf", "plyr", "glmmTMB")
sapply(pcks, require, character = TRUE)

setwd("Your_directory_where_data_are_stored.csv")

#Import GPS locations
s.bou <- read.csv("Summer_SouthRegion_UsePts_Extract.csv")

#For efficiency, select a sample of caribou
#First, get only those caribou with > 200 locations in a given year
mt <- ddply(s.bou, .(AIDYr), 'nrow')
mt200 <- mt[mt$nrow >=200,]
mt200$AIDYr <- droplevels(mt200)$AIDYr
#Then select a subsample of 60 caribou-years
sub.bou <- sample(levels(mt200$AIDYr), 60)
bou <- s.bou[s.bou$AIDYr %in% sub.bou,]
#check monitoring times
mt <- ddply(bou, .(AIDYr), 'nrow')
mt
bou$AIDYr <- droplevels(bou)$AIDYr

#Import random locations (100K). Environmental covariates were extracted to t
hese points in ArcGIS
rpts <- read.csv("SouthBou_100MCP_100KRpts_EV.csv")

#Bind GPS locations and random points together and run sensitivity analysis
uAID <- unique(bou$AIDYr)
res <- data.frame()
s.dat <- data.frame()

sens <- data.frame()
for(j in c(1, 500, 750, 1000, 1500, 2000, 2500, 3000, 5000)){
  res <- data.frame()
  for(k in 1:30){ #run 30 iterations of each sample size of random points
    bou.dat <- data.frame()
    for(i in uAID){
      caribou <- bou %>% dplyr::select(AIDYr, AID, Yr, Region, Habitat, lc, l
d1000_10:burn, p_broad_d, p_broad_o, p_mix_o, p_consparse, p_mix_dens) %>% dp
lyr::filter(AIDYr==i) %>% add_column(use = 1)
      avail <- rpts %>% dplyr::select(-c(FID, CID, POINT_X, POINT_Y)) %>% add
_column(AIDYr = i, AID = caribou$AID[1], Yr = caribou$Yr[1], Region = caribou
$Region[1], Habitat = caribou$Habitat[1], use = 0)
```

```
      avail2 <- if(j < 2){avail[sample(nrow(avail), nrow(caribou)),]}else{ava
il[sample(nrow(avail), j),]}
      bou.dat <- rbind.data.frame(bou.dat, caribou, avail2)
    }

    bou.dat$lc2 <- bou.dat$lc
    bou.dat$burn[is.na(bou.dat$burn)] <- 0
    bou.dat$burn[bou.dat$burn==-9999] <- 0

    #Format variables
    #Line Density Variables
    bou.dat <- bou.dat %>% mutate(ld1000 = if_else(Yr <= 2010, ld1000_10, ld1
000_15))

    #Distance to Roads Variable
    bou.dat <- bou.dat %>% mutate(dist_roads = if_else(Yr <= 2010, dist_roads
10, dist_roads15))
    #exponential decay of distance to roads (decays where 0.95 value occurs a
t 1250-m -> Leblond et al. 2011 reported road effects at 1.25 km)
    bou.dat$exp.rds <- 1- exp(-0.0025*bou.dat$dist_roads)

    #Distance to Polygonal Disturbance Variable
    bou.dat <- bou.dat %>% mutate(dist_poly = if_else(Yr <= 2010, dist_poly10
, dist_poly15))
    #exponential decay of distance to polygonal disturbance (decays to 0.95 b
y 1-km)
    bou.dat$exp.poly <- 1- exp(-0.003*bou.dat$dist_poly)

    #Distance to Settlements Variable
    #exponential decay of distance to settlements (decays to 0.95 by 5-km)
    bou.dat$exp.settle <- 1- exp(-0.000625*bou.dat$dto_settle)

    #To create burn variables in 10 year increments
    bou.dat$fire10 <- ifelse(bou.dat$burn >= bou.dat$Yr - 10 & bou.dat$burn <
bou.dat$Yr, 1, 0) #fires 1-10 y.o.
    bou.dat$fire20 <- ifelse(bou.dat$burn >= bou.dat$Yr - 20 & bou.dat$burn <
bou.dat$Yr - 10, 1, 0) #fires 11-20 y.o.
    bou.dat$fire30 <- ifelse(bou.dat$burn >= bou.dat$Yr - 30 & bou.dat$burn <
bou.dat$Yr - 20, 1, 0) #fires 21-30 y.o
    bou.dat$fire40 <- ifelse(bou.dat$burn >= bou.dat$Yr - 40 & bou.dat$burn <
bou.dat$Yr - 30, 1, 0) #fires 31-40 y.o.
    bou.dat$fire60 <- ifelse(bou.dat$burn >= bou.dat$Yr - 60 & bou.dat$burn <
bou.dat$Yr - 40, 1, 0) #fires 41-60 y.o.

    #then create burn classes  within land cover variable
    bou.dat$lc2 <- ifelse(bou.dat$fire10 == 1, 199, bou.dat$lc2)
    bou.dat$lc2 <- ifelse(bou.dat$fire20 == 1, 299, bou.dat$lc2)
    bou.dat$lc2 <- ifelse(bou.dat$fire30 == 1, 399, bou.dat$lc2)
    bou.dat$lc2 <- ifelse(bou.dat$fire40 == 1, 499, bou.dat$lc2)
    bou.dat$lc2 <- ifelse(bou.dat$fire60 == 1, 699, bou.dat$lc2)
```

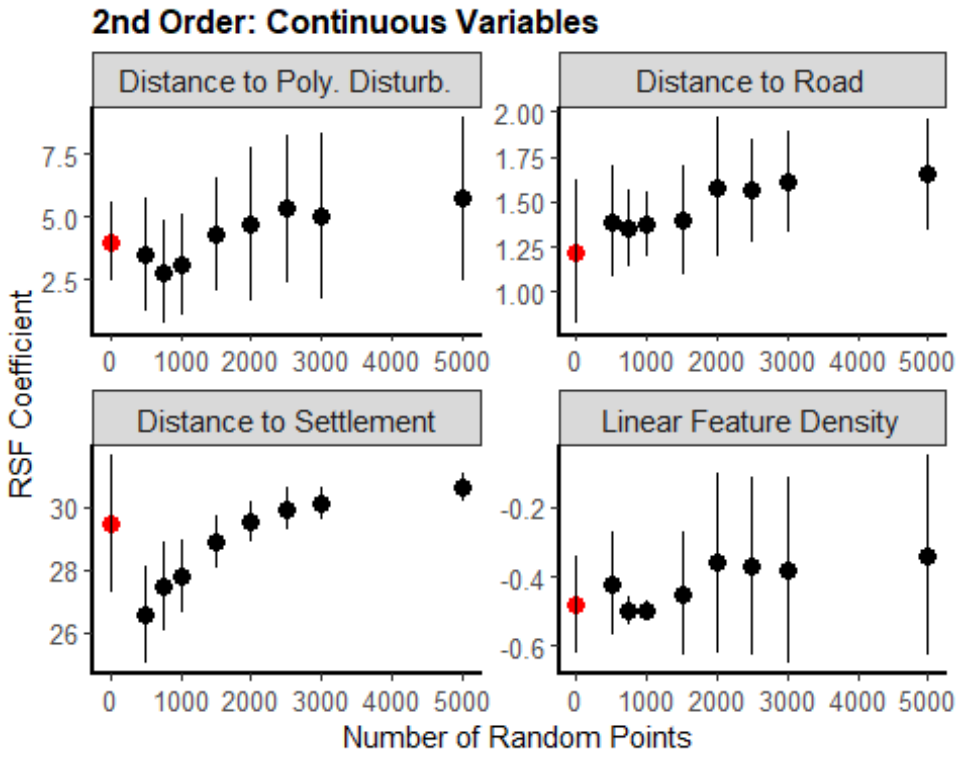
```
    #create dummy variables. Need to transform back to data frame
    bou.dat <- as.data.frame(bou.dat)
    bou.dat <- dummy.data.frame(bou.dat, names="lc2")

    #rename variables
    bou.dat <- dplyr::rename(bou.dat, water = lc220, rock = lc232, exp.land =
lc233, exp.land2 = lc234, bryoids = lc240, t.shrub = lc251, s.shrub = lc252,
t.wet = lc281, s.wet = lc282, h.wet = lc283, herb = lc2100, con.dens = lc2211
, con.open = lc2212, con.sp = lc2213, broad.d = lc2221, broad.o = lc2222, mix
.dens = lc2231, mix.o = lc2232, burn10 = lc2199, burn20 = lc2299, burn30 = lc
2399, burn40 = lc2499, burn60 = lc2699)

    #create non-veg category
    bou.dat <- bou.dat %>% mutate(nonveg = rock + exp.land + exp.land2)
    bou.dat$nonveg <- ifelse(bou.dat$nonveg >= 1, 1, 0)

    bou.dat <- mutate(bou.dat, p_broad = p_broad_d + p_broad_o + p_mix_dens)

    #run RSF model
    mod <- glmmTMB(use ~ bryoids + t.shrub + s.shrub + t.wet + s.wet + h.wet
+ herb + con.open + con.sp + broad.d + broad.o + mix.o + mix.dens + water + n
onveg + p_broad + p_consparse + burn10 + burn20 + burn30 + burn40  + burn60 +
ld1000 + exp.rds + exp.poly + exp.settle + (1|Habitat/AIDYr), family=binomial
, data=bou.dat)
    #store results
    df <- as.data.frame(summary(mod)$coefficients$cond) %>% rownames_to_colum
n(var="Var")
    df$Rpts <- j
    df$Trial <- k
    res <- rbind.data.frame(res, df)
    }
  sens <- rbind.data.frame(sens, res)
}

head(sens)
```

```
##   X         Var     Estimate Std..Error     z.value     Pr...z.. Rpts Tria
l
## 1 1 (Intercept) -33.93262520 2.65871236 -12.7628042 2.645048e-37    1
1
## 2 2     bryoids  -1.61548477 0.38711709  -4.1731166 3.004610e-05    1
1
## 3 3     t.shrub  -1.22663995 0.39265413  -3.1239706 1.784283e-03    1
1
## 4 4     s.shrub  -0.89816672 0.10775285  -8.3354337 7.721463e-17    1
1
## 5 5       t.wet  -0.04252081 0.06170246  -0.6891266 4.907436e-01    1
1
```

```
## 6 6       s.wet  -0.45956640 0.06908720  -6.6519762 2.891835e-11    1
1

#Get mean and standard deviation of each RSF coefficient for each sample size
of random points
beta <- ddply(sens, .(Var, Rpts), summarize, coef = round(mean(Estimate), 2),
sd = round(sd(Estimate), 2))
#Creat new column to specify where RSF was estimated using 1 random location
per 1 GPS location
beta <- mutate(beta, one_to_one = ifelse(Rpts <= 1, T, F))

#Burn variables
burn <- beta[beta$Var=="burn10" | beta$Var=="burn20" | beta$Var=="burn30" | b
eta$Var=="burn40",]

#Create better variable labels
levels(burn$Var)[levels(burn$Var)=="burn10"] <- "Burns 1-10 y.o."
levels(burn$Var)[levels(burn$Var)=="burn20"] <- "Burns 11-20 y.o."
levels(burn$Var)[levels(burn$Var)=="burn30"] <- "Burns 21-30 y.o."
levels(burn$Var)[levels(burn$Var)=="burn40"] <- "Burns 31-40 y.o."

#Plot
b <- ggplot(burn, aes(x=Rpts, y=coef)) + geom_point(aes(color=one_to_one), si
ze=3) + facet_wrap(~Var, scales= "free")
b <- b + theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.mi
nor=element_blank(), panel.border=element_blank(), axis.line.x = element_line
(color="black", size = 1), axis.line.y = element_line(color="black", size = 1
), axis.text.x=element_text(size=10), axis.text.y=element_text(size=10), axis
.title.y=element_text(size = 11), axis.title.x=element_text(size = 11), strip
.text.x=element_text(size=11), legend.position = 'none', plot.title = element
_text(size = 12, face="bold")) + scale_colour_manual(values = c('black', 'red
')) + geom_errorbar(aes(ymin = coef - sd, ymax = coef + sd), width=0.25, colo
r="black") + ylab("RSF Coefficient ") + xlab("Number of Random Points") + ggt
itle("2nd Order: Burn Variables")
b
```




```
#Continuous variables
cont <- beta[beta$Var=="ld1000" | beta$Var=="exp.settle" | beta$Var=="exp.pol
y" | beta$Var=="exp.rds",]

levels(cont$Var)[levels(cont$Var)=="ld1000"] <- "Linear Feature Density"
levels(cont$Var)[levels(cont$Var)=="exp.settle"] <- "Distance to Settlement"
levels(cont$Var)[levels(cont$Var)=="exp.poly"] <- "Distance to Poly. Disturb.
"
levels(cont$Var)[levels(cont$Var)=="exp.rds"] <- "Distance to Road"

c <- ggplot(cont, aes(x=Rpts, y=coef)) + geom_point(aes(color=one_to_one), si
ze=3) + facet_wrap(~Var, scales= "free")
c <- c + theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.mi
nor=element_blank(), panel.border=element_blank(), axis.line.x = element_line
(color="black", size = 1), axis.line.y = element_line(color="black", size = 1
), axis.text.x=element_text(size=10), axis.text.y=element_text(size=10), axis
.title.y=element_text(size=11), axis.title.x=element_text(size=11), strip.tex
t.x=element_text(size=11), legend.position = 'none', plot.title = element_tex
t(size = 12, face="bold")) + scale_colour_manual(values = c('black', 'red'))
+ geom_errorbar(aes(ymin = coef - sd, ymax = coef + sd), width=0.25, color="b
lack") + ylab("RSF Coefficient ") + xlab("Number of Random Points") + ggtitle
("2nd Order: Continuous Variables")
c
```



Literature Cited

Benson, J. F. 2013. Improving rigour and efficiency of use-availability habitat selection analyses with systematic estimation of availability. R. B. O'Hara, editor. Methods in Ecology and Evolution 4:244–251.

Northrup, J. M., M. B. Hooten, C. R. Anderson Jr, and G. Wittemyer. 2013. Practical guidance on characterizing availability in resource selection functions under a use-availability design. Ecology 94:1456–1463.

APPENDIX D: MOVEMENT ANALYSES FOR DEFINING SEASONS

Seasonal changes in resource availability and life history status (e.g. rutting, calving) can cause habitat selection by boreal caribou to vary throughout the year. To assess for these potential changes, we used movement-based analyses to help inform the identification of seasonal periods that were biologically relevant to caribou. These analyses evaluated for changes in daily movement rates and assumed that such changes indicated seasonal changes in caribou behaviour. Here, we outline these analyses and provide R code for each step.

We first calculated mean rates of daily movement (m/hr) across individual caribou in each regional study area (Dehcho, Inuvik, North Slave, Sahtu, and South Slave). These rates were calculated by measuring the Euclidean distance travelled between successive GPS locations, summing these distances for each Julian day, then dividing by 24. The following code executes this process.

```r
#Load necessary libraries
pcks <- c("plyr", "tidyverse", "sp", "sf", "lubridate", "adehabitatLT", "mgcv
", "segmented")
sapply(pcks, require, character = TRUE)

#Import MoveBank data
#all.dat <- read.csv("your_directory\\Movebank_data.csv") #NOT RUN. Load data
from your directory

head(all.dat)

##     trackId individual_id local_identifier location_lat location_long
## 1 BWCA17600     469002982        BWCA17600     62.25693     -116.2770
## 2 BWCA17600     469002982        BWCA17600     62.25686     -116.2768
## 3 BWCA17600     469002982        BWCA17600     62.25724     -116.2753
## 4 BWCA17600     469002982        BWCA17600     62.25744     -116.2757
## 5 BWCA17600     469002982        BWCA17600     62.25718     -116.2760
## 6 BWCA17600     469002982        BWCA17600     62.25646     -116.2687
##             timestamp Region
## 1 2017-03-22 04:00:00 nslave
## 2 2017-03-22 08:00:00 nslave
## 3 2017-03-22 12:00:00 nslave
## 4 2017-03-22 16:00:00 nslave
## 5 2017-03-22 20:00:00 nslave
## 6 2017-03-23 00:00:00 nslave

#Ensure timestamp column is in POSIXct format
all.dat$timestamp <- ymd_hms(all.dat$timestamp)
regs <- unique(all.dat$Region)

#Calculate mean rates of daily movement for each regional study area
movedat <- data.frame()
for(i in regs){
```

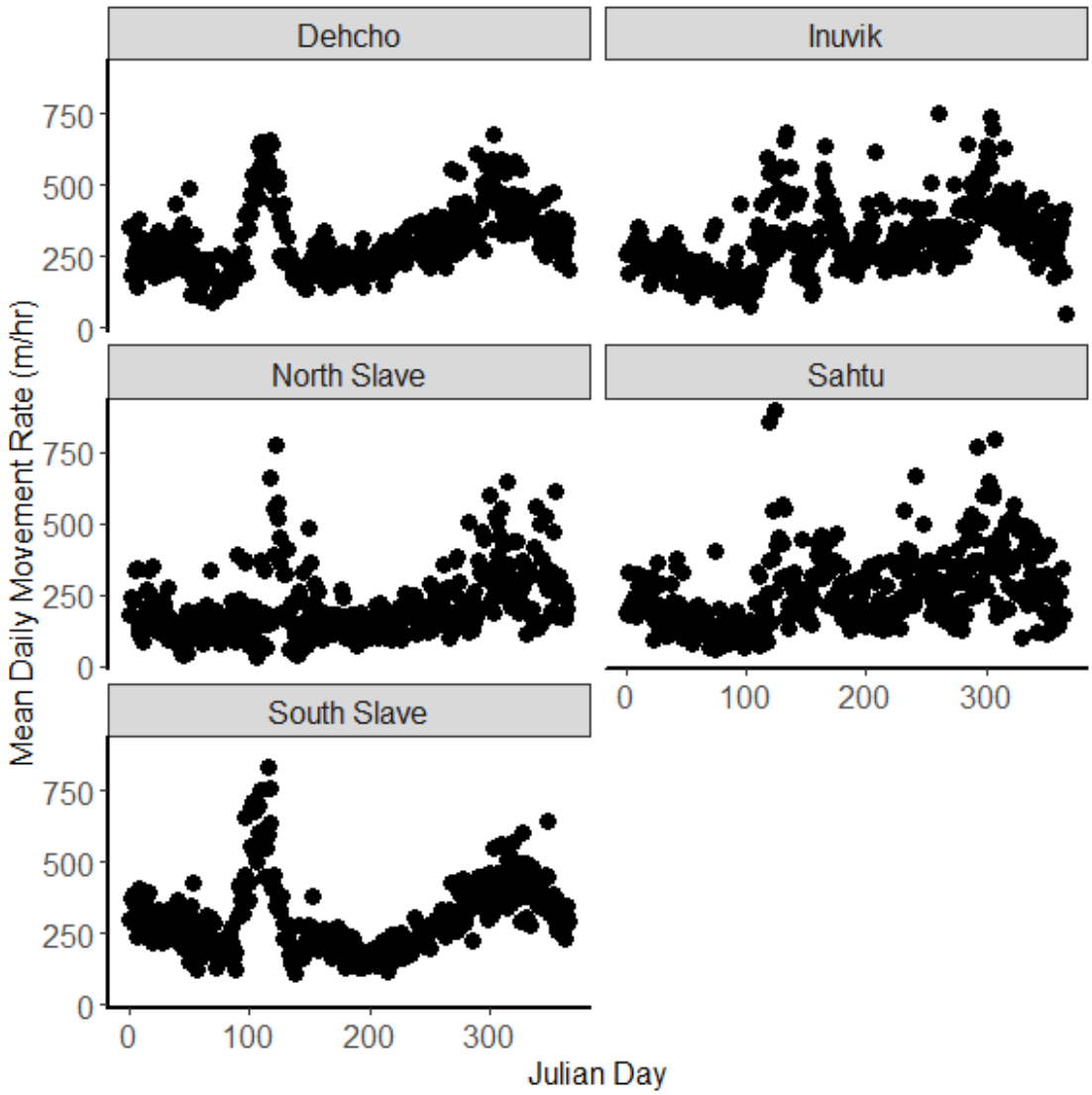
```
  d <- all.dat[all.dat$Region==i,]
  d <- d[!duplicated(d$timestamp),]
  d$local_identifier <- droplevels(d)$local_identifier
  coordinates(d) <- c("location_long", "location_lat")
  proj4string(d) <- CRS("+init=epsg:4326")
  d <- as.data.frame(spTransform(d, CRS("+proj=utm +zone=10 ellps=WGS84"))) #
convert to UTMs to get meters
  idf <- data.frame()
  lt <- as.ltraj(d[6:7], d$timestamp, id = d$local_identifier) #create moveme
nt trajectories for each individual
  for(j in 1:length(lt)){
    boudf <- as.data.frame(lt[[j]]) #store trajectories as data frame
    boudf$AID <- adehabitatLT::burst(lt[j])
    idf <- rbind.data.frame(idf, boudf)
  }
  idf$JD <- as.numeric(strftime(idf$date, format="%j"))
  msum <- ddply(idf, .(AID,JD), summarize, meanmov = sum(dist, na.rm=T)/24) #
individual means on each Julian day
  msum2 <- ddply(msum, .(JD), summarize, moveRate = mean(meanmov, na.rm=T)) #
mean across individuals on each Julian day
  msum2$region <- i
  movedat <- rbind.data.frame(movedat, msum2)
}
head(movedat)
```

```
##   JD moveRate region
## 1  1 179.1217 nslave
## 2  2 240.8502 nslave
## 3  3 232.9673 nslave
## 4  4 227.4012 nslave
## 5  5 333.7590 nslave
## 6  6 344.5698 nslave
```

The following code generates a facet plot that shows the temporal trend in mean rates of daily movement for each regional study area.

```
#Facet plot of all regions
movedat$region <- as.factor(movedat$region)
levels(movedat$region)[levels(movedat$region)=="dehcho"] <- "Dehcho"
levels(movedat$region)[levels(movedat$region)=="nslave"] <- "North Slave"
levels(movedat$region)[levels(movedat$region)=="sslave"] <- "South Slave"
levels(movedat$region)[levels(movedat$region)=="inuvik"] <- "Inuvik"
levels(movedat$region)[levels(movedat$region)=="sahtu"] <- "Sahtu"

p <- ggplot(movedat, aes(x=JD, y=moveRate)) + geom_point(size=3) + facet_wrap
(~region, ncol=2)
p <- p + theme_bw() + theme(panel.grid.major = element_blank(), panel.grid.mi
```

```
nor=element_blank(), panel.border=element_blank(), axis.line.x = element_line
(color="black", size = 1), axis.line.y = element_line(color="black", size = 1
), axis.text.x=element_text(size=12), axis.text.y=element_text(size=12), axis
.title.y=element_text(size=12), axis.title.x=element_text(size=12), strip.tex
t.x=element_text(size=12)) + ylab("Mean Daily Movement Rate (m/hr)") + xlab("
Julian Day")
p
```

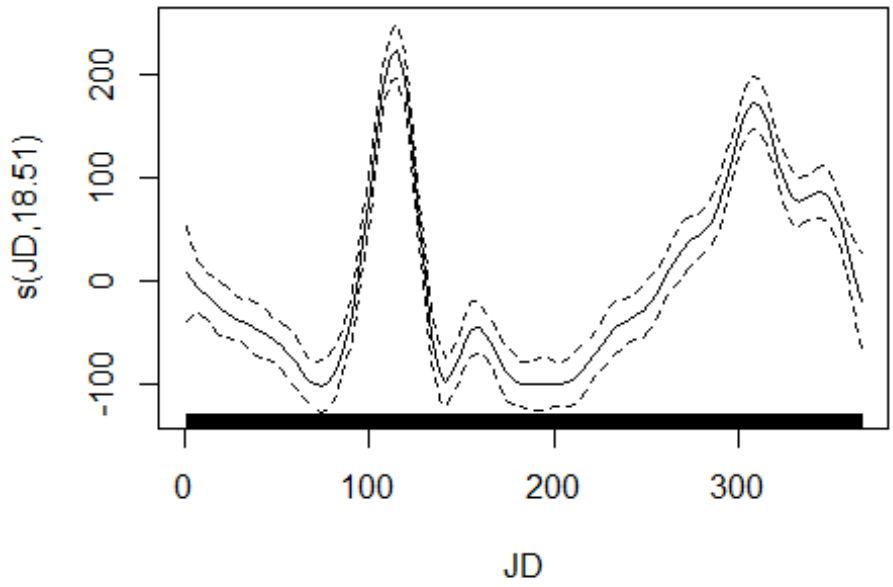


The above plots suggest similar movement patterns among the Dehcho, North Slave and South Slave regional study areas, which corresponds to South grouping identified for second-order resource selection analyses (see Appendix B), and similar movement patterns between the Inuvik and Sahtu regional study areas, which corresponds to the North grouping. We therefore evaluated for seasonal breaks in daily movements in each of these groupings. As noted in the main text, we maintained the estimated mean rates of daily movement for each regional study area and pooled these data into North

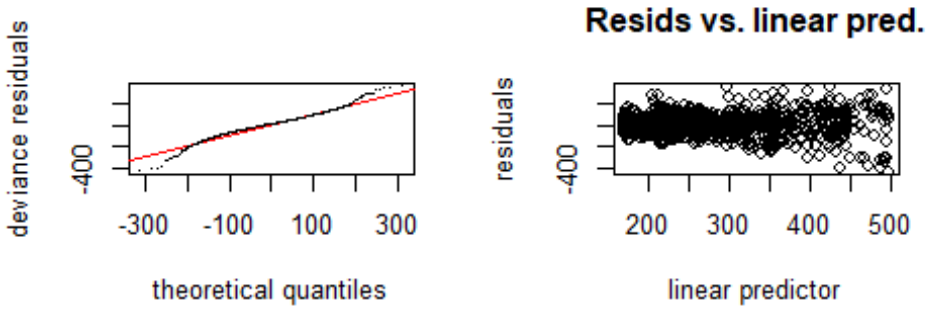
and South data sets. This approach reduces potential spatial bias in movement rates as some regional study areas had much larger sample sizes than others.

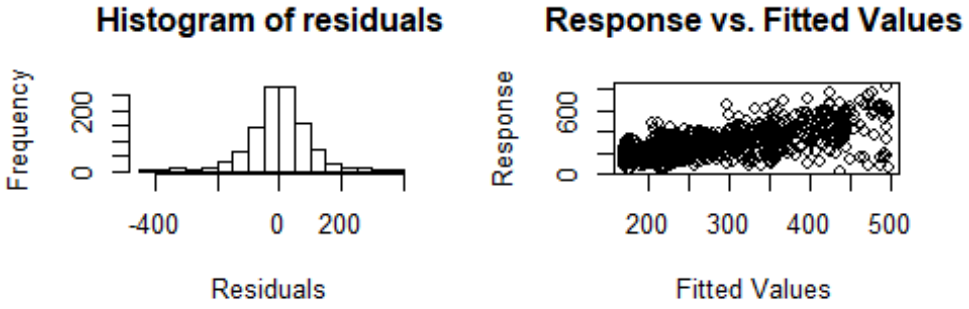
To identify break points in the temporal distribution of grouping's movement rates, we fit generalized additive models (GAMs) to each data set and used the model predictions in a piecewise (or segmented) regression. The estimated break points from these models were assumed to be indicative of seasonal changes in caribou behaviour. The following code demonstrates this modelling process.

```
#South Region
south <- movedat[movedat$region == "South Slave" | movedat$region == "North S
lave" | movedat$region == "Dehcho",]
sr <- gam(moveRate ~ s(JD, bs = "cs", k = 20), data= south)


#plot GAM prediction
plot(sr)
```




```
#GAM diagnostic check
gam.check(sr)
```





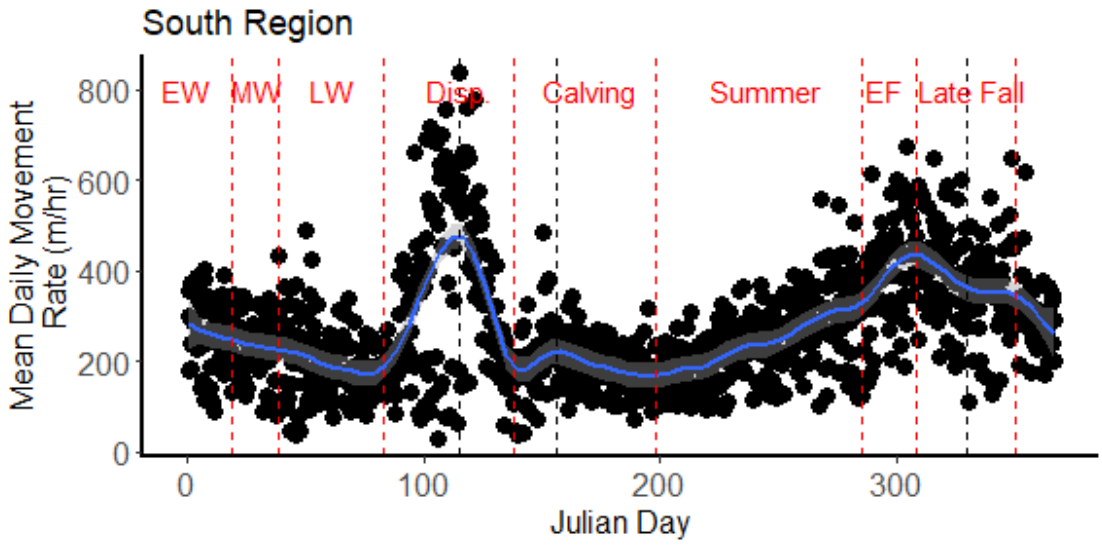

```
##
## Method: GCV   Optimizer: magic
## Smoothing parameter selection converged after 7 iterations.
## The RMS GCV score gradient at convergence was 0.03375366 .
## The Hessian was positive definite.
## Model rank =  20 / 20
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##         k'  edf k-index p-value
## s(JD) 19.0 18.5    1.24       1
```

```
#Create data frame to store GAM predictions
sr.df <- data.frame(JD = south$JD, pred = predict(sr))


#Piecewise regression model
lm.sr <- lm(pred~JD, data=sr.df)
seg.sr <- segmented(lm.sr, seg.Z = ~ JD, psi = c(15, 40, 80, 110, 140, 160, 2
00, 280, 305, 320, 340))
summary(seg.sr)
```

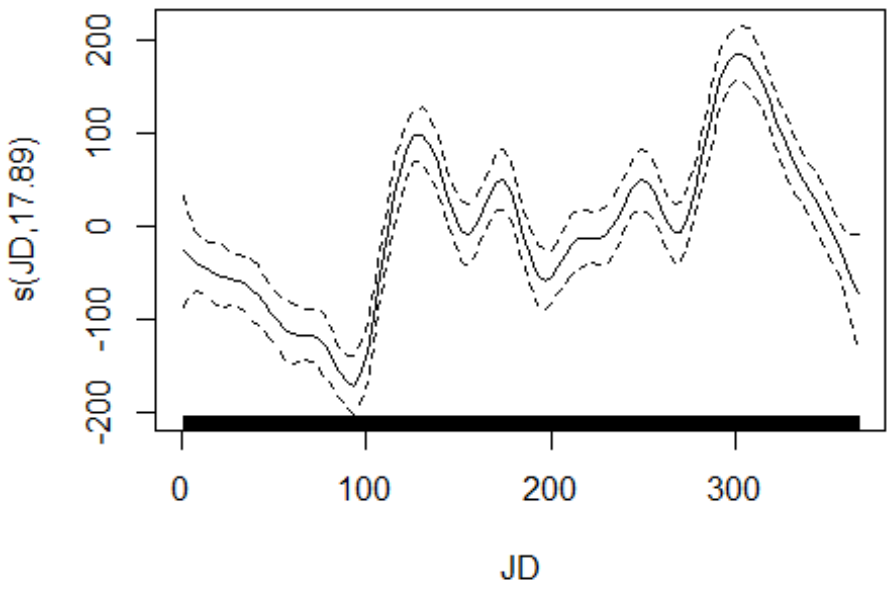
```
##
##  ***Regression Model with Segmented Relationship(s)***
##
## Call:
```

```
## segmented.lm(obj = lm.sr, seg.Z = ~JD, psi = c(15, 40, 80, 110,
##     140, 160, 200, 280, 305, 320, 340))
##
## Estimated Break-Point(s):
##              Est. St.Err
## psi1.JD   18.671  3.046
## psi2.JD   37.044  5.682
## psi3.JD   83.293  0.137
## psi4.JD  114.773  0.076
## psi5.JD  137.656  0.126
## psi6.JD  155.872  0.458
## psi7.JD  198.450  0.399
## psi8.JD  284.825  0.470
## psi9.JD  308.175  0.212
## psi10.JD 328.651  0.428
## psi11.JD 349.534  0.385
##
## Meaningful coefficients of the linear terms:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept) 280.68007    1.85466  151.338   <2e-16 ***
## JD           -1.82891    0.17134  -10.674   <2e-16 ***
## U1.JD         0.81604    0.23305    3.502       NA
## U2.JD        -0.35481    0.16343   -2.171       NA
## U3.JD        12.85010    0.08654  148.481       NA
## U4.JD       -27.20747    0.14068 -193.401       NA
## U5.JD        18.86895    0.20836   90.560       NA
## U6.JD        -4.71390    0.17750  -26.557       NA
## U7.JD         3.52850    0.04916   71.781       NA
## U8.JD         3.65116    0.11241   32.479       NA
## U9.JD       -10.80641    0.18373  -58.816       NA
## U10.JD        5.51709    0.19965   27.633       NA
## U11.JD       -6.42014    0.23516  -27.301       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.532 on 1073 degrees of freedom
## Multiple R-Squared: 0.9946,  Adjusted R-squared: 0.9945
##
## Convergence attained in 4 iter. (rel. change 5.8458e-06)



#Plot estimated seasonal breaks
sr.p <- ggplot(south, aes(x=JD, y=moveRate)) + geom_point(size=3) + geom_smoo
th(method="gam", formula = y ~ s(x, bs = "cs", k = 60))
sr.p <- sr.p + theme_bw() + theme(panel.grid.major = element_blank(), panel.g
rid.minor=element_blank(), panel.border=element_blank(), axis.line.x = elemen
t_line(color="black", size = 1), axis.line.y = element_line(color="black", si
ze = 1), axis.text.x=element_text(size=12), axis.text.y=element_text(size=12)
, axis.title.y=element_text(size=12), axis.title.x=element_text(size=12)) + y
```

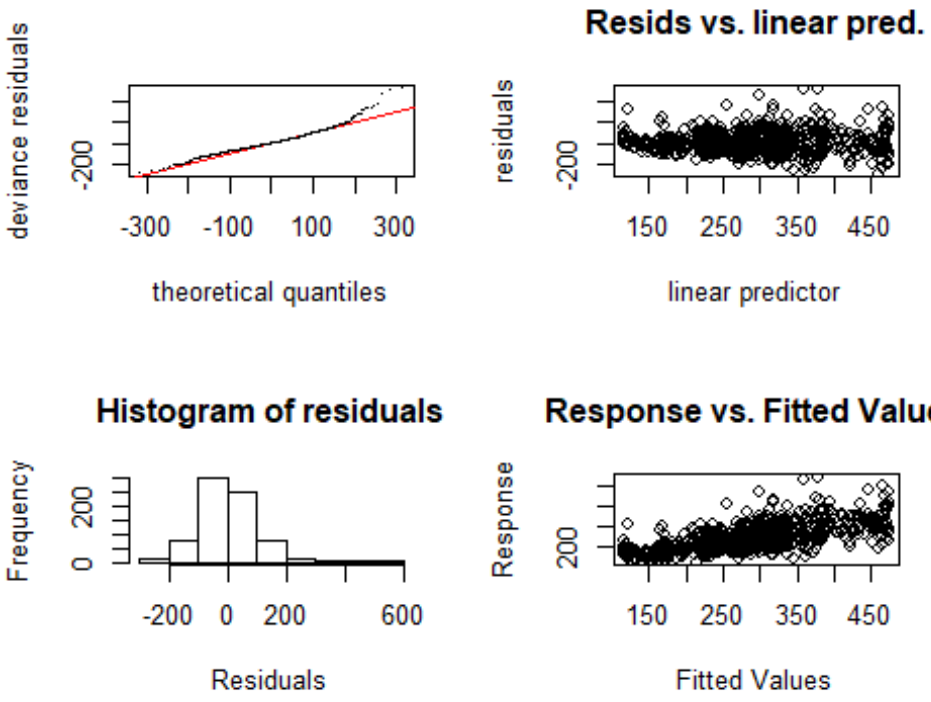
```
lab("Mean Daily Movement\n Rate (m/hr)") + xlab("Julian Day")
sr.p <- sr.p + geom_vline(xintercept = c(19, 39, 83, 138, 198, 285, 308, 350)
, linetype="dashed", color = "red")#12, 83, 112, 118, 137, 156, 198, 286, 304
sr.p <- sr.p + geom_vline(xintercept = c(115, 156, 329), linetype="dashed")
sr.p <- sr.p +  annotate("text", x = 170, y = 800, label = "Calving", color =
"red") + annotate("text", x = 0, y = 800, label = "EW", color = "red") + anno
tate("text", x = 30, y = 800, label = "MW", color = "red") + annotate("text",
x = 62, y = 800, label = "LW", color = "red") + annotate("text", x = 115, y =
800, label = "Disp.", color = "red") + annotate("text", x = 245, y = 800, lab
el = "Summer", color = "red") + annotate("text", x = 295, y = 800, label = "E
F", color = "red") + annotate("text", x = 332, y = 800, label = "Late Fall",
color = "red") + labs(title = "South Region")
sr.p
```




```
#North Region
north <- movedat[movedat$region == "Sahtu" | movedat$region == "Inuvik",]
nr <- gam(moveRate ~ s(JD, bs = "cs", k = 20), data= north)
plot(nr)
```


s(JD,17.89)
200
100
0
-100
-200
0
100
200
300
JD

```
gam.check(nr)
```


deviance residuals
-200
-300
-100
100
300
theoretical quantiles
Resids vs. linear pred.
residuals
-200
150
250
350
450
linear predictor
Histogram of residuals
Frequency
0
200
-200
0
200
600
Residuals
Response vs. Fitted Values
Response
200
150
250
350
450
Fitted Values

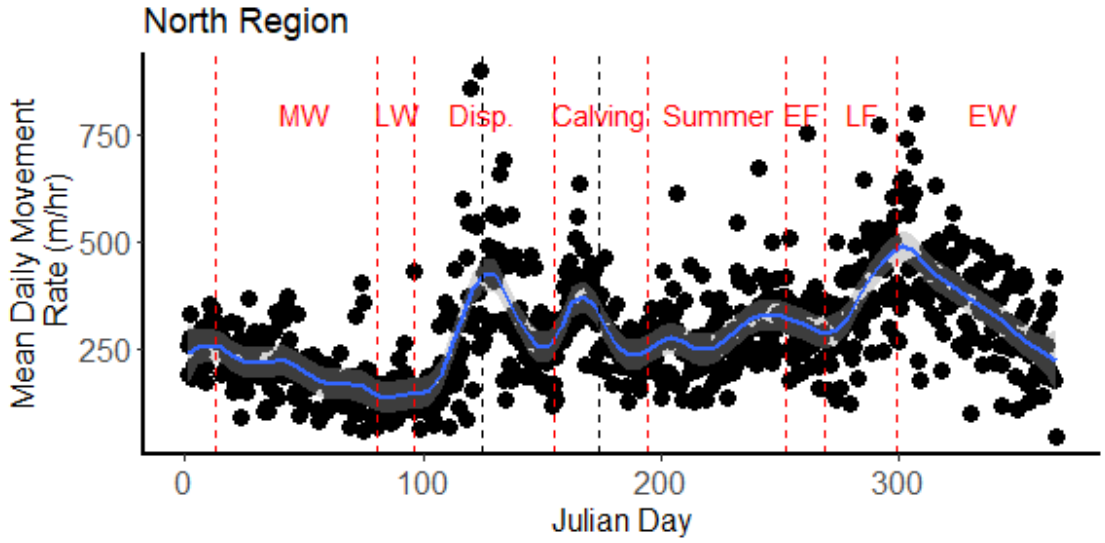
```
##
## Method: GCV   Optimizer: magic
## Smoothing parameter selection converged after 4 iterations.
## The RMS GCV score gradient at convergence was 0.01409022 .
## The Hessian was positive definite.
## Model rank =  20 / 20
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##         k'  edf k-index p-value
## s(JD) 19.0 17.9    0.98    0.28
```

```
nr.df <- data.frame(JD = north$JD, pred = predict(nr))
lm.nr <- lm(pred~JD, data=nr.df)
seg.nr <- segmented(lm.nr, seg.Z = ~ JD, psi = c(40, 70, 90, 120, 150, 175, 2
00, 250, 270, 300))
seg.nr
```

```
## Call: segmented.lm(obj = lm.nr, seg.Z = ~JD, psi = c(40, 70, 90, 120,
##     150, 175, 200, 250, 270, 300))
##
## Meaningful coefficients of the linear terms:
## (Intercept)           JD        U1.JD        U2.JD        U3.JD        U4.
JD
##    260.2780      -0.7823      -0.6120      -1.3429      12.9985     -14.68
99
##       U5.JD        U6.JD        U7.JD        U8.JD        U9.JD       U10.
JD
##      8.3356      -9.9688       7.9420      -5.5936      11.3832     -11.75
90
##
## Estimated Break-Point(s):
##  psi1.JD   psi2.JD   psi3.JD   psi4.JD   psi5.JD   psi6.JD   psi7.JD   psi
8.JD
##     8.00     77.45     95.53    124.67    154.80    173.84    193.93     25
2.01
##  psi9.JD  psi10.JD
##   269.53    298.82
```

```
nr.p <- ggplot(north, aes(x=JD, y=moveRate)) + geom_point(size=3) + geom_smoo
th(method="gam", formula = y ~ s(x, bs = "cs", k = 60))
nr.p <- nr.p + theme_bw() + theme(panel.grid.major = element_blank(), panel.g
rid.minor=element_blank(), panel.border=element_blank(), axis.line.x = elemen
t_line(color="black", size = 1), axis.line.y = element_line(color="black", si
ze = 1), axis.text.x=element_text(size=12), axis.text.y=element_text(size=12)
, axis.title.y=element_text(size=12), axis.title.x=element_text(size=12)) + y
lab("Mean Daily Movement\n Rate (m/hr)") + xlab("Julian Day")
nr.p <- nr.p + geom_vline(xintercept = c(13, 81, 96, 155, 194, 252, 269, 299)
, linetype="dashed", color = "red")#12, 83, 112, 118, 137, 156, 198, 286, 304
```

```
nr.p <- nr.p + geom_vline(xintercept = c(125, 174), linetype="dashed")
nr.p <- nr.p +  annotate("text", x = 174, y = 800, label = "Calving", color =
"red") + annotate("text", x = 340, y = 800, label = "EW", color = "red") + an
notate("text", x = 50, y = 800, label = "MW", color = "red") + annotate("text
", x = 90, y = 800, label = "LW", color = "red") + annotate("text", x = 125,
y = 800, label = "Disp.", color = "red") + annotate("text", x = 225, y = 800,
label = "Summer", color = "red") + annotate("text", x = 260, y = 800, label =
"EF", color = "red") + annotate("text", x = 285, y = 800, label = "LF", color
= "red") + labs(title = "North Region")
nr.p
```



On the following page, the plots for the Northern and Southern groups are combined to allow for a more direct comparison of movement changes in both groups. Note that x-axis has been modified from Julian day to calendar date.

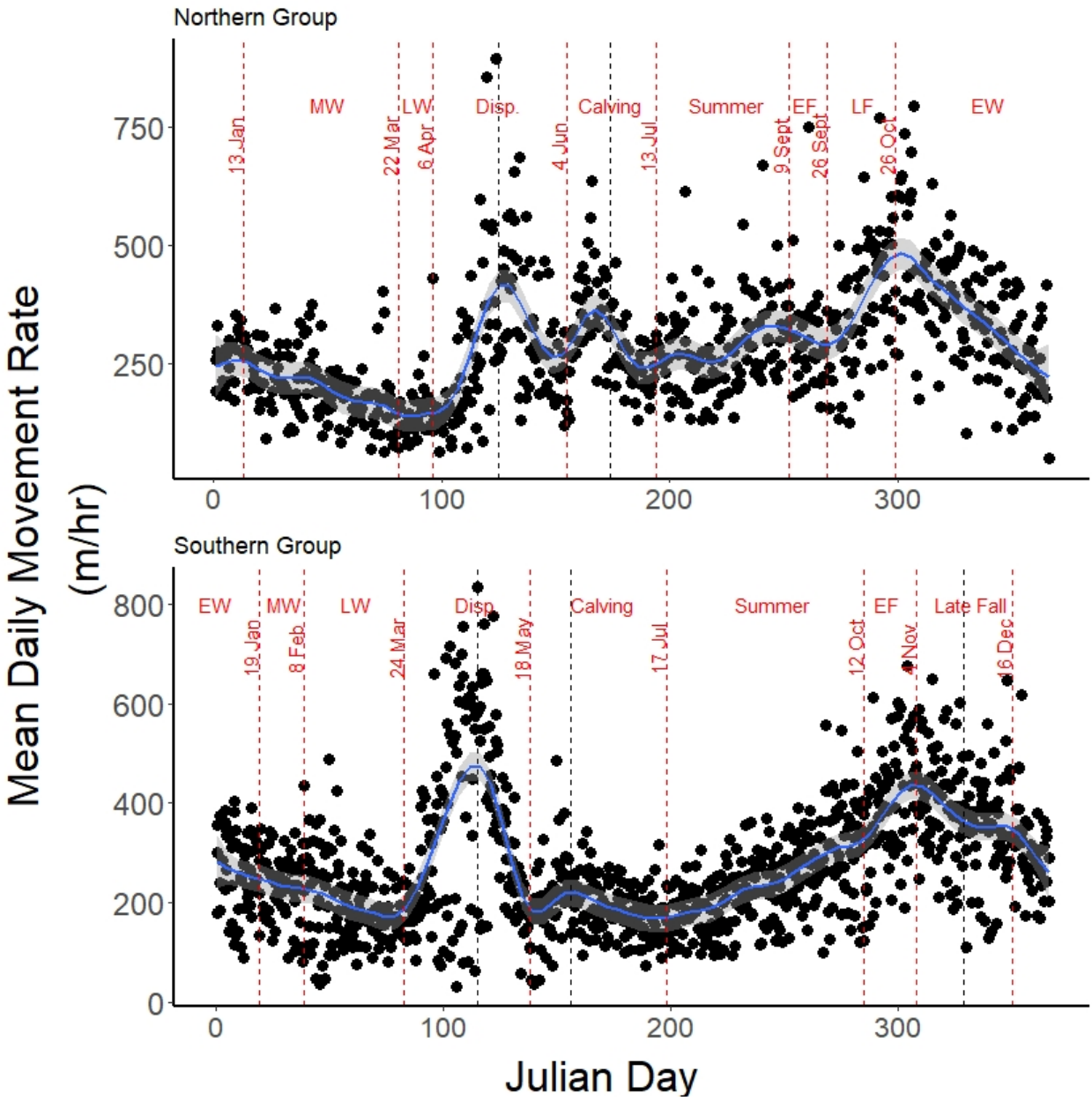


Figure D 1: Seasonal movement patterns of boreal caribou in the Northern and Southern groups (see main text) within the Northwest Territories. Each black dot represents the mean daily movement rate calculated across all individual caribou in a monitoring region (Northern group: Inuvik and Sahtu; Southern group: Dehcho, North Slave, South Slave). Break points indicative of seasonal changes in movement (red dashed lines) were identified using segmented regression applied to the predicted fit of a generalized additive model (blue line).

APPENDIX E: ESTIMATING AND VALIDATING RESOURCE SELECTION FUNCTIONS

We estimated resource selection functions (RSFs) to model seasonal habitat selection by boreal caribou in the Northwest Territories. This appendix illustrates the R code used to estimate and validate RSFs. As an example, we use data from the calving season and estimate an RSF at a second-order scale.

The first step is to load the necessary R packages.

```
pcks <- c("plyr", "tidyverse", "raster", "sf","glmmTMB", "lme4", "adehabitatH
R", "adehabitatLT", "lubridate", "rgdal", "sp", "dummies", "classInt", "caret
", "MuMIn", "forcats", "foreach", "doParallel")
sapply(pcks, require, character = TRUE)
```

Next, the caribou GPS locations and the second-order random locations are imported. These data have had data from all resource covariates previously extracted to them.

```
#Import caribou GPS locations for the calving season.
bou.use <- read.csv("YourFileSystem\\Calving_UsePts_Extract_20200310.csv")


length(unique(bou.use$AID))#Number of caribou

## [1] 276

length(unique(bou.use$AIDYr)) #Number of caribou-seasons

## [1] 480

colnames(bou.use)[31:32] <- c("POINT_X", "POINT_Y")
bou.use <- dplyr::select(bou.use, -X)
bou.use$date <- ymd_hms(bou.use$date)
bou.use$use <- 1


#Display first row of data.
head(bou.use, 1)

##                  date          dx         dy      dist    dt       R2n
## 1 2007-06-04 08:01:55   -8.649065 -292.71090 292.83865 28800      0.00
##     abs.angle  rel.angle       AIDYr    AID   Yr Month Day Hr Min Region
## 1 -1.60033588         NA IN0701.2007 IN0701 2007     6   4  8   1 inuvik
##         Habitat  lc burn      p_broad p_consparse ld1000_10 ld1000_15
## 1 Gwichin North 213   NA 0.0000000000   0.4699325 0.8171973 0.8171910
##   dist_roads10 dist_roads15 dist_maj_rds dist_poly10 dist_poly15 dto_settl
e
## 1     8233.401     8083.873     8247.764    8103.555    8103.555   17495.7
```

```
9
##     POINT_X POINT_Y use
## 1 -867965.0 3264431   1


#Separate into North and South locations.
n.bou <- bou.use[bou.use$Region=="inuvik" | bou.use$Region=="sahtu",]

s.bou <- bou.use[bou.use$Region=="nslave" | bou.use$Region=="sslave" | bou.us
e$Region=="dehcho",]


#Import random points.
#Random points from North MCP
n.rpts <- read.csv("YourFileSystem\\SecondOrder_NorthRegion_RanPts_Extract_Ma
jRds.csv")
colnames(n.rpts)[32:33] <- c("POINT_X", "POINT_Y")
n.rpts <- dplyr::select(n.rpts, -c(X, X.1, X.2))
n.rpts <- mutate(n.rpts, p_broad = p_broad_d + p_broad_o + p_mix_dens) #creat
e variable describing the proportion of broadleaf forest in a 1-km radius
n.rpts <- n.rpts[sample(nrow(n.rpts), 3000),] #subsample to 3000 random point
s based on sensitivity analysis

#Random points from South MCP
s.rpts <- read.csv("YourFileSystem \\SecondOrder_SouthRegion_RanPts_Extract_M
ajRds.csv")
colnames(s.rpts)[32:33] <- c("POINT_X", "POINT_Y")
s.rpts <- dplyr::select(s.rpts, -c(X, X.1, X.2))
s.rpts <- mutate(s.rpts, p_broad = p_broad_d + p_broad_o + p_mix_dens)
s.rpts <- s.rpts[sample(nrow(s.rpts), 3000),] #subsample to 3000 random point
s based on sensitivity analysis

#Next, bind the random points to each individual caribou.
#First, the northern caribou
n.bou <- as_tibble(n.bou)
n.rpts <- as_tibble(n.rpts)
nAIDYr <- unique(n.bou$AIDYr)
n.dat <- tibble()
for(i in nAIDYr){
  caribou <- n.bou %>% dplyr::select(AIDYr, AID, Yr, Region, Habitat, lc:use)
%>% dplyr::filter(AIDYr==i)
  avail <- n.rpts %>% dplyr::select(lc, ld1000_10:burn, p_consparse, p_broad,
dist_maj_rds, POINT_X, POINT_Y) %>% add_column(AIDYr = i, AID = caribou$AID[1
], Yr = caribou$Yr[1], Region = caribou$Region[1], Habitat = caribou$Habitat[
1], use = 0)
  n.dat <- rbind.data.frame(n.dat, caribou, avail)
}

#Then the southern caribou
s.bou <- as_tibble(s.bou)
```

```
s.rpts <- as_tibble(s.rpts)
sAIDYr <- unique(s.bou$AIDYr)
s.dat <- tibble()
for(i in sAIDYr){
  caribou <- s.bou %>% dplyr::select(AIDYr, AID, Yr, Region, Habitat, lc:use)
%>% dplyr::filter(AIDYr==i)
  avail <- s.rpts %>% dplyr::select(lc, ld1000_10:burn, p_consparse, p_broad,
dist_maj_rds, POINT_X, POINT_Y) %>% add_column(AIDYr = i, AID = caribou$AID[1
], Yr = caribou$Yr[1], Region = caribou$Region[1], Habitat = caribou$Habitat[
1], use = 0)
  s.dat <- rbind.data.frame(s.dat, caribou, avail)
}

#Bind the two data sets together
bou.dat <- rbind.data.frame(n.dat, s.dat)

rm(caribou, avail, n.dat, s.dat, s.rpts, n.rpts, bou.use)
```

Prior to estimating the RSF model, we formatted the data, including creating 'dummy' variables for local land-cover, creating exponential decay variables from 'distance-to' variables (see *Methods* in the main report), and matching the timestamp of the location data to the relevant timestamp of the covariate data.

```
#Create a duplicate land cover column to preserve the original data
bou.dat$lc2 <- bou.dat$lc
#Turn NAs in burn column to zeroes
bou.dat$burn[is.na(bou.dat$burn)] <- 0

#Line Density Variables
##Create a continuous variable whose values depend on the time stamp of the l
ocation
bou.dat <- bou.dat %>% mutate(ld1000 = if_else(Yr <= 2010, ld1000_10, ld1000_
15))

#Distance to Roads Variable
##Create a continuous variable whose values depend on the time stamp of the l
ocation
bou.dat <- bou.dat %>% mutate(dist_roads = if_else(Yr <= 2010, dist_roads10,
dist_roads15))
#Exponential decay of distance to roads (decays where 0.95 value occurs at 12
50-m -> Leblond et al. 2011 reported road effects at 1.25 km)
bou.dat$exp.rds <- 1- exp(-0.0025*bou.dat$dist_roads)

#Distance to Major Roads Variable
```

```r
#Exponential decay of distance to roads (decays where 0.95 value occurs at 12
50-m -> Leblond et al. 2011 reported road effects at 1.25 km)
bou.dat$exp.maj.rds <- 1- exp(-0.0025*bou.dat$dist_maj_rds)

#Distance to Polygonal Disturbance Variable
##Create a continuous variable whose values depend on the time stamp of the l
ocation
bou.dat <- bou.dat %>% mutate(dist_poly = if_else(Yr <= 2010, dist_poly10, di
st_poly15))
#Exponential decay of distance to polygonal disturbance (decays to 0.95 by 1-
km)
bou.dat$exp.poly <- 1- exp(-0.003*bou.dat$dist_poly)

#Distance to Settlements Variable
#Exponential decay of distance to settlements (decays to 0.95 by 5-km)
bou.dat$exp.settle <- 1- exp(-0.000625*bou.dat$dto_settle)

#Burn Variables
#Create burn age classes
bou.dat$fire10 <- ifelse(bou.dat$burn >= bou.dat$Yr - 10 & bou.dat$burn < bou
.dat$Yr, 1, 0) #fires 1-10 y.o.
bou.dat$fire20 <- ifelse(bou.dat$burn >= bou.dat$Yr - 20 & bou.dat$burn < bou
.dat$Yr - 10, 1, 0) #fires 11-20 y.o.
bou.dat$fire30 <- ifelse(bou.dat$burn >= bou.dat$Yr - 30 & bou.dat$burn < bou
.dat$Yr - 20, 1, 0) #fires 21-30 y.o
bou.dat$fire40 <- ifelse(bou.dat$burn >= bou.dat$Yr - 40 & bou.dat$burn < bou
.dat$Yr - 30, 1, 0) #fires 31-40 y.o.
bou.dat$fire60 <- ifelse(bou.dat$burn >= bou.dat$Yr - 60 & bou.dat$burn < bou
.dat$Yr - 40, 1, 0) #fires 41-60 y.o.

#then create new burn classes  within land cover variable
bou.dat$lc2 <- ifelse(bou.dat$fire10 == 1, 199, bou.dat$lc2)
bou.dat$lc2 <- ifelse(bou.dat$fire20 == 1, 299, bou.dat$lc2)
bou.dat$lc2 <- ifelse(bou.dat$fire30 == 1, 399, bou.dat$lc2)
bou.dat$lc2 <- ifelse(bou.dat$fire40 == 1, 499, bou.dat$lc2)
bou.dat$lc2 <- ifelse(bou.dat$fire60 == 1, 699, bou.dat$lc2)

#Create dummy variables. Need to first transform back to data frame
bou.dat <- as.data.frame(bou.dat)
bou.dat <- dummy.data.frame(bou.dat, names="lc2")

#Rename variables to something more intuitive
bou.dat <- dplyr::rename(bou.dat, snow = lc212, water = lc220, rock = lc232,
exp.land = lc233, exp.land2 = lc234, bryoids = lc240, t.shrub = lc251, s.shru
b = lc252, t.wet = lc281, s.wet = lc282, h.wet = lc283, herb = lc2100, con.de
ns = lc2211, con.open = lc2212, con.sp = lc2213, broad.d = lc2221, broad.o =
lc2222, mix.dens = lc2231, mix.o = lc2232, burn10 = lc2199, burn20 = lc2299,
burn30 = lc2399, burn40 = lc2499, burn60 = lc2699)
```

```r
#Create non-veg category
bou.dat <- bou.dat %>% mutate(nonveg = snow + rock + exp.land + exp.land2)
bou.dat$nonveg <- ifelse(bou.dat$nonveg >= 1, 1, 0)

#Create an indicator variables for lowlands (t.wet, s.wet, h.wet, herb, con.s
p), uplands non-treed, uplands conifer (con.dens, con.open), uplands broadlea
f.
bou.dat$low <- 0
bou.dat$low[bou.dat$lc==81 | bou.dat$lc==82 | bou.dat$lc==83| bou.dat$lc==100
| bou.dat$lc==213] <- 1

bou.dat$up.nt <- 0
bou.dat$up.nt[bou.dat$lc==40 | bou.dat$lc==51 | bou.dat$lc==52] <- 1

bou.dat$up.con <- 0
bou.dat$up.con[bou.dat$lc==211 | bou.dat$lc==212] <- 1

bou.dat$up.dec <- 0
bou.dat$up.dec[bou.dat$lc==221 | bou.dat$lc==222 | bou.dat$lc==231 | bou.dat$
lc==232] <- 1

#Burn in interactions.
#Burned lowlands
bou.dat$burn10low <- bou.dat$burn10 + bou.dat$low
bou.dat$burn10low <- ifelse(bou.dat$burn10low >= 2, 1, 0)
bou.dat$burn20low <- bou.dat$burn20 + bou.dat$low
bou.dat$burn20low <- ifelse(bou.dat$burn20low >= 2, 1, 0)
bou.dat$burn30low <- bou.dat$burn30 + bou.dat$low
bou.dat$burn30low <- ifelse(bou.dat$burn30low >= 2, 1, 0)
bou.dat$burn40low <- bou.dat$burn40 + bou.dat$low
bou.dat$burn40low <- ifelse(bou.dat$burn40low >= 2, 1, 0)
bou.dat$burn60low <- bou.dat$burn60 + bou.dat$low
bou.dat$burn60low <- ifelse(bou.dat$burn60low >= 2, 1, 0)
#to change 'low' variable to 'low unburned'
bou.dat$low <- ifelse(bou.dat$burn10low==1 | bou.dat$burn20low==1 | bou.dat$b
urn30low==1 | bou.dat$burn40low==1 | bou.dat$burn60low==1, 0, bou.dat$low)
#burn in lowland burn categories
bou.dat$t.wet <- ifelse(bou.dat$burn10low==1 | bou.dat$burn20low==1 | bou.dat
$burn30low==1 | bou.dat$burn40low==1 | bou.dat$burn60low==1, 0, bou.dat$t.wet
)
bou.dat$s.wet <- ifelse(bou.dat$burn10low==1 | bou.dat$burn20low==1 | bou.dat
$burn30low==1 | bou.dat$burn40low==1 | bou.dat$burn60low==1, 0, bou.dat$s.wet
)
bou.dat$h.wet <- ifelse(bou.dat$burn10low==1 | bou.dat$burn20low==1 | bou.dat
$burn30low==1 | bou.dat$burn40low==1 | bou.dat$burn60low==1, 0, bou.dat$h.wet
)
bou.dat$herb <- ifelse(bou.dat$burn10low==1 | bou.dat$burn20low==1 | bou.dat$
burn30low==1 | bou.dat$burn40low==1 | bou.dat$burn60low==1, 0, bou.dat$herb)
bou.dat$con.sp <- ifelse(bou.dat$burn10low==1 | bou.dat$burn20low==1 | bou.da
```

```
t$burn30low==1 | bou.dat$burn40low==1 | bou.dat$burn60low==1, 0, bou.dat$con.
sp)

#Burned non-treed uplands
bou.dat$burn10up.nt <- bou.dat$burn10 + bou.dat$up.nt
bou.dat$burn10up.nt <- ifelse(bou.dat$burn10up.nt >= 2, 1, 0)
bou.dat$burn20up.nt <- bou.dat$burn20 + bou.dat$up.nt
bou.dat$burn20up.nt <- ifelse(bou.dat$burn20up.nt >= 2, 1, 0)
bou.dat$burn30up.nt <- bou.dat$burn30 + bou.dat$up.nt
bou.dat$burn30up.nt <- ifelse(bou.dat$burn30up.nt >= 2, 1, 0)
bou.dat$burn40up.nt <- bou.dat$burn40 + bou.dat$up.nt
bou.dat$burn40up.nt <- ifelse(bou.dat$burn40up.nt >= 2, 1, 0)
bou.dat$burn60up.nt <- bou.dat$burn60 + bou.dat$up.nt
bou.dat$burn60up.nt <- ifelse(bou.dat$burn60up.nt >= 2, 1, 0)
#to change 'up.nt' variable to 'up.nt unburned'
bou.dat$up.nt <- ifelse(bou.dat$burn10up.nt==1 | bou.dat$burn20up.nt==1 | bou
.dat$burn30up.nt==1 | bou.dat$burn40up.nt==1 | bou.dat$burn60up.nt==1, 0, bou
.dat$up.nt)
#burn in not-treed upland burn categories
bou.dat$t.shrub <- ifelse(bou.dat$burn10up.nt==1 | bou.dat$burn20up.nt==1 | b
ou.dat$burn30up.nt==1 | bou.dat$burn40up.nt==1 | bou.dat$burn60up.nt==1, 0, b
ou.dat$t.shrub)
bou.dat$s.shrub <- ifelse(bou.dat$burn10up.nt==1 | bou.dat$burn20up.nt==1 | b
ou.dat$burn30up.nt==1 | bou.dat$burn40up.nt==1 | bou.dat$burn60up.nt==1, 0, b
ou.dat$s.shrub)
bou.dat$bryoids <- ifelse(bou.dat$burn10up.nt==1 | bou.dat$burn20up.nt==1 | b
ou.dat$burn30up.nt==1 | bou.dat$burn40up.nt==1 | bou.dat$burn60up.nt==1, 0, b
ou.dat$bryoids)

#Burned upland conifer
bou.dat$burn10up.con <- bou.dat$burn10 + bou.dat$up.con
bou.dat$burn10up.con <- ifelse(bou.dat$burn10up.con >= 2, 1, 0)
bou.dat$burn20up.con <- bou.dat$burn20 + bou.dat$up.con
bou.dat$burn20up.con <- ifelse(bou.dat$burn20up.con >= 2, 1, 0)
bou.dat$burn30up.con <- bou.dat$burn30 + bou.dat$up.con
bou.dat$burn30up.con <- ifelse(bou.dat$burn30up.con >= 2, 1, 0)
bou.dat$burn40up.con <- bou.dat$burn40 + bou.dat$up.con
bou.dat$burn40up.con <- ifelse(bou.dat$burn40up.con >= 2, 1, 0)
bou.dat$burn60up.con <- bou.dat$burn60 + bou.dat$up.con
bou.dat$burn60up.con <- ifelse(bou.dat$burn60up.con >= 2, 1, 0)
#to change 'up.con' variable to 'up.con unburned'
bou.dat$up.con <- ifelse(bou.dat$burn10up.con==1 | bou.dat$burn20up.con==1 |
bou.dat$burn30up.con==1 | bou.dat$burn40up.con==1 | bou.dat$burn60up.con==1,
0, bou.dat$up.con)
#burn in upland conifer burn categories
bou.dat$con.dens <- ifelse(bou.dat$burn10up.con==1 | bou.dat$burn20up.con==1
| bou.dat$burn30up.con==1 | bou.dat$burn40up.con==1 | bou.dat$burn60up.con==1
, 0, bou.dat$con.dens)
bou.dat$con.open <- ifelse(bou.dat$burn10up.con==1 | bou.dat$burn20up.con==1
| bou.dat$burn30up.con==1 | bou.dat$burn40up.con==1 | bou.dat$burn60up.con==1
```

```
, 0, bou.dat$con.open)

#Burned broadleaf (or deciduous)
bou.dat$burn10up.dec <- bou.dat$burn10 + bou.dat$up.dec
bou.dat$burn10up.dec <- ifelse(bou.dat$burn10up.dec >= 2, 1, 0)
bou.dat$burn20up.dec <- bou.dat$burn20 + bou.dat$up.dec
bou.dat$burn20up.dec <- ifelse(bou.dat$burn20up.dec >= 2, 1, 0)
bou.dat$burn30up.dec <- bou.dat$burn30 + bou.dat$up.dec
bou.dat$burn30up.dec <- ifelse(bou.dat$burn30up.dec >= 2, 1, 0)
bou.dat$burn40up.dec <- bou.dat$burn40 + bou.dat$up.dec
bou.dat$burn40up.dec <- ifelse(bou.dat$burn40up.dec >= 2, 1, 0)
bou.dat$burn60up.dec <- bou.dat$burn60 + bou.dat$up.dec
bou.dat$burn60up.dec <- ifelse(bou.dat$burn60up.dec >= 2, 1, 0)
#to change 'up.dec' variable to 'up.dec unburned'
bou.dat$up.dec <- ifelse(bou.dat$burn10up.dec==1 | bou.dat$burn20up.dec==1 |
bou.dat$burn30up.dec==1 | bou.dat$burn40up.dec==1 | bou.dat$burn60up.dec==1,
0, bou.dat$up.dec)
#burn in upland deciduous burn categories
bou.dat$broad.d <- ifelse(bou.dat$burn10up.dec==1 | bou.dat$burn20up.dec==1 |
bou.dat$burn30up.dec==1 | bou.dat$burn40up.dec==1 | bou.dat$burn60up.dec==1,
0, bou.dat$broad.d)
bou.dat$broad.o <- ifelse(bou.dat$burn10up.dec==1 | bou.dat$burn20up.dec==1 |
bou.dat$burn30up.dec==1 | bou.dat$burn40up.dec==1 | bou.dat$burn60up.dec==1,
0, bou.dat$broad.o)
bou.dat$mix.dens <- ifelse(bou.dat$burn10up.dec==1 | bou.dat$burn20up.dec==1
| bou.dat$burn30up.dec==1 | bou.dat$burn40up.dec==1 | bou.dat$burn60up.dec==1
, 0, bou.dat$mix.dens)
bou.dat$mix.o <- ifelse(bou.dat$burn10up.dec==1 | bou.dat$burn20up.dec==1 | b
ou.dat$burn30up.dec==1 | bou.dat$burn40up.dec==1 | bou.dat$burn60up.dec==1, 0
, bou.dat$mix.o)
```

With data formatted, the next step is to estimate the RSF. To do so, we fit a generalized linear mixed-effects model using the 'glmmTMB' function from the 'glmmTMB' package. Models were fit to the whole data set and a data set where caribou in the Mackenzie sub-region were excluded.

```
#Run mixed-effects model
full.m <- glmmTMB(use ~ bryoids + t.shrub + s.shrub + t.wet + s.wet + h.wet +
herb + con.open + con.sp + broad.d + broad.o + mix.o + mix.dens + water + non
veg + p_broad + p_consparse + burn10low + burn20low + burn30low + burn40low +
burn60low + burn10up.nt + burn20up.nt + burn30up.nt + burn40up.nt + burn60up.
nt + burn10up.con + burn20up.con + burn30up.con + burn40up.con + burn60up.con
+ burn10up.dec + burn20up.dec + burn30up.dec + burn40up.dec + burn60up.dec +
ld1000 + exp.maj.rds + exp.poly + exp.settle + (1|Habitat/AIDYr), family=bino
mial, data=bou.dat)

#Run model with Mackenzie caribou excluded
```

```
bou.dat.noMac <- bou.dat[bou.dat$Habitat != "Mackenzie",]
bou.dat.noMac$Habitat <- droplevels(bou.dat.noMac)$Habitat

noMac <- glmmTMB(use ~ bryoids + t.shrub + s.shrub + t.wet + s.wet + h.wet +
herb + con.open + con.sp + broad.d + broad.o + mix.o + mix.dens + water + non
veg + p_broad + p_consparse + burn10low + burn20low + burn30low + burn40low +
burn60low + burn10up.nt + burn20up.nt + burn30up.nt + burn40up.nt + burn60up.
nt + burn10up.con + burn20up.con + burn30up.con + burn40up.con + burn60up.con
+ burn10up.dec + burn20up.dec + burn30up.dec + burn40up.dec + burn60up.dec +
ld1000 + exp.maj.rds + exp.poly + exp.settle + (1|Habitat/AIDYr), family=bino
mial, data=bou.dat.noMac)
```

The final step is to evaluate the predictive performance of the RSF model. We used *k*-fold cross validation, which involves iteratively partitioning the data by individual caribou into a training set (4 folds or 80% of the individual caribou), estimating the RSF, then testing model predictions on the withheld caribou. See the *Methods* section in the main report for further details. Because RSF models with these large data sets can take > 2 hours to converge, we used parallel computing to speed up the process. The results are returned in list form, which is then transformed into a data frame.

```
#If not already done before
bou.dat.noMac <- bou.dat[bou.dat$Habitat != "Mackenzie",]
bou.dat.noMac$Habitat <- droplevels(bou.dat.noMac)$Habitat

#get range (available) points. these have already been formatted (year = 2017
)
rpts <- read.csv("I:\\Contract_Work\\ABMI\\NWT_RSF\\Tables\\SecondOrderRSFDat
a\\SecondOrderRandomPoints_Formatted_20200131.csv")

#Use parallel computing
detectCores() #My computer has 8 cores


#Specify that 5 cores be used
myCluster <- makeCluster(5, type = "PSOCK")
registerDoParallel(myCluster)

kAID <- unique(bou.dat.noMac$AID) #specify animal IDs


#Run the 10 iterations, which will be spread among the 5 cores.  Need to spec
ify the R packages to be used within the 'foreach' loop.
kfold.res <- foreach(i = 1:10, .packages = c("caret", "glmmTMB", "MuMIn", "cl
assInt"), .errorhandling = 'pass') %dopar% {
  folds <- createFolds(kAID, k=5) #creates 5 groups of data

  test <- kAID[folds[[1]][1:length(folds[[1]])]]
```

```
  train <- bou.dat.noMac[!(bou.dat.noMac$AID %in% test),]

  testpts <- bou.dat.noMac[(bou.dat.noMac$AID %in% test),]
  testrange <- testpts[testpts$use==0,]
  testpts <- testpts[testpts$use==1,]
  testpts <- testpts[complete.cases(testpts),]

  #train model
  km <- glmmTMB(use ~ bryoids + t.shrub + s.shrub + t.wet + s.wet + h.wet + h
erb + con.open + con.sp + broad.d + broad.o + mix.o + mix.dens + water + nonv
eg + p_broad + p_consparse + burn10low + burn20low + burn30low + burn40low +
burn60low + burn10up.nt + burn20up.nt + burn30up.nt + burn40up.nt + burn60up.
nt + burn10up.con + burn20up.con + burn30up.con + burn40up.con + burn60up.con
+ burn10up.dec + burn20up.dec + burn30up.dec + burn40up.dec + burn60up.dec +
ld1000 + exp.maj.rds + exp.poly + exp.settle + (1|Habitat/AIDYr), family=bino
mial, data=train)
  betas <- coefTable(km)

  #kfold (map-based): availability is constant for each caribou (see Methods
in main report)
  av <- rpts
  av <- av[complete.cases(av),]

  map <- exp(betas[2,1]*av$bryoids + betas[3,1]*av$t.shrub + betas[4,1]*av$s.
shrub + betas[5,1]*av$t.wet + betas[6,1]*av$s.wet + betas[7,1]*av$h.wet + bet
as[8,1]*av$herb + betas[9,1]*av$con.open + betas[10,1]*av$con.sp + betas[11,1
]*av$broad.d + betas[12,1]*av$broad.o + betas[13,1]*av$mix.o + betas[14,1]*av
$mix.dens + betas[15,1]*av$water + betas[16,1]*av$nonveg + betas[17,1]*av$p_b
road + betas[18,1]*av$p_consparse + betas[19,1]*av$burn10low + betas[20,1]*av
$burn20low + betas[21,1]*av$burn30low + betas[22,1]*av$burn40low + betas[23,1
]*av$burn60low + betas[24,1]*av$burn10up.nt + betas[25,1]*av$burn20up.nt + be
tas[26,1]*av$burn30up.nt + betas[27,1]*av$burn40up.nt + betas[28,1]*av$burn60
up.nt + betas[29,1]*av$burn10up.con + betas[30,1]*av$burn20up.con + betas[31,
1]*av$burn30up.con + betas[32,1]*av$burn40up.con + betas[33,1]*av$burn60up.co
n + betas[34,1]*av$burn10up.dec + betas[35,1]*av$burn20up.dec + betas[36,1]*a
v$burn30up.dec + betas[37,1]*av$burn40up.dec + betas[38,1]*av$burn60up.dec +
betas[39,1]*av$ld1000 + betas[40,1]*av$exp.maj.rds + betas[41,1]*av$exp.poly
+ betas[42,1]*av$exp.settle)

  #Standardize
  mapN <- (map - min(map))/(max(map)-min(map))

  #Split range points into equal intervals from min to max. This creates deci
le bins based on availability
  eq <- classIntervals(mapN, 10, style="quantile")
  eq <- eq$brks

  testpred <- exp(betas[2,1]*testpts$bryoids + betas[3,1]*testpts$t.shrub + b
etas[4,1]*testpts$s.shrub + betas[5,1]*testpts$t.wet + betas[6,1]*testpts$s.w
```

```
et + betas[7,1]*testpts$h.wet + betas[8,1]*testpts$herb + betas[9,1]*testpts$
con.open + betas[10,1]*testpts$con.sp + betas[11,1]*testpts$broad.d + betas[1
2,1]*testpts$broad.o + betas[13,1]*testpts$mix.o + betas[14,1]*testpts$mix.de
ns + betas[15,1]*testpts$water + betas[16,1]*testpts$nonveg + betas[17,1]*tes
tpts$p_broad + betas[18,1]*testpts$p_consparse + betas[19,1]*testpts$burn10lo
w + betas[20,1]*testpts$burn20low + betas[21,1]*testpts$burn30low + betas[22,
1]*testpts$burn40low + betas[23,1]*testpts$burn60low + betas[24,1]*testpts$bu
rn10up.nt + betas[25,1]*testpts$burn20up.nt + betas[26,1]*testpts$burn30up.nt
+ betas[27,1]*testpts$burn40up.nt + betas[28,1]*testpts$burn60up.nt + betas[2
9,1]*testpts$burn10up.con + betas[30,1]*testpts$burn20up.con + betas[31,1]*te
stpts$burn30up.con + betas[32,1]*testpts$burn40up.con + betas[33,1]*testpts$b
urn60up.con + betas[34,1]*testpts$burn10up.dec + betas[35,1]*testpts$burn20up
.dec + betas[36,1]*testpts$burn30up.dec + betas[37,1]*testpts$burn40up.dec +
betas[38,1]*testpts$burn60up.dec + betas[39,1]*testpts$ld1000 + betas[40,1]*t
estpts$exp.maj.rds + betas[41,1]*testpts$exp.poly + betas[42,1]*testpts$exp.s
ettle)

  testpredN <- (testpred - min(map))/(max(map)-min(map))

  #Classify predictions of range points
  bin <- ifelse(mapN < eq[[2]], 1, ifelse(mapN < eq[[3]], 2, ifelse(mapN < eq
[[4]], 3, ifelse(mapN < eq[[5]], 4, ifelse(mapN < eq[[6]], 5, ifelse(mapN < e
q[[7]] , 6, ifelse(mapN < eq[[8]], 7, ifelse(mapN < eq[[9]], 8, ifelse(mapN <
eq[[10]], 9, 10)))))))))
  #Classify predictions of test points
  pts.use <- ifelse(testpredN < eq[[2]], 1, ifelse(testpredN < eq[[3]], 2, if
else(testpredN < eq[[4]], 3, ifelse(testpredN < eq[[5]], 4, ifelse(testpredN
< eq[[6]], 5, ifelse(testpredN < eq[[7]] , 6, ifelse(testpredN < eq[[8]], 7,
ifelse(testpredN < eq[[9]], 8, ifelse(testpredN < eq[[10]], 9, 10)))))))))

  #Sum range predictions
  freq.a <- c(sum(bin==1), sum(bin==2), sum(bin==3), sum(bin==4), sum(bin==5)
, sum(bin==6), sum(bin==7), sum(bin==8), sum(bin==9), sum(bin==10))
  #Sum test pt predictions
  freq.u <- c(sum(pts.use==1), sum(pts.use==2), sum(pts.use==3), sum(pts.use=
=4), sum(pts.use==5), sum(pts.use==6), sum(pts.use==7), sum(pts.use==8), sum(
pts.use==9), sum(pts.use==10))

  #Selection ratios
  a <- freq.a/length(bin)
  u <- freq.u/length(pts.use)
  sr <- u/a

  #Calculate r for area-adjusted frequency
  spear <- cor.test(sr, 1:10, method='spearman')

  #kfold (model-based): availability is specific to each individual caribou (
see Methods section in main report).
  uAIDYr <- unique(testpts$AIDYr)
```

```
  freq.aM <- rep(0,10)
  freq.uM <- rep(0,10)
  binM.all <- vector()
  pts.useM.all <- vector()
  for(k in uAIDYr){
    submap <- testrange[testrange$AIDYr==k,]
    submap <- submap[complete.cases(submap),]

    mapM <- exp(betas[2,1]*submap$bryoids + betas[3,1]*submap$t.shrub + betas
[4,1]*submap$s.shrub + betas[5,1]*submap$t.wet + betas[6,1]*submap$s.wet + be
tas[7,1]*submap$h.wet + betas[8,1]*submap$herb + betas[9,1]*submap$con.open +
betas[10,1]*submap$con.sp + betas[11,1]*submap$broad.d + betas[12,1]*submap$b
road.o + betas[13,1]*submap$mix.o + betas[14,1]*submap$mix.dens + betas[15,1]
*submap$water + betas[16,1]*submap$nonveg + betas[17,1]*submap$p_broad + beta
s[18,1]*submap$p_consparse + betas[19,1]*submap$burn10low + betas[20,1]*subma
p$burn20low + betas[21,1]*submap$burn30low + betas[22,1]*submap$burn40low + b
etas[23,1]*submap$burn60low + betas[24,1]*submap$burn10up.nt + betas[25,1]*su
bmap$burn20up.nt + betas[26,1]*submap$burn30up.nt + betas[27,1]*submap$burn40
up.nt + betas[28,1]*submap$burn60up.nt + betas[29,1]*submap$burn10up.con + be
tas[30,1]*submap$burn20up.con + betas[31,1]*submap$burn30up.con + betas[32,1]
*submap$burn40up.con + betas[33,1]*submap$burn60up.con + betas[34,1]*submap$b
urn10up.dec + betas[35,1]*submap$burn20up.dec + betas[36,1]*submap$burn30up.d
ec + betas[37,1]*submap$burn40up.dec + betas[38,1]*submap$burn60up.dec + beta
s[39,1]*submap$ld1000 + betas[40,1]*submap$exp.maj.rds + betas[41,1]*submap$e
xp.poly + betas[42,1]*submap$exp.settle)

    #Standardize
    mapMN <- (mapM - min(mapM))/(max(mapM)-min(mapM))

    #Split range points into equal intervals from min to max. This creates de
cile bins based on availability
    eqM <- classIntervals(mapMN, 10, style="quantile")
    eqM <- eqM$brks

    yrpts <- testpts[testpts$AIDYr==k,]

    yrpred <- exp(betas[2,1]*yrpts$bryoids + betas[3,1]*yrpts$t.shrub + betas
[4,1]*yrpts$s.shrub + betas[5,1]*yrpts$t.wet + betas[6,1]*yrpts$s.wet + betas
[7,1]*yrpts$h.wet + betas[8,1]*yrpts$herb + betas[9,1]*yrpts$con.open + betas
[10,1]*yrpts$con.sp + betas[11,1]*yrpts$broad.d + betas[12,1]*yrpts$broad.o +
betas[13,1]*yrpts$mix.o + betas[14,1]*yrpts$mix.dens + betas[15,1]*yrpts$wate
r + betas[16,1]*yrpts$nonveg + betas[17,1]*yrpts$p_broad + betas[18,1]*yrpts$
p_consparse + betas[19,1]*yrpts$burn10low + betas[20,1]*yrpts$burn20low + bet
as[21,1]*yrpts$burn30low + betas[22,1]*yrpts$burn40low + betas[23,1]*yrpts$bu
rn60low + betas[24,1]*yrpts$burn10up.nt + betas[25,1]*yrpts$burn20up.nt + bet
as[26,1]*yrpts$burn30up.nt + betas[27,1]*yrpts$burn40up.nt + betas[28,1]*yrpt
s$burn60up.nt + betas[29,1]*yrpts$burn10up.con + betas[30,1]*yrpts$burn20up.c
on + betas[31,1]*yrpts$burn30up.con + betas[32,1]*yrpts$burn40up.con + betas[
33,1]*yrpts$burn60up.con + betas[34,1]*yrpts$burn10up.dec + betas[35,1]*yrpts
```

```
$burn20up.dec + betas[36,1]*yrpts$burn30up.dec + betas[37,1]*yrpts$burn40up.d
ec + betas[38,1]*yrpts$burn60up.dec + betas[39,1]*yrpts$ld1000 + betas[40,1]*
yrpts$exp.maj.rds + betas[41,1]*yrpts$exp.poly + betas[42,1]*yrpts$exp.settle
)

    yrpredN <- (yrpred - min(mapM))/(max(mapM)-min(mapM))

    #Classify predictions of range points
    binM <- ifelse(mapMN < eqM[[2]], 1, ifelse(mapMN < eqM[[3]], 2, ifelse(ma
pMN < eqM[[4]], 3, ifelse(mapMN < eqM[[5]], 4, ifelse(mapMN < eqM[[6]], 5, if
else(mapMN < eqM[[7]] , 6, ifelse(mapMN < eqM[[8]], 7, ifelse(mapMN < eqM[[9]
], 8, ifelse(mapMN < eqM[[10]], 9, 10)))))))))
    binM.all <- c(binM.all, binM)
    #Classify predictions of test points
    pts.useM <- ifelse(yrpredN < eqM[[2]], 1, ifelse(yrpredN < eqM[[3]], 2, i
felse(yrpredN < eqM[[4]], 3, ifelse(yrpredN < eqM[[5]], 4, ifelse(yrpredN < e
qM[[6]], 5, ifelse(yrpredN < eqM[[7]] , 6, ifelse(yrpredN < eqM[[8]], 7, ifel
se(yrpredN < eqM[[9]], 8, ifelse(yrpredN < eqM[[10]], 9, 10)))))))))
    pts.useM.all <- c(pts.useM.all, pts.useM)

    #Sum range predictions
    freq.aM2 <- c(sum(binM==1), sum(binM==2), sum(binM==3), sum(binM==4), sum
(binM==5), sum(binM==6), sum(binM==7), sum(binM==8), sum(binM==9), sum(binM==
10))
    #Sum test pt predictions
    freq.uM2 <- c(sum(pts.useM==1), sum(pts.useM==2), sum(pts.useM==3), sum(p
ts.useM==4), sum(pts.useM==5), sum(pts.useM==6), sum(pts.useM==7), sum(pts.us
eM==8), sum(pts.useM==9), sum(pts.useM==10))

    freq.aM <- freq.aM + freq.aM2
    freq.uM <- freq.uM + freq.uM2
  }
    #Selection ratios
    aM <- freq.aM/length(binM.all)
    uM <- freq.uM/length(pts.useM.all)
    srM <- uM/aM

    #Calculate r for area-adjusted frequency
    spearM <- cor.test(srM, 1:10, method='spearman')

    data.frame(Iteration = i, Spearman.Corr.Map = unname(spear[[4]]), p.value
.Map = spear[[3]], Spearman.Corr.Model = unname(spearM[[4]]), p.value.Model =
spearM[[3]])

}
stopCluster(myCluster)

#Collate results from list format to data frame
```

```r
kfold.df <- data.frame()
for(i in c(1:10)){
  df <- kfold.res[[i]]
  kfold.df <- rbind.data.frame(kfold.df, df)
}
#kfold.df ###NOT RUN
```

APPENDIX F: MODEL COEFFICIENTS FROM RESOURCE SELECTION FUNCTIONS

To assess seasonal habitat selection by boreal caribou in the Northwest Territories, resource selection functions (RSFs) were estimated at two separate scales (second- and third-order) and across seven distinct seasons within each scale. Here, model coefficients and their standard errors are shown for seasonal second-order RSFs (Table F 1), seasonal third-order RSFs (Table F 2), and all-year RSFs at both scales (Table F 3).

Table F 1: Model coefficients (β), their standard errors (SE) and *p*-values (*p*) from seasonal resource selection functions estimated at a second-order scale for boreal caribou in the Northwest Territories.

	Calving (*n* = 249 caribou [444 caribou-seasons])			Summer (*n* = 211 caribou [336 caribou-seasons])			Early Fall (*n* = 221 caribou [364 caribou-seasons])			Late Fall (*n* = 242 caribou [405 caribou-seasons])			Early Winter (*n* = 268 caribou [432 caribou-seasons])			Mid Winter (*n* = 340 caribou [623 caribou-seasons]			Late Winter (*n* = 350 caribou [659 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
(Intercept)	-11.60	0.42	0.00	-13.92	0.59	0.00	-12.82	0.63	0.00	-11.27	0.54	0.00	-14.94	0.55	0.00	-6.29	0.28	0.00	-6.12	0.31	0.00
Bryoids	0.08	0.06	0.17	-0.19	0.09	0.03	0.25	0.13	0.05	1.30	0.08	0.00	1.93	0.05	0.00	1.41	0.05	0.00	0.61	0.11	0.00
Tall shrub	0.15	0.07	0.03	-0.03	0.08	0.65	0.27	0.15	0.07	0.44	0.13	0.00	1.15	0.06	0.00	0.93	0.06	0.00	0.36	0.11	0.00
Short shrub	-0.06	0.03	0.04	0.02	0.03	0.44	0.91	0.04	0.00	0.72	0.04	0.00	0.75	0.03	0.00	0.50	0.03	0.00	0.33	0.05	0.00
Treed wetland	0.30	0.02	0.00	0.22	0.02	0.00	0.95	0.03	0.00	1.24	0.03	0.00	1.40	0.02	0.00	1.24	0.02	0.00	0.95	0.03	0.00
Shrub wetland	0.27	0.02	0.00	0.12	0.03	0.00	0.99	0.03	0.00	1.35	0.03	0.00	1.34	0.02	0.00	1.23	0.02	0.00	0.87	0.03	0.00
Herb wetland	0.43	0.03	0.00	-0.10	0.04	0.02	1.00	0.05	0.00	1.56	0.04	0.00	1.45	0.03	0.00	1.21	0.03	0.00	0.55	0.05	0.00
Herb	0.34	0.07	0.00	0.08	0.08	0.28	0.50	0.11	0.00	-0.13	0.13	0.30	0.01	0.10	0.95	-1.45	0.19	0.00	-1.51	0.41	0.00
Conifer open	0.30	0.02	0.00	0.09	0.02	0.00	0.64	0.03	0.00	0.49	0.03	0.00	0.60	0.02	0.00	0.69	0.02	0.00	0.66	0.02	0.00
Conifer sparse	0.24	0.02	0.00	0.02	0.02	0.44	0.81	0.04	0.00	0.78	0.03	0.00	0.87	0.02	0.00	1.03	0.02	0.00	0.71	0.03	0.00
Broadleaf dense	-1.00	0.15	0.00	-1.08	0.15	0.00	-0.50	0.22	0.02	-0.99	0.27	0.00	-1.67	0.25	0.00	-1.70	0.21	0.00	-1.40	0.24	0.00
Broadleaf open	0.00	0.11	0.98	-0.76	0.15	0.00	-0.56	0.25	0.03	-0.21	0.18	0.25	0.00	0.13	1.00	-0.62	0.14	0.00	-0.79	0.26	0.00
Mixedwood open	-0.22	0.07	0.00	0.01	0.07	0.94	-0.19	0.14	0.16	-0.52	0.14	0.00	-0.19	0.10	0.05	0.69	0.05	0.00	1.04	0.06	0.00
Mixedwood dense	0.53	0.05	0.00	0.12	0.06	0.03	0.49	0.08	0.00	0.76	0.07	0.00	1.50	0.04	0.00	0.82	0.03	0.00	0.53	0.07	0.00
Water	-1.56	0.03	0.00	-1.85	0.03	0.00	-1.83	0.06	0.00	-1.39	0.04	0.00	-0.62	0.03	0.00	-1.06	0.03	0.00	-1.36	0.04	0.00
Non-vegetated	0.20	0.05	0.00	0.08	0.06	0.23	-0.06	0.12	0.64	-1.87	0.25	0.00	-1.55	0.16	0.00	-2.23	0.20	0.00	-3.22	0.58	0.00
Proportion of broadleaf (1-km radius)	-11.08	0.12	0.00	-10.01	0.13	0.00	-9.08	0.16	0.00	-10.46	0.16	0.00	-8.56	0.11	0.00	-6.11	0.08	0.00	-6.26	0.13	0.00
Proportion of conifer sparse (1-km radius)	-0.52	0.03	0.00	-0.48	0.04	0.00	-0.93	0.06	0.00	-0.83	0.05	0.00	-1.44	0.04	0.00	-1.21	0.03	0.00	-0.49	0.06	0.00
Burned lowlands (1-10 y.o.)	0.84	0.02	0.00	0.23	0.03	0.00	0.46	0.05	0.00	0.80	0.04	0.00	0.64	0.03	0.00	0.18	0.03	0.00	-0.49	0.06	0.00
																					(*cont'd*)
Burned lowlands (11-	-0.44	0.03	0.00	-1.02	0.05	0.00	-0.52	0.06	0.00	-0.54	0.06	0.00	-1.15	0.06	0.00	-2.27	0.09	0.00	-2.16	0.12	0.00

	Calving (*n* = 249 caribou [444 caribou-seasons])			Summer (*n* = 211 caribou [336 caribou-seasons])			Early Fall (*n* = 221 caribou [364 caribou-seasons])			Late Fall (*n* = 242 caribou [405 caribou-seasons])			Early Winter (*n* = 268 caribou [432 caribou-seasons])			Mid Winter (*n* = 340 caribou [623 caribou-seasons]			Late Winter (*n* = 350 caribou [659 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
20 y.o.)																					
Burned lowlands (21-30 y.o.)	-0.33	0.03	0.00	-0.20	0.03	0.00	0.22	0.05	0.00	-0.16	0.05	0.00	-1.36	0.07	0.00	-1.83	0.07	0.00	-3.52	0.21	0.00
Burned lowlands (31-40 y.o.)	0.48	0.03	0.00	0.53	0.03	0.00	1.52	0.04	0.00	1.61	0.03	0.00	1.04	0.03	0.00	-0.67	0.04	0.00	-1.20	0.08	0.00
Burned lowlands (41-60 y.o.)	-1.06	0.08	0.00	0.03	0.05	0.54	0.47	0.07	0.00	0.87	0.05	0.00	0.98	0.04	0.00	0.47	0.04	0.00	0.24	0.06	0.00
Burned uplands non-treed (1-10 y.o.)	0.64	0.03	0.00	0.47	0.03	0.00	0.54	0.06	0.00	0.85	0.05	0.00	0.38	0.04	0.00	-0.50	0.06	0.00	-1.10	0.11	0.00
Burned uplands non-treed (11-20 y.o.)	-0.69	0.03	0.00	-0.88	0.04	0.00	-0.59	0.06	0.00	-0.92	0.07	0.00	-1.46	0.07	0.00	-2.87	0.12	0.00	-3.09	0.19	0.00
Burned uplands non-treed (21-30 y.o.)	-0.18	0.04	0.00	-0.05	0.03	0.11	0.53	0.05	0.00	-0.10	0.05	0.06	-1.72	0.08	0.00	-2.51	0.10	0.00	-4.77	0.45	0.00
Burned uplands non-treed (31-40 y.o.)	-0.47	0.07	0.00	-0.89	0.10	0.00	1.15	0.07	0.00	0.81	0.06	0.00	0.86	0.05	0.00	-1.67	0.13	0.00	-4.08	0.71	0.00
Burned uplands non-treed (41-60 y.o.)	-1.03	0.16	0.00	0.79	0.07	0.00	0.70	0.13	0.00	1.07	0.09	0.00	1.40	0.06	0.00	0.01	0.09	0.93	-0.49	0.18	0.01
Burned upland conifer (1-10 y.o.)	0.00	0.03	0.95	-0.79	0.04	0.00	-0.59	0.06	0.00	-0.51	0.06	0.00	-0.28	0.04	0.00	-0.49	0.04	0.00	-0.83	0.06	0.00
Burned upland conifer (11-20 y.o.)	0.20	0.06	0.00	-0.79	0.12	0.00	-0.29	0.15	0.05	-0.43	0.15	0.00	-1.26	0.16	0.00	-1.58	0.16	0.00	-1.55	0.25	0.00
Burned upland conifer (21-30 y.o.)	0.14	0.06	0.02	0.03	0.07	0.63	0.24	0.12	0.04	-0.30	0.14	0.02	-1.48	0.17	0.00	-2.03	0.18	0.00	-3.18	0.50	0.00
																					(*cont'd*)
Burned upland conifer (31-40	0.63	0.04	0.00	0.30	0.05	0.00	1.12	0.06	0.00	0.94	0.05	0.00	0.40	0.05	0.00	-0.44	0.06	0.00	-0.93	0.11	0.00

	Calving (*n* = 249 caribou [444 caribou-seasons])			Summer (*n* = 211 caribou [336 caribou-seasons])			Early Fall (*n* = 221 caribou [364 caribou-seasons])			Late Fall (*n* = 242 caribou [405 caribou-seasons])			Early Winter (*n* = 268 caribou [432 caribou-seasons])			Mid Winter (*n* = 340 caribou [623 caribou-seasons]			Late Winter (*n* = 350 caribou [659 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
y.o.)																					
Burned upland conifer (41-60 y.o.)	-0.14	0.08	0.09	-1.00	0.09	0.00	0.51	0.09	0.00	0.76	0.08	0.00	0.97	0.06	0.00	0.77	0.04	0.00	1.03	0.06	0.00
Burned upland broadleaf (1-10 y.o.)	-0.09	0.11	0.45	0.41	0.09	0.00	-0.82	0.32	0.01	-0.54	0.28	0.05	-0.83	0.18	0.00	-0.81	0.16	0.00	-0.93	0.23	0.00
Burned upland broadleaf (11-20 y.o.)	-1.02	0.15	0.00	-2.35	0.36	0.00	-2.20	0.58	0.00	-1.08	0.36	0.00	-1.58	0.30	0.00	-3.33	0.58	0.00	-3.63	1.00	0.00
Burned upland broadleaf (21-30 y.o.)	-0.91	0.16	0.00	-0.83	0.16	0.00	-0.52	0.25	0.03	-1.33	0.45	0.00	-2.04	0.45	0.00	-3.09	0.45	0.00	-13.77	146.02	0.92
Burned upland broadleaf (31-40 y.o.)	0.48	0.07	0.00	0.10	0.08	0.23	0.53	0.13	0.00	0.93	0.11	0.00	0.62	0.09	0.00	-1.67	0.17	0.00	-3.55	0.71	0.00
Burned upland broadleaf (41-60 y.o.)	-2.01	0.38	0.00	-2.94	0.50	0.00	-1.60	0.45	0.00	-1.09	0.38	0.00	-0.49	0.25	0.05	-1.44	0.24	0.00	-2.19	0.58	0.00
Linear feature density (1-km radius)	-0.16	0.01	0.00	-0.15	0.01	0.00	-0.17	0.02	0.00	-0.23	0.01	0.00	-0.19	0.01	0.00	-0.13	0.01	0.00	0.02	0.01	0.16
Distance to major road	5.96	0.30	0.00	5.04	0.31	0.00	3.94	0.35	0.00	4.83	0.39	0.00	7.79	0.46	0.00	3.26	0.18	0.00	2.12	0.21	0.00
Distance to polygonal disturbance	5.43	0.30	0.00	7.70	0.46	0.00	6.03	0.49	0.00	2.18	0.26	0.00	4.35	0.28	0.00	1.54	0.12	0.00	1.07	0.16	0.00
Distance to settlement	-2.44	0.11	0.00	-1.64	0.13	0.00	-1.18	0.16	0.00	0.32	0.24	0.19	-0.57	0.14	0.00	-1.90	0.10	0.00	-1.51	0.13	0.00

Table F 2: Model coefficients (β), their standard errors (SE) and *p*-values (*p*) from seasonal resource selection functions estimated at a third-order scale for boreal caribou in the Northwest Territories.

	Calving (*n* = 194 caribou [298 caribou-seasons])			Summer (*n* = 170 caribou [258 caribou-seasons])			Early Fall (*n* = 196 caribou [308 caribou-seasons])			Late Fall (*n* = 210 caribou [349 caribou-seasons])			Early Winter (*n* = 226 caribou [343 caribou-seasons])			Mid Winter (*n* = 209 caribou [324 caribou-seasons])			Late Winter (*n* = 241 caribou [368 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
(Intercept)	-18.19	0.65	0.00	-14.91	0.56	0.00	-15.68	0.66	0.00	-20.33	0.66	0.00	-19.29	0.63	0.00	-10.72	0.36	0.00	-9.65	0.43	0.00
Bryoids	0.31	0.07	0.00	-0.12	0.09	0.20	0.75	0.13	0.00	1.70	0.08	0.00	1.93	0.05	0.00	1.44	0.07	0.00	0.44	0.15	0.00
Tall shrub	0.28	0.08	0.00	0.20	0.09	0.03	0.58	0.17	0.00	0.76	0.14	0.00	1.06	0.08	0.00	1.06	0.08	0.00	0.55	0.14	0.00
Short shrub	0.21	0.03	0.00	0.26	0.03	0.00	1.33	0.05	0.00	1.07	0.04	0.00	1.00	0.03	0.00	0.59	0.04	0.00	0.33	0.06	0.00
Treed wetland	0.29	0.02	0.00	0.19	0.02	0.00	1.02	0.03	0.00	1.35	0.03	0.00	1.41	0.02	0.00	1.27	0.03	0.00	0.97	0.04	0.00
Shrub wetland	0.19	0.03	0.00	0.04	0.03	0.17	0.98	0.04	0.00	1.31	0.03	0.00	1.18	0.03	0.00	1.11	0.03	0.00	0.76	0.04	0.00
Herb wetland	0.24	0.04	0.00	-0.15	0.05	0.00	0.76	0.06	0.00	1.36	0.04	0.00	1.36	0.03	0.00	0.94	0.04	0.00	0.25	0.07	0.00
Herb	0.35	0.08	0.00	0.62	0.08	0.00	1.25	0.13	0.00	0.79	0.14	0.00	0.45	0.11	0.00	-1.12	0.26	0.00	-1.82	0.50	0.00
Conifer open	0.26	0.02	0.00	0.16	0.02	0.00	0.70	0.03	0.00	0.56	0.03	0.00	0.52	0.02	0.00	0.69	0.02	0.00	0.74	0.03	0.00
Conifer sparse	0.24	0.02	0.00	0.18	0.03	0.00	0.95	0.04	0.00	0.87	0.03	0.00	0.92	0.03	0.00	0.95	0.03	0.00	0.75	0.04	0.00
Broadleaf dense	-0.36	0.17	0.04	-0.39	0.16	0.02	0.19	0.23	0.39	-0.22	0.28	0.43	-0.85	0.27	0.00	-1.36	0.29	0.00	-1.10	0.34	0.00
Broadleaf open	0.00	0.13	0.97	-0.48	0.16	0.00	-0.23	0.25	0.36	0.30	0.19	0.11	0.37	0.13	0.00	-0.96	0.23	0.00	-1.94	0.50	0.00
Mixedwood open	-0.24	0.09	0.01	0.02	0.07	0.75	-0.21	0.14	0.14	-0.52	0.15	0.00	-0.55	0.11	0.00	-0.74	0.13	0.00	1.03	0.08	0.00
Mixedwood dense	0.15	0.06	0.01	-0.11	0.06	0.06	0.24	0.08	0.00	0.48	0.07	0.00	0.89	0.05	0.00	0.72	0.05	0.00	0.09	0.08	0.27
Water	-1.24	0.03	0.00	-1.57	0.04	0.00	-1.35	0.06	0.00	-0.86	0.05	0.00	-0.16	0.03	0.00	-0.59	0.04	0.00	-0.84	0.06	0.00
Non-vegetated	1.17	0.07	0.00	0.38	0.12	0.00	0.37	0.21	0.08	-0.57	0.27	0.04	-0.15	0.17	0.37	-1.94	0.50	0.00	-2.00	0.58	0.00
Proportion of broadleaf (1-km radius)	-9.10	0.15	0.00	-6.86	0.14	0.00	-6.75	0.18	0.00	-8.93	0.18	0.00	-6.78	0.13	0.00	-3.97	0.12	0.00	-3.18	0.17	0.00
Proportion of conifer sparse (1-km radius)	0.93	0.05	0.00	1.36	0.05	0.00	1.24	0.07	0.00	0.76	0.06	0.00	0.81	0.05	0.00	0.80	0.06	0.00	0.79	0.09	0.00
Burned lowlands (1-10 y.o.)	0.56	0.03	0.00	-0.05	0.03	0.09	0.21	0.05	0.00	0.49	0.04	0.00	0.13	0.04	0.00	-0.47	0.05	0.00	-1.32	0.09	0.00
																					(*cont'd*)
Burned lowlands (11-	0.26	0.04	0.00	-0.43	0.06	0.00	0.37	0.07	0.00	0.35	0.06	0.00	-0.68	0.07	0.00	-2.01	0.14	0.00	-1.95	0.21	0.00

	Calving (*n* = 194 caribou [298 caribou-seasons])			Summer (*n* = 170 caribou [258 caribou-seasons])			Early Fall (*n* = 196 caribou [308 caribou-seasons])			Late Fall (*n* = 210 caribou [349 caribou-seasons])			Early Winter (*n* = 226 caribou [343 caribou-seasons])			Mid Winter (*n* = 209 caribou [324 caribou-seasons])			Late Winter (*n* = 241 caribou [368 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
20 y.o.)																					
Burned lowlands (21-30 y.o.)	0.10	0.04	0.01	0.27	0.04	0.00	0.84	0.05	0.00	0.27	0.06	0.00	-1.16	0.08	0.00	-1.33	0.10	0.00	-3.67	0.36	0.00
Burned lowlands (31-40 y.o.)	0.16	0.03	0.00	0.09	0.03	0.00	1.26	0.04	0.00	1.36	0.03	0.00	0.43	0.03	0.00	-1.31	0.06	0.00	-2.18	0.12	0.00
Burned lowlands (41-60 y.o.)	-1.07	0.09	0.00	0.12	0.05	0.02	0.71	0.07	0.00	1.15	0.06	0.00	1.44	0.04	0.00	-0.11	0.09	0.21	0.04	0.10	0.71
Burned uplands non-treed (1-10 y.o.)	-0.06	0.04	0.11	-0.47	0.04	0.00	-0.16	0.07	0.02	0.30	0.05	0.00	-0.14	0.05	0.00	-1.51	0.10	0.00	-1.90	0.15	0.00
Burned uplands non-treed (11-20 y.o.)	0.32	0.05	0.00	0.20	0.06	0.00	0.95	0.07	0.00	0.72	0.08	0.00	-0.58	0.08	0.00	-1.96	0.17	0.00	-3.03	0.45	0.00
Burned uplands non-treed (21-30 y.o.)	0.07	0.04	0.07	0.24	0.04	0.00	1.18	0.05	0.00	0.37	0.06	0.00	-1.33	0.09	0.00	-1.72	0.14	0.00	-4.26	0.50	0.00
Burned uplands non-treed (31-40 y.o.)	0.19	0.08	0.01	-0.42	0.10	0.00	1.68	0.07	0.00	1.70	0.07	0.00	1.04	0.06	0.00	-1.09	0.18	0.00	-3.23	0.71	0.00
Burned uplands non-treed (41-60 y.o.)	-0.91	0.16	0.00	0.68	0.08	0.00	1.20	0.13	0.00	1.46	0.10	0.00	1.77	0.07	0.00	-0.37	0.25	0.13	-1.04	0.34	0.00
Burned upland conifer (1-10 y.o.)	0.16	0.03	0.00	-0.58	0.04	0.00	-0.32	0.06	0.00	-0.32	0.06	0.00	-0.34	0.05	0.00	-0.66	0.06	0.00	-1.07	0.10	0.00
Burned upland conifer (11-20 y.o.)	0.46	0.08	0.00	-0.31	0.12	0.01	0.39	0.15	0.01	0.05	0.16	0.75	-0.88	0.17	0.00	-1.84	0.32	0.00	-3.37	1.00	0.00
Burned upland conifer (21-30 y.o.)	0.22	0.07	0.00	0.05	0.08	0.57	0.18	0.13	0.15	-0.34	0.16	0.03	-2.26	0.28	0.00	-1.53	0.22	0.00	-17.55	803.22	0.98
																					(*cont'd*)
Burned upland conifer (31-40	0.00	0.05	0.96	-0.42	0.05	0.00	0.42	0.06	0.00	0.58	0.05	0.00	-0.18	0.06	0.00	-1.09	0.08	0.00	-1.33	0.14	0.00

	Calving (*n* = 194 caribou [298 caribou-seasons])			Summer (*n* = 170 caribou [258 caribou-seasons])			Early Fall (*n* = 196 caribou [308 caribou-seasons])			Late Fall (*n* = 210 caribou [349 caribou-seasons])			Early Winter (*n* = 226 caribou [343 caribou-seasons])			Mid Winter (*n* = 209 caribou [324 caribou-seasons])			Late Winter (*n* = 241 caribou [368 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
y.o.)																					
Burned upland conifer (41-60 y.o.)	-0.77	0.09	0.00	-1.10	0.09	0.00	0.19	0.09	0.04	0.46	0.08	0.00	0.53	0.06	0.00	0.67	0.07	0.00	0.38	0.10	0.00
Burned upland broadleaf (1-10 y.o.)	0.37	0.12	0.00	0.57	0.09	0.00	-0.94	0.34	0.01	-0.94	0.32	0.00	-0.58	0.19	0.00	-0.53	0.20	0.01	-1.21	0.36	0.00
Burned upland broadleaf (11-20 y.o.)	0.15	0.17	0.36	-1.47	0.41	0.00	-0.94	0.58	0.11	-0.11	0.36	0.75	-0.96	0.36	0.01	-14.31	305.61	0.96	-18.85	4113.68	1.00
Burned upland broadleaf (21-30 y.o.)	-0.70	0.22	0.00	-0.30	0.19	0.10	-0.01	0.26	0.97	-1.40	0.58	0.02	-2.03	0.50	0.00	-2.99	0.71	0.00	-18.74	2502.38	0.99
Burned upland broadleaf (31-40 y.o.)	0.41	0.08	0.00	-0.12	0.08	0.16	0.29	0.13	0.02	0.64	0.11	0.00	-0.03	0.10	0.75	-3.17	0.41	0.00	-17.29	669.91	0.98
Burned upland broadleaf (41-60 y.o.)	-1.47	0.45	0.00	-2.69	0.71	0.00	-0.92	0.58	0.11	-0.09	0.38	0.82	-0.04	0.26	0.89	-1.82	0.58	0.00	-2.34	1.00	0.02
Linear feature density (1-km radius)	-0.12	0.01	0.00	-0.12	0.01	0.00	-0.21	0.02	0.00	-0.15	0.02	0.00	-0.15	0.01	0.00	0.06	0.01	0.00	0.20	0.01	0.00
Distance to major road	8.07	0.43	0.00	6.59	0.36	0.00	5.52	0.42	0.00	8.03	0.51	0.00	11.61	0.58	0.00	4.51	0.24	0.00	3.78	0.30	0.00
Distance to polygonal disturbance	6.91	0.53	0.00	5.09	0.41	0.00	4.23	0.48	0.00	1.04	0.23	0.00	1.93	0.22	0.00	1.10	0.16	0.00	1.06	0.22	0.00
Distance to settlement	0.27	0.16	0.09	0.02	0.15	0.88	1.37	0.23	0.00	6.90	0.36	0.00	1.97	0.20	0.00	1.17	0.16	0.00	-0.02	0.20	0.91

Table F 3: Model coefficients (β), their standard errors (SE) and *p*-values (*p*) from resource selection functions (RSFs) estimated using data collected across the year from boreal caribou in the Northwest Territories. RSFs were estimated at second- and third-order scales.

	Scale					
	Second Order (*n* = 194 caribou [301 caribou-seasons])			Third Order (*n* = 194 caribou [301 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*
(Intercept)	-8.36	0.28	0.00	-11.40	0.29	0.00
Bryoids	0.90	0.03	0.00	0.91	0.03	0.00
Tall shrub	0.79	0.04	0.00	0.66	0.04	0.00
Short shrub	0.35	0.02	0.00	0.51	0.02	0.00
Treed wetland	0.71	0.01	0.00	0.65	0.01	0.00
Shrub wetland	0.68	0.01	0.00	0.53	0.01	0.00
Herb wetland	0.85	0.02	0.00	0.55	0.02	0.00
Herb	0.06	0.05	0.17	0.45	0.05	0.00
Conifer open	0.38	0.01	0.00	0.37	0.01	0.00
Conifer sparse	0.38	0.01	0.00	0.49	0.01	0.00
Broadleaf dense	-0.94	0.07	0.00	-0.17	0.07	0.02
Broadleaf open	-0.02	0.06	0.72	0.14	0.06	0.02
Mixedwood open	0.05	0.04	0.17	0.01	0.04	0.80
Mixedwood dense	0.72	0.03	0.00	0.40	0.02	0.00
Water	-1.15	0.01	0.00	-0.77	0.01	0.00
Non-vegetated	-0.93	0.05	0.00	0.33	0.06	0.00
Proportion of broadleaf (1-km radius)	-8.80	0.06	0.00	-6.08	0.06	0.00
Proportion of conifer sparse (1-km radius)	-0.26	0.02	0.00	1.55	0.03	0.00
Burned lowlands (1-10 y.o.)	0.53	0.02	0.00	0.07	0.02	0.00
Burned lowlands (11-20 y.o.)	-0.91	0.02	0.00	-0.26	0.03	0.00
Burned lowlands (21-30 y.o.)	-0.51	0.02	0.00	-0.20	0.02	0.00
Burned lowlands (31-40 y.o.)	0.63	0.02	0.00	0.04	0.02	0.00
Burned lowlands (41-60 y.o.)	0.27	0.03	0.00	0.36	0.03	0.00
Burned uplands non-treed (1-10 y.o.)	0.49	0.02	0.00	-0.36	0.02	0.00

(*cont'd*)

	Scale					
	Second Order (*n* = 194 caribou [301 caribou-seasons])			Third Order (*n* = 194 caribou [301 caribou-seasons])		
Variable	β	SE	*p*	β	SE	*p*
Burned uplands non-treed (11-20 y.o.)	-1.00	0.02	0.00	0.10	0.03	0.00
Burned uplands non-treed (21-30 y.o.)	-0.44	0.02	0.00	-0.08	0.02	0.00
Burned uplands non-treed (31-40 y.o.)	-0.08	0.03	0.02	0.31	0.04	0.00
Burned uplands non-treed (41-60 y.o.)	0.49	0.04	0.00	0.54	0.05	0.00
Burned upland conifer (1-10 y.o.)	-0.39	0.02	0.00	-0.30	0.02	0.00
Burned upland conifer (11-20 y.o.)	-0.66	0.05	0.00	-0.16	0.05	0.00
Burned upland conifer (21-30 y.o.)	-0.51	0.05	0.00	-0.35	0.05	0.00
Burned upland conifer (31-40 y.o.)	0.32	0.03	0.00	-0.42	0.02	0.00
Burned upland conifer (41-60 y.o.)	0.16	0.03	0.00	-0.13	0.03	0.00
Burned upland broadleaf (1-10 y.o.)	-0.26	0.07	0.00	-0.16	0.07	0.02
Burned upland broadleaf (11-20 y.o.)	-1.49	0.12	0.00	-0.71	0.12	0.00
Burned upland broadleaf (21-30 y.o.)	-0.77	0.09	0.00	-0.49	0.09	0.00
Burned upland broadleaf (31-40 y.o.)	0.42	0.04	0.00	-0.32	0.04	0.00
Burned upland broadleaf (41-60 y.o.)	-1.39	0.15	0.00	-1.02	0.15	0.00
Linear feature density (1-km radius)	-0.14	0.01	0.00	-0.08	0.01	0.00
Distance to major road	4.56	0.13	0.00	5.72	0.14	0.00
Distance to polygonal disturbance	5.07	0.15	0.00	2.69	0.11	0.00
Distance to settlement	-2.72	0.07	0.00	1.16	0.08	0.00

APPENDIX G: RELATIVE CONTRIBUTION OF ENVIRONMENTAL VARIABLES TO MAPPED BINS OF SEASONAL RESOURCE SELECTION

We used outputs of seasonal resource selection functions (RSFs) to develop maps of predicted space use by boreal caribou in the Northwest Territories. Although RSFs generate a continuous surface of resource selection, we binned map pixels into 10 classes (1= weakest selection, 10 = strongest selection) to improve visual interpretation of predicted selection by caribou (Morris et al. 2016). In this appendix, we provide graphical representations of the proportional contribution of each resource covariate to each RSF bin for second-order RSF maps, beginning with categorical variables of local land-cover (Figs. G 1–8) followed by all continuous variables (Figs. G 9–14).

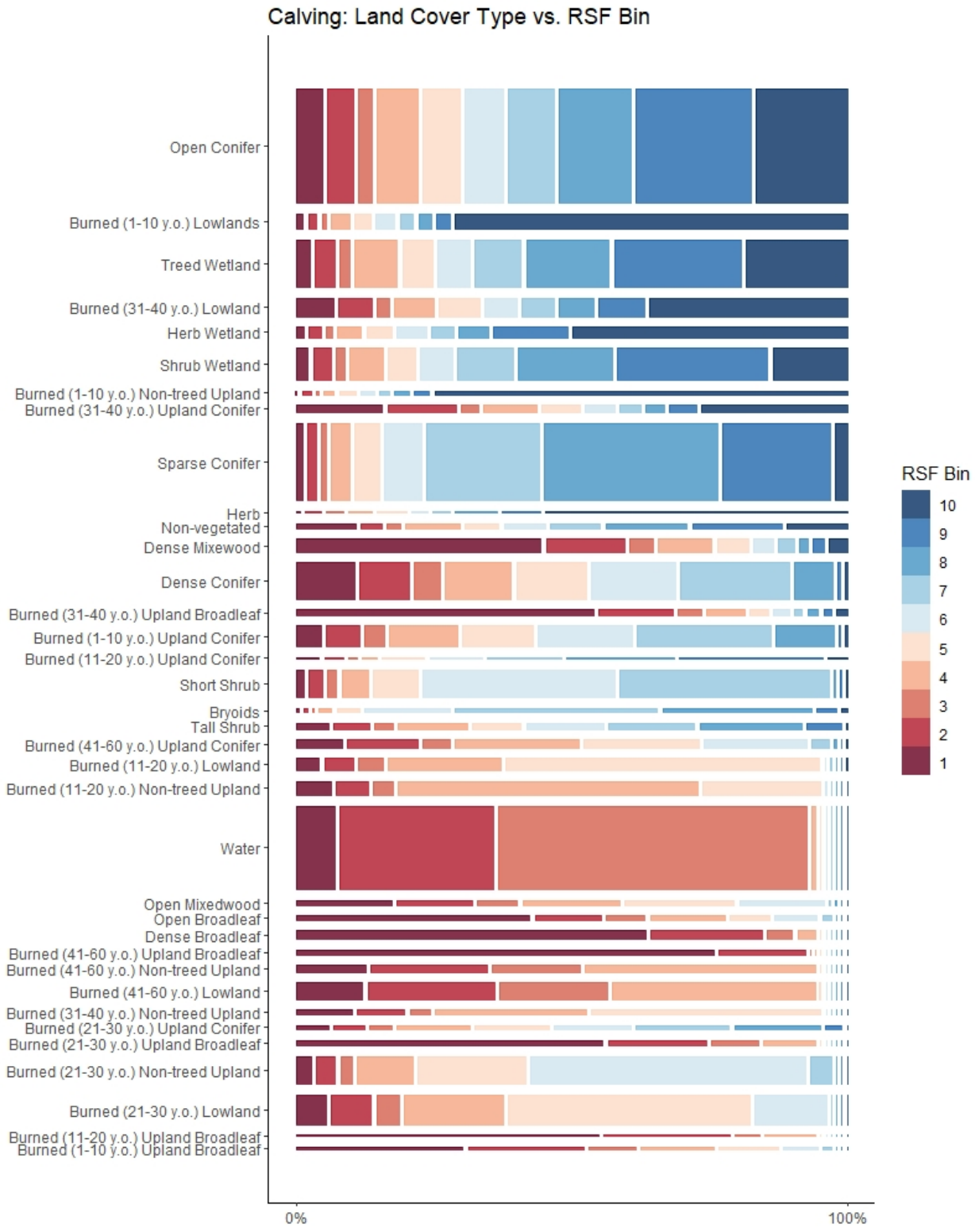


Figure G 1: The relative contribution of local land-cover variables to mapped bin values of resource selection during the calving season at a second-order scale by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

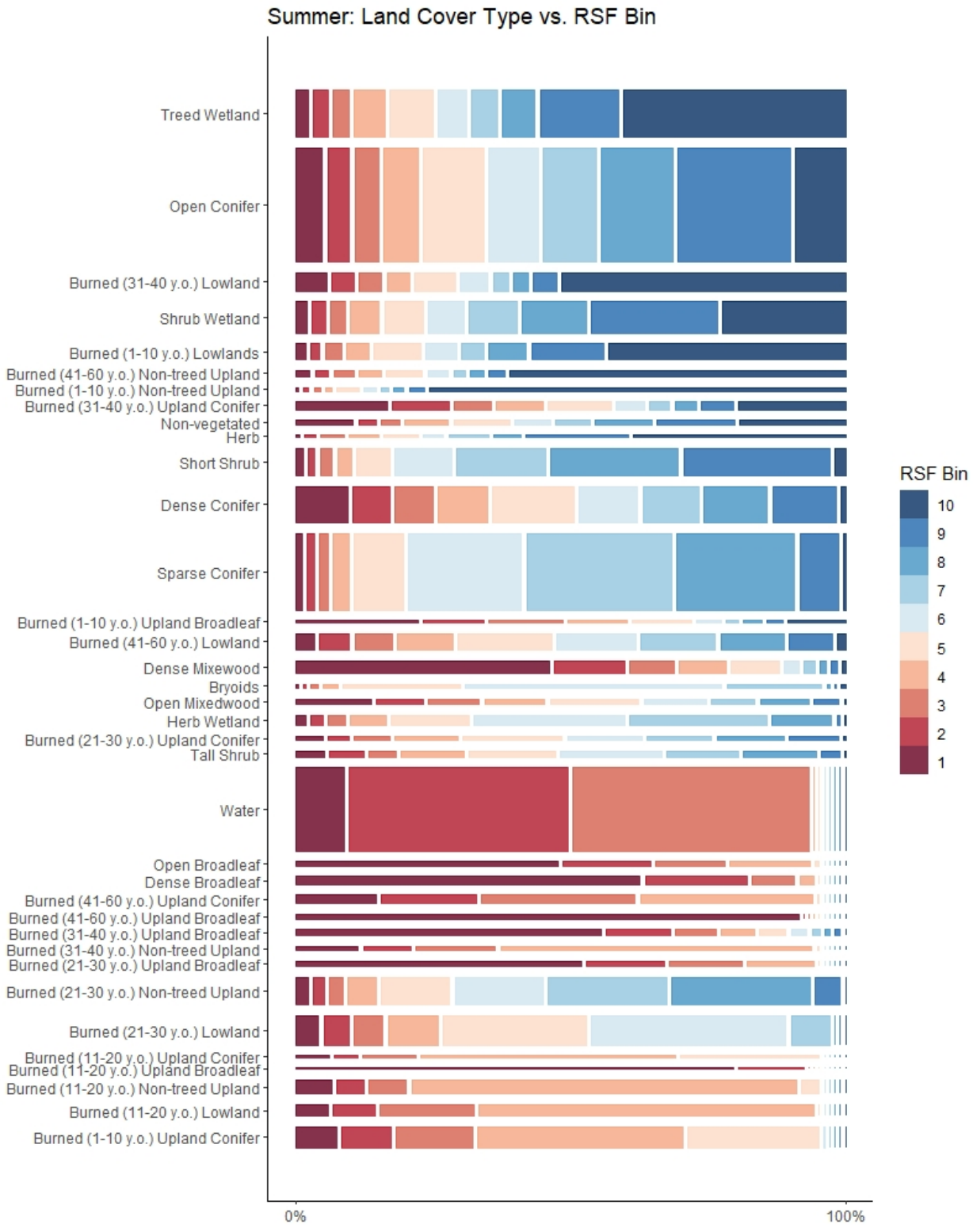


Figure G 2: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale during the summer by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

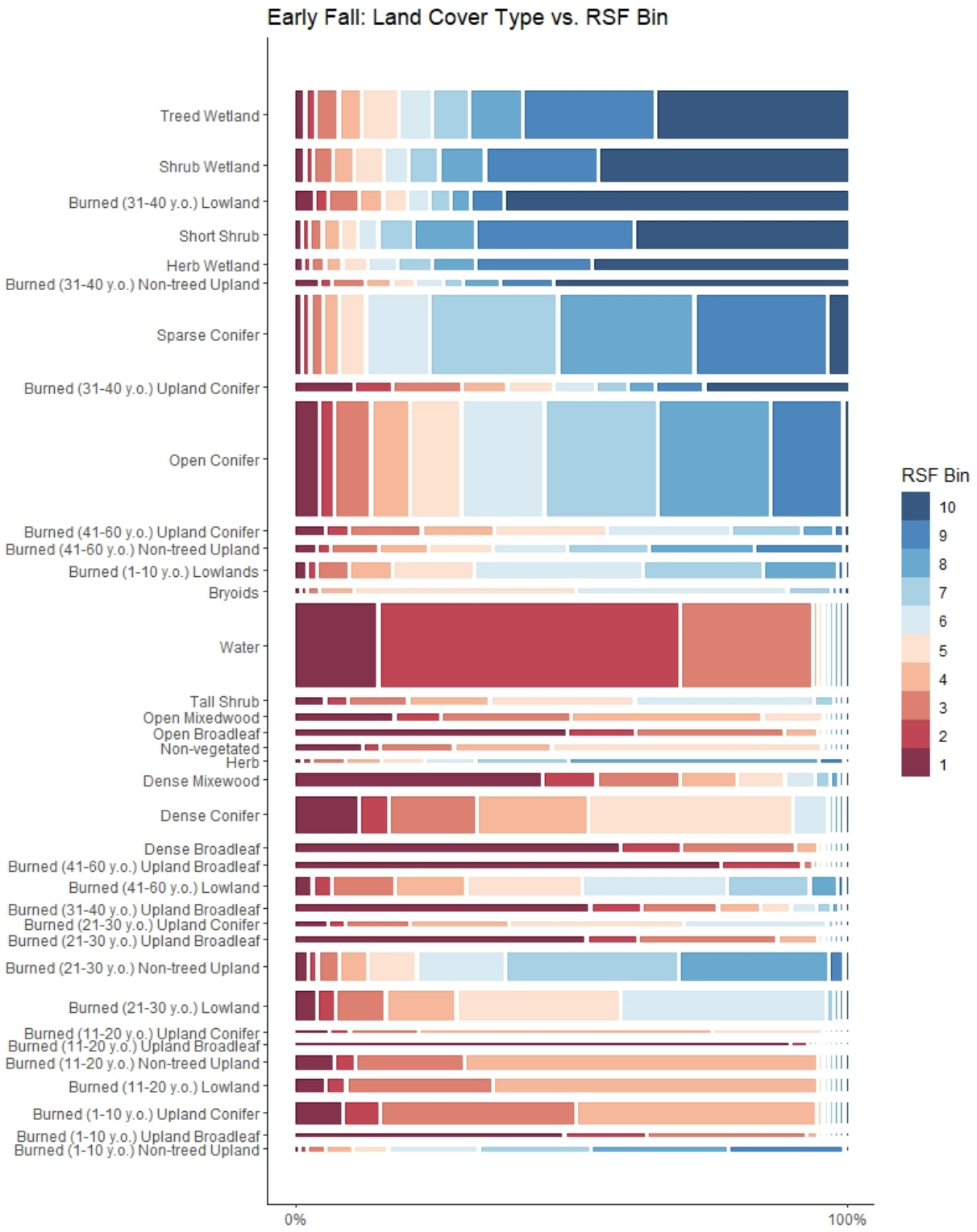


Figure G 3: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale during the early fall by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

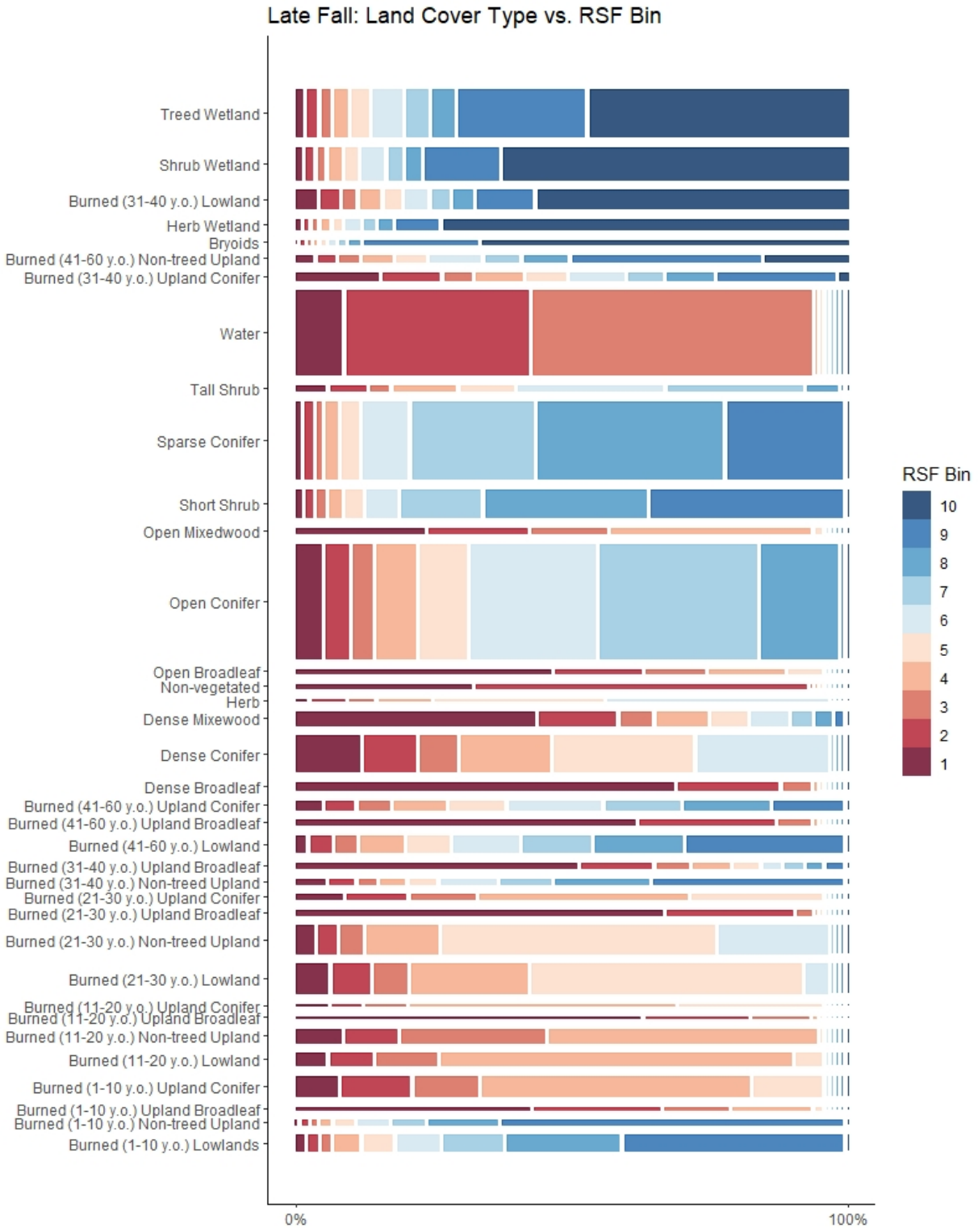


Figure G 4: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale during the late fall by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

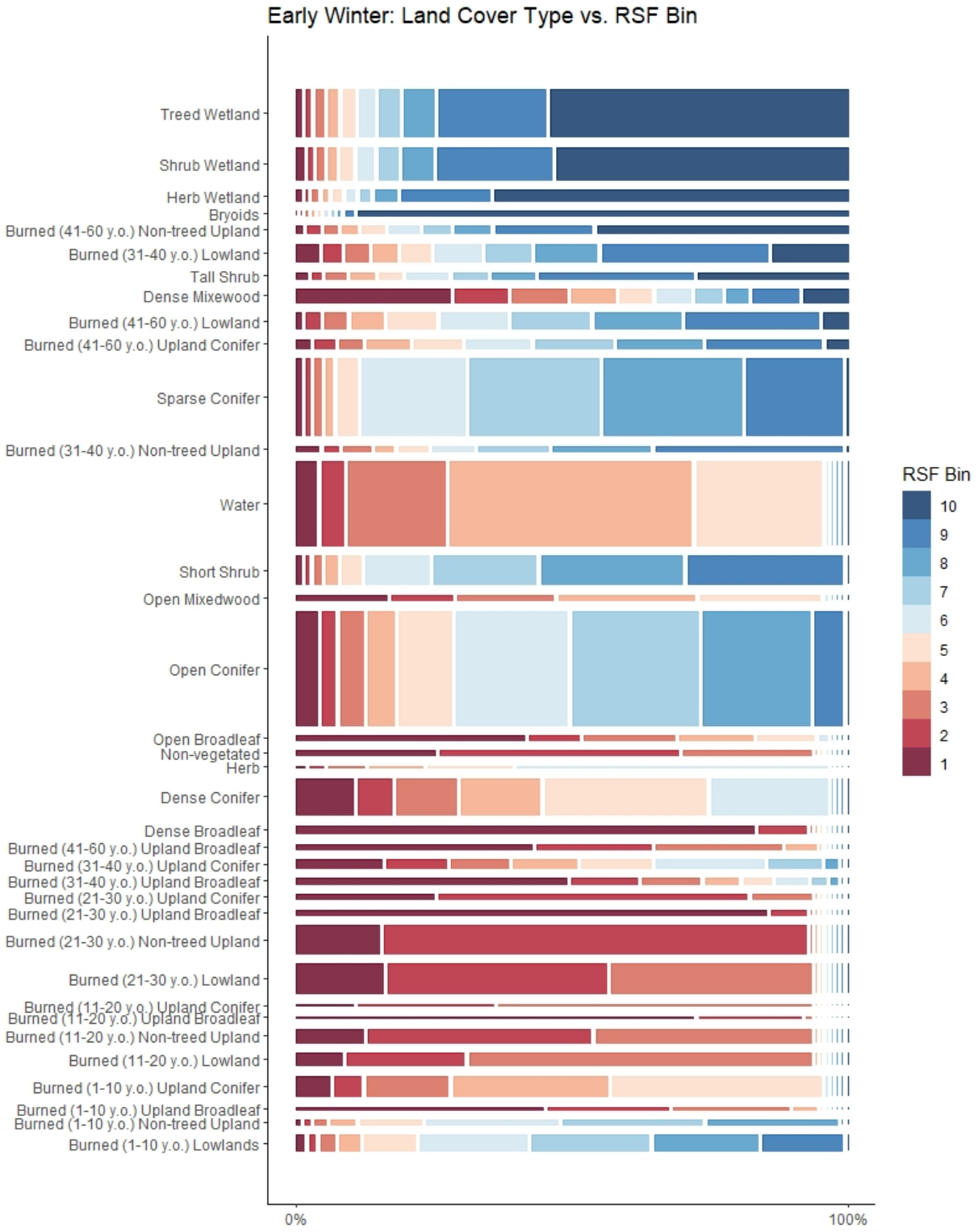


Figure G 5: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale during the early winter by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

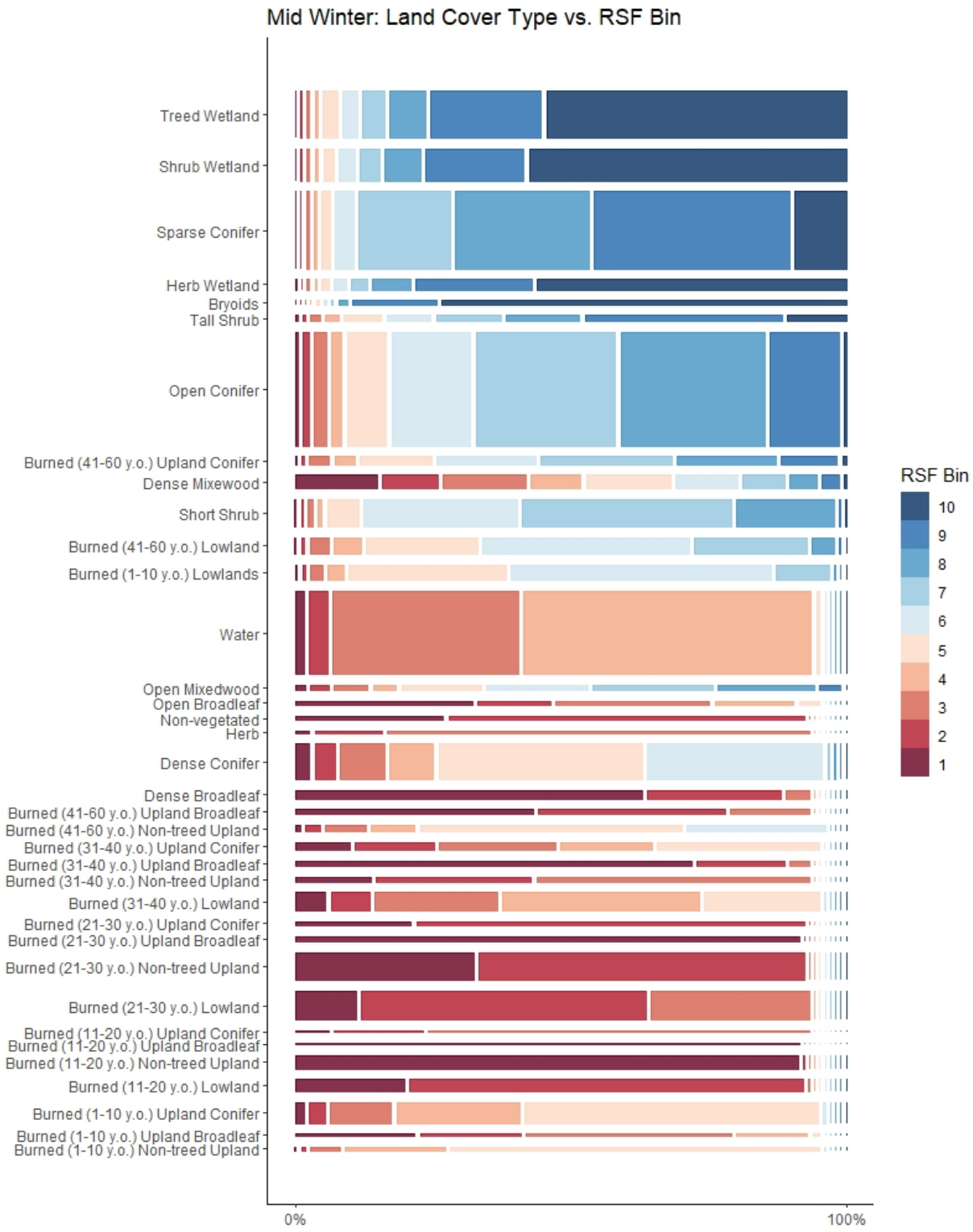


Figure G 6: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale during the mid-winter by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

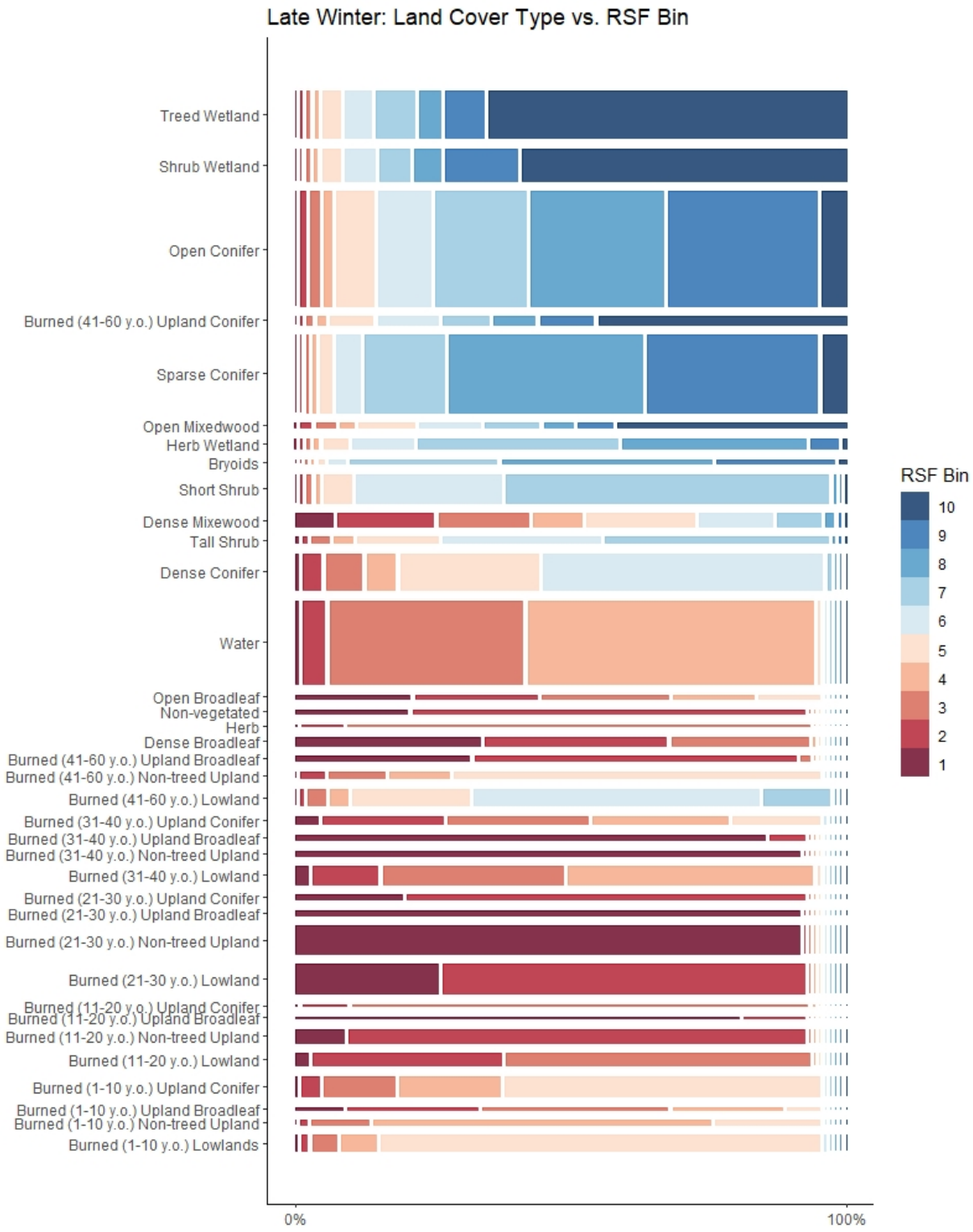


Figure G 7: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale during the late winter by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

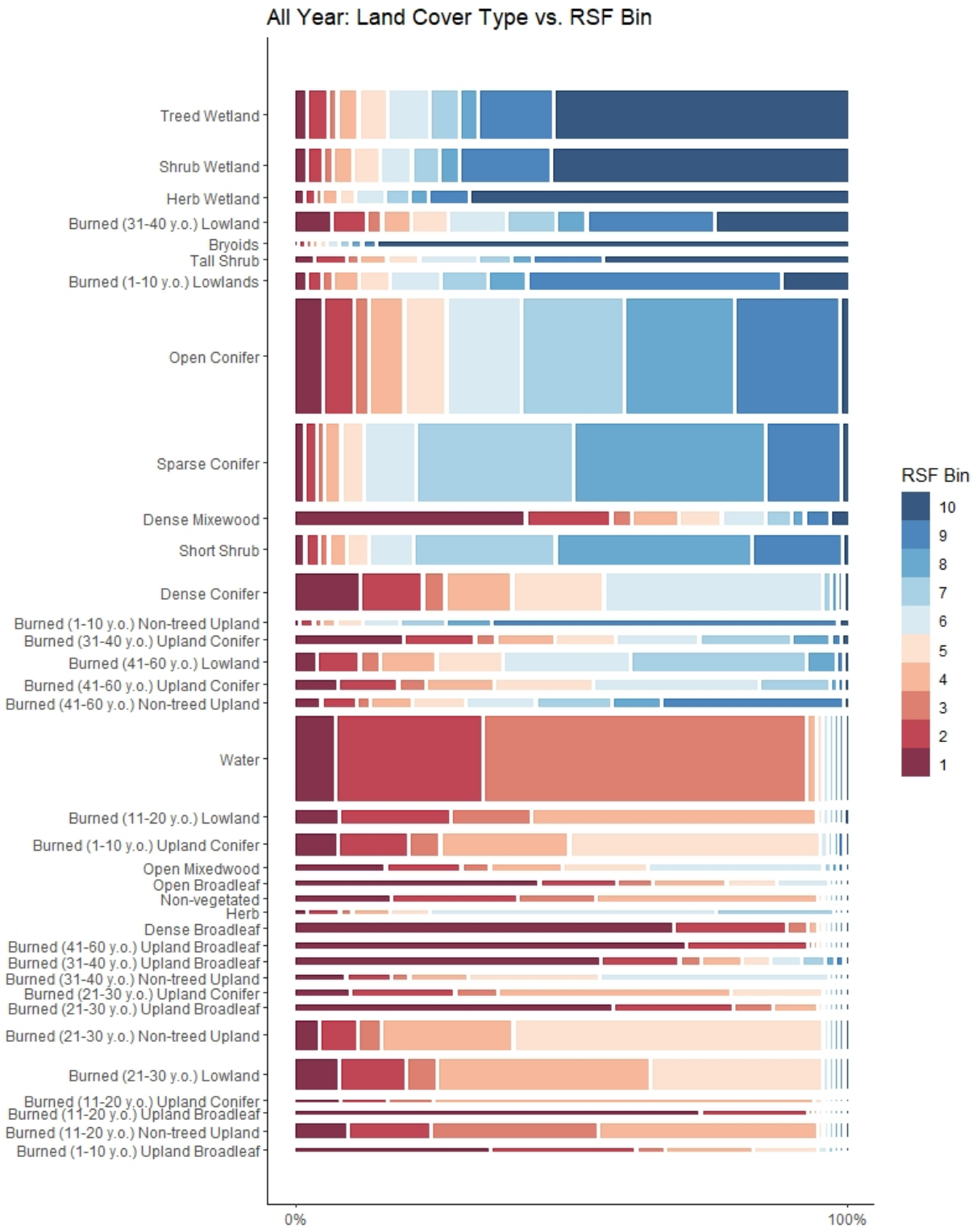


Figure G 8: The relative contribution of local land-cover variables to mapped bin values of resource selection at a second-order scale across the entire year by boreal caribou in the Northwest Territories. Bar width in the histogram is proportional to the area covered by each variable in the study area. Variables are ranked by their relative contribution to bin 10 (strongest selection).

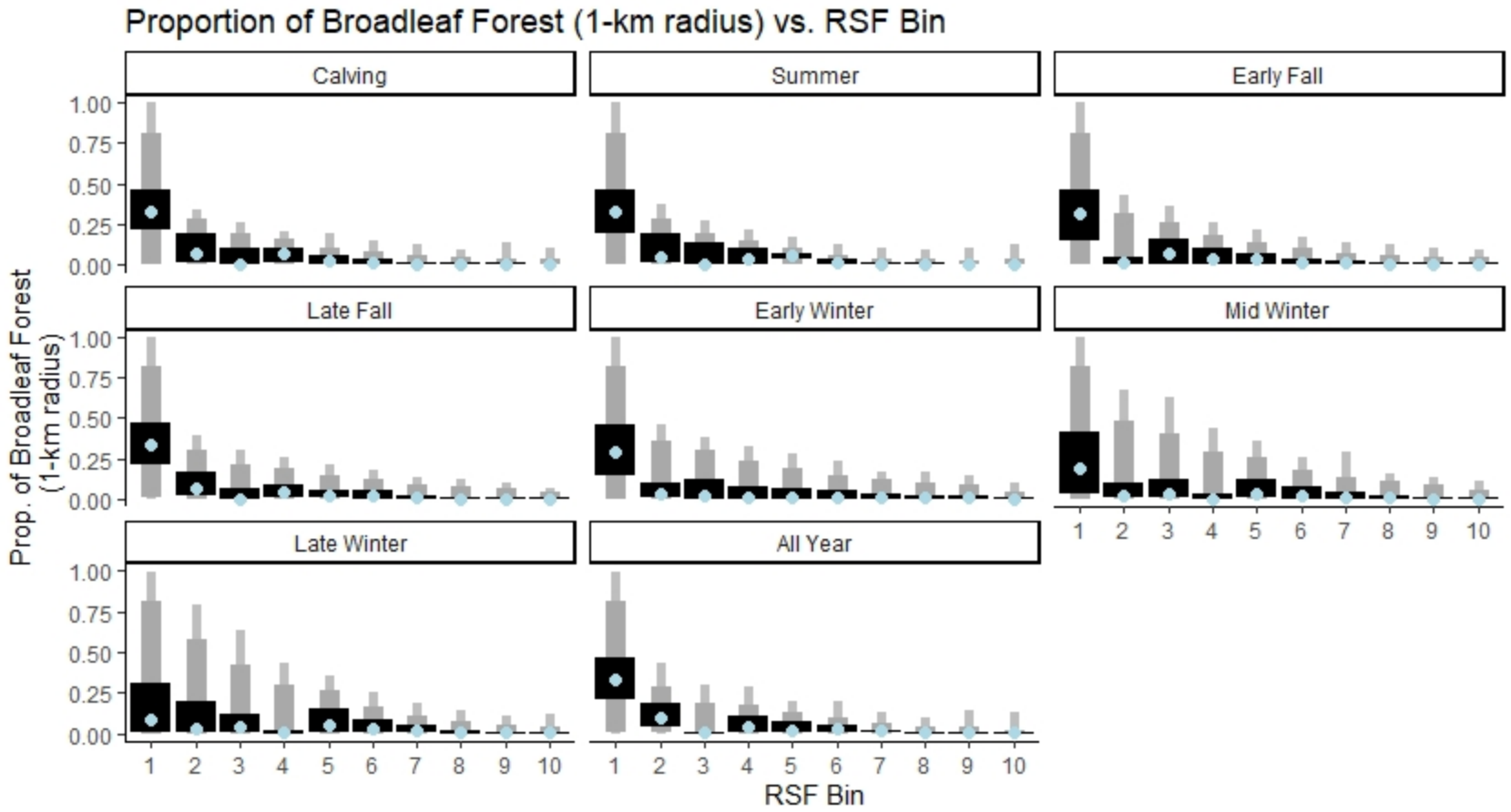


Figure G 9: The distribution of values measuring the proportion of broadleaf forest in a 1-km radius within mapped bin values of seasonal resource selection by boreal caribou in the Northwest Territories. Resource selection was estimated at a second-order scale. Blue points indicate the median value within a bin. Thin grey bars indicate the overall range of the data within a bin. Thick grey bars indicate values falling within the 95% quantile. Black bars indicate values falling within the inner 50% quantile.

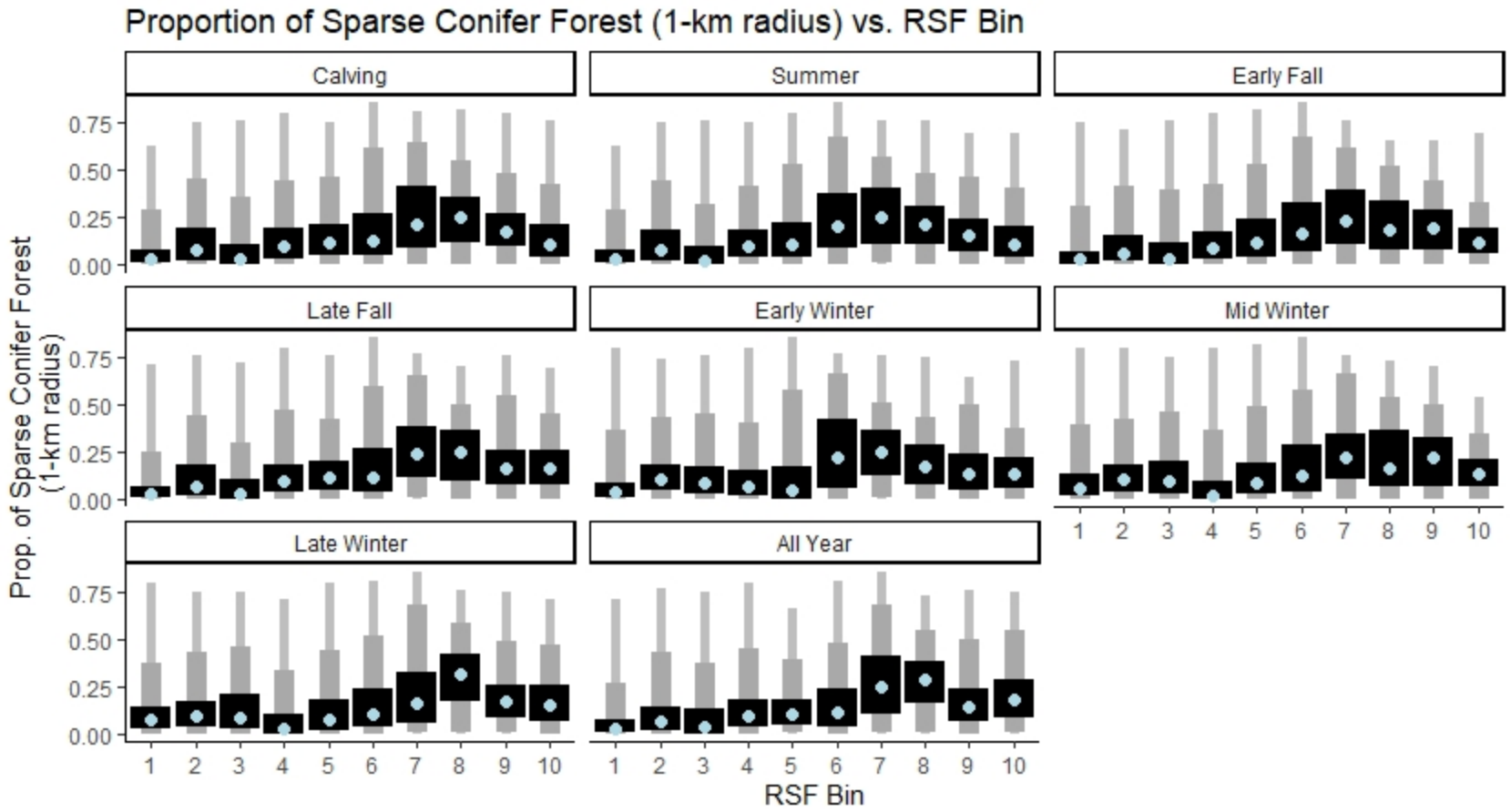


Figure G 10: The distribution of values measuring the proportion of sparse conifer forest in a 1-km radius within mapped bin values of seasonal resource selection by boreal caribou in the Northwest Territories. Resource selection was estimated at a second-order scale. Blue points indicate the median value within a bin. Thin grey bars indicate the overall range of the data within a bin. Thick grey bars indicate values falling within the 95% quantile. Black bars indicate values falling within the inner 50% quantile.

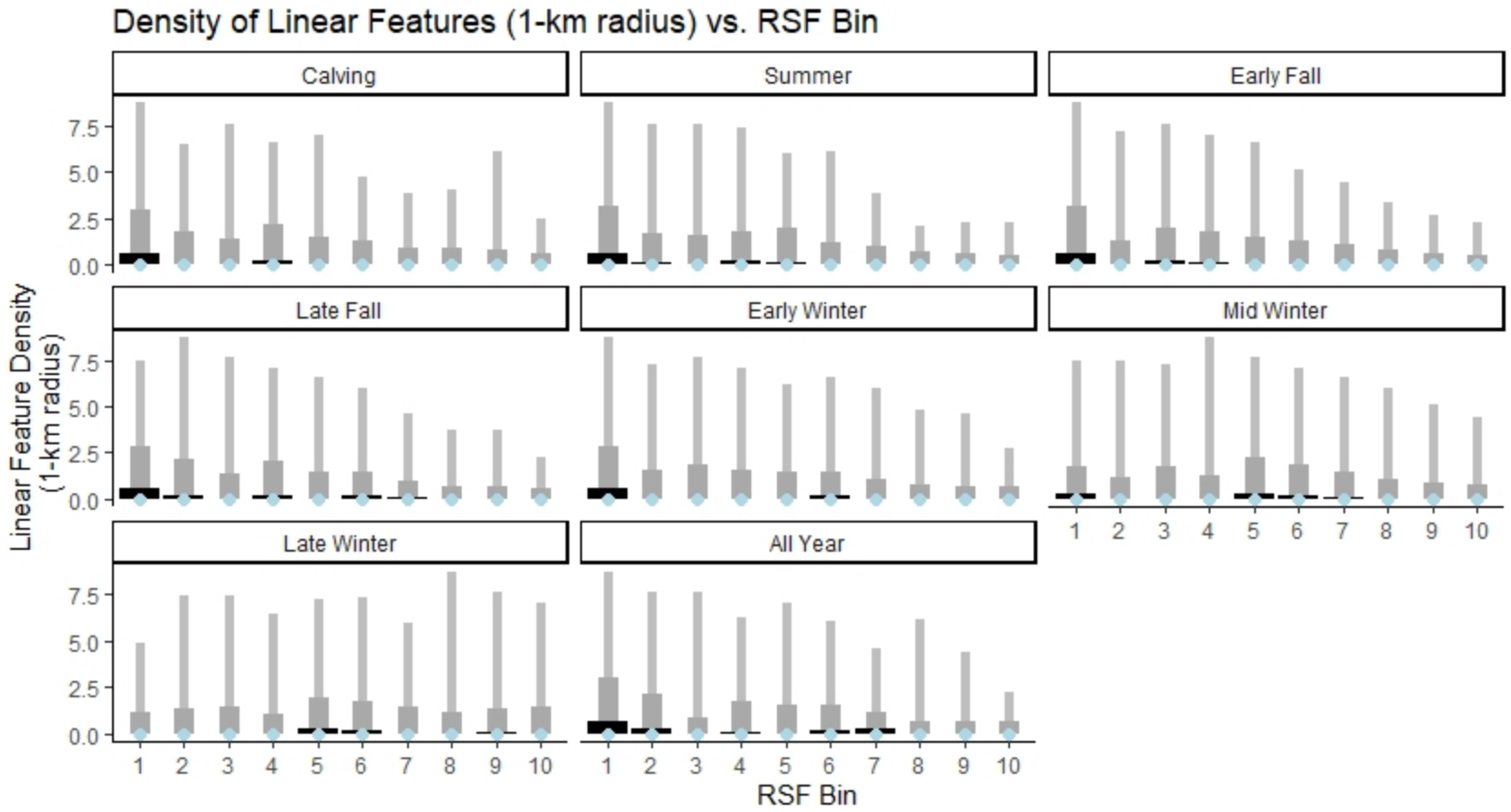


Figure G 11: The distribution of linear feature densities within mapped bin values of seasonal resource selection at a second-order scale by boreal caribou in the Northwest Territories. Blue points indicate the median value within a bin. Thin grey bars indicate the overall range of the data within a bin. Thick grey bars indicate values falling within the 95% quantile. Black bars indicate values falling within the inner 50% quantile.

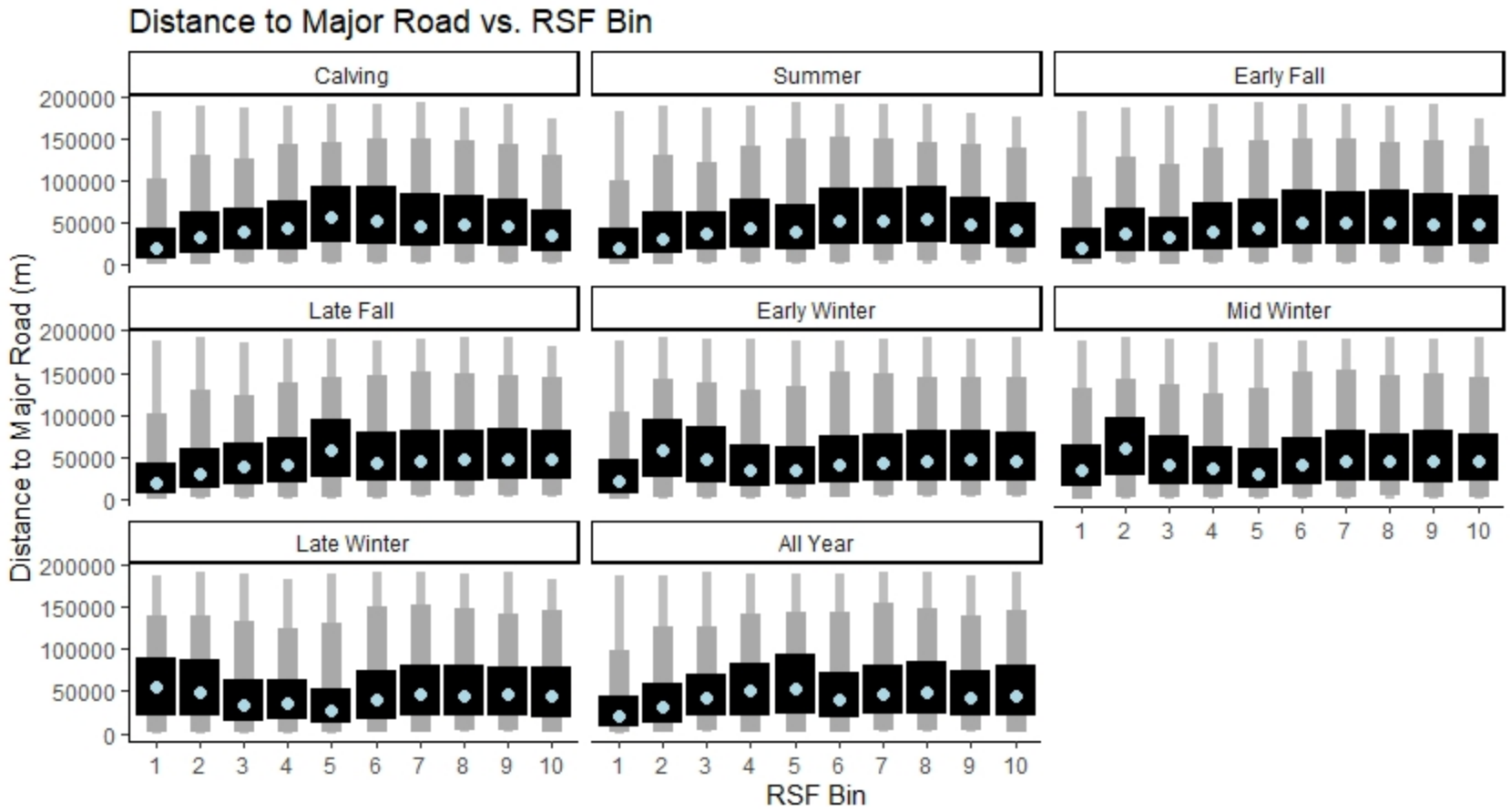


Figure G 12: The distribution of distances to the nearest major road within mapped bin values of seasonal resource selection by boreal caribou in the Northwest Territories. Resource selection was estimated at a second-order scale. Blue points indicate the median value within a bin. Thin grey bars indicate the overall range of the data within a bin. Thick grey bars indicate values falling within the 95% quantile. Black bars indicate values falling within the inner 50% quantile.

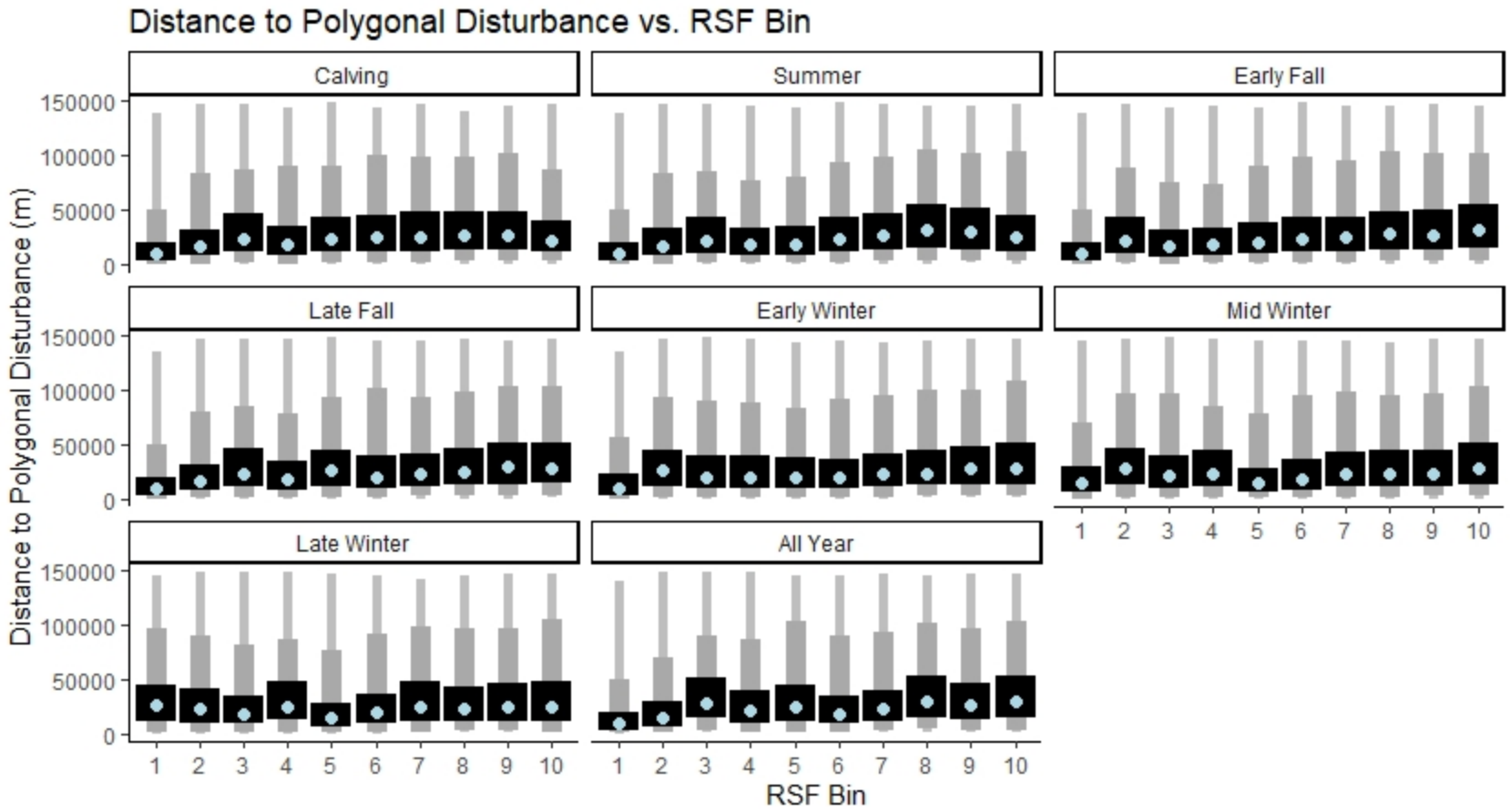


Figure G 13: The distribution of distances to the nearest polygonal disturbance (e.g. cut block or well pad) within mapped bin values of seasonal resource selection by boreal caribou in the Northwest Territories. Resource selection was estimated at a second-order scale. Blue points indicate the median value within a bin. Thin grey bars indicate the overall range of the data within a bin. Thick grey bars indicate values falling within the 95% quantile. Black bars indicate values falling within the inner 50% quantile.

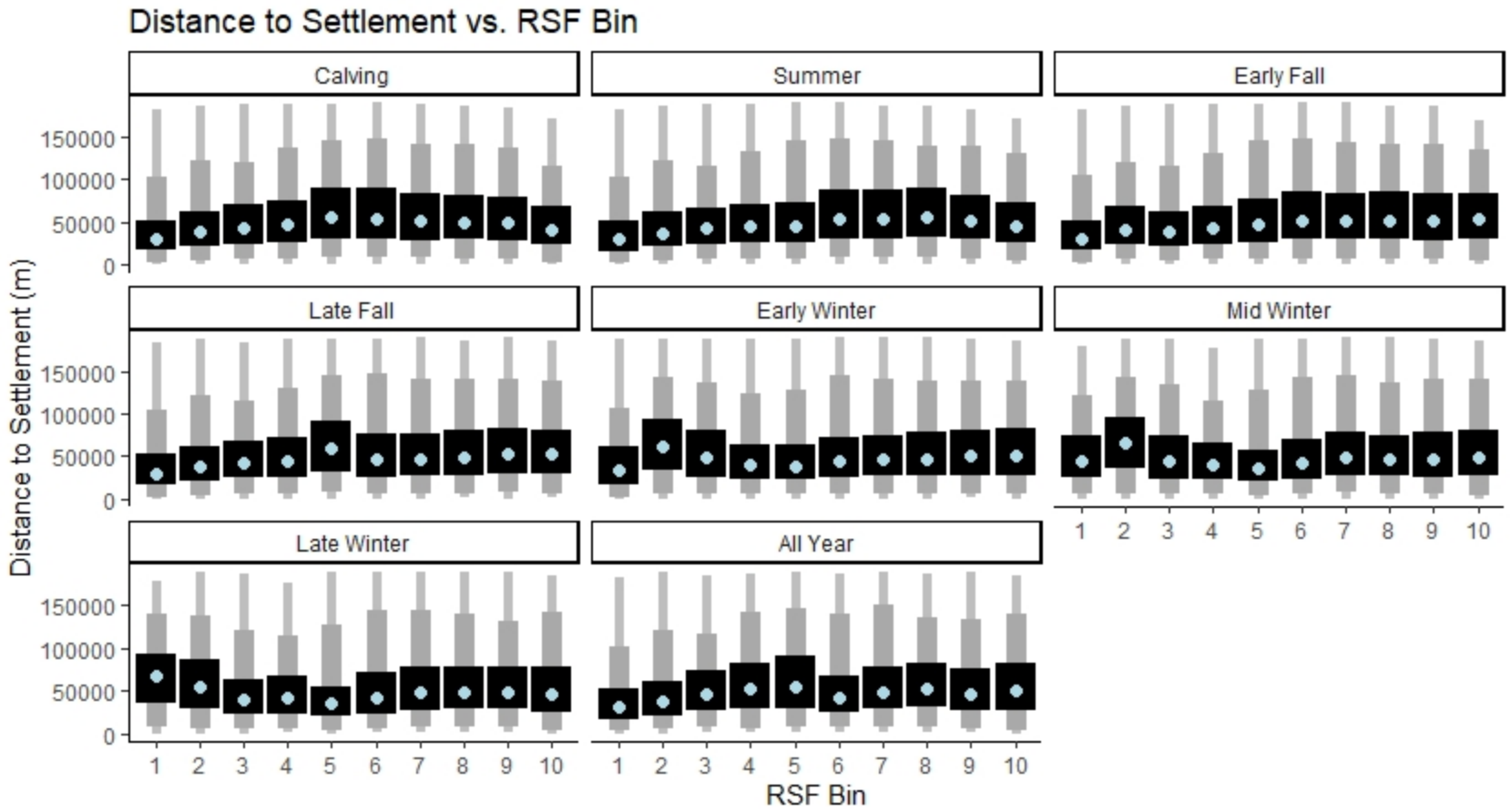


Figure G 14: The distribution of distances to the nearest settlement within mapped bin values of seasonal resource selection by boreal caribou in the Northwest Territories. Resource selection was estimated at a second-order scale. Blue points indicate the median value within a bin. Thin grey bars indicate the overall range of the data within a bin. Thick grey bars indicate values falling within the 95% quantile. Black bars indicate values falling within the inner 50% quantile.

Literature Cited

Morris, L. R., K. M. Proffitt, and J. K. Blackburn. 2016. Mapping resource selection functions in wildlife studies: Concerns and recommendations. Applied Geography 76:173–183.

APPENDIX H: COMPARISONS OF RESOURCE USE AND AVAILABILITY

Analyses of resource selection are used to assess how an organism's use of a particular resource (or environmental attribute; e.g., land-cover type) compares to how available the resource is in the spatial scale of interest. In the main report, results focused primarily on this "selection" ratio (use / availability), but inferences on selection can often be better informed by evaluating both the numerator and denominator of this ratio. In this appendix, we present graphs showing how resource use by caribou—as indexed by GPS locations from radio-collared females—compares to the availability of that resource at a second-order scale [note: third-order graphs are not provided as availability is unique to each caribou-year and providing matched comparisons of use versus availability is difficult to graph given the large sample sizes within each year]. Availability at the second-order scale was defined separately for caribou in the Northern group (Inuvik and Sahtu monitoring regions) and caribou in the Southern Group (Dehcho, North Slave and South Slave monitoring regions). For each group, we delineated availability by fitting a minimum convex polygon (MCP) around all GPS locations pooled from radio-collared caribou within the group then buffered each MCP by 15-km (approximately the maximum distance moved by caribou in a 24-hr period—see Appendix B) and clipped them to the boundaries of the study area. Note that the spatial scale of availability was therefore constant for all caribou within a group (Northern or Southern) but differed between groups. For each caribou-year (e.g., for caribou *i* with GPS locations recorded during year *j*), we sampled availability by generating 5000 random points within the MCP of the individual's group. Caribou GPS locations and random locations were then matched to year-specific explanatory variables (e.g., GPS and caribou locations in 2012 were matched to land-cover, fire, and human disturbance data estimated for 2012).

For each graph, we compared caribou use to availability within each regional monitoring area (Inuvik, Sahtu, Dehcho, North Slave, and South Slave). Because of the sampling framework outlined above, availability is relatively constant between Inuvik and Sahtu (the Northern group) and among Dehcho, North Slave, and South Slave (the Southern group), though small variations will occur for some resources among monitoring areas within a group (see below). For land-cover resources, which were categorical variables, proportional use (the number of GPS locations in a given land-cover / the total number of GPS locations) is compared to proportional availability (the number of random locations in a given land-cover / the total number of random locations). For continuous variables (e.g. distance to nearest major road), the mean value of the GPS locations is compared to the mean value of the random locations. In all instances, proportions and mean values are first calculated for each caribou-year, then averaged across caribou-years to derive population-level estimates, which are accompanied by 95% confidence intervals that represent an estimate of the variation among individual caribou-years. Note that because the entire data set of caribou GPS locations spanned 2002–2017 and random locations were matched to year-specific explanatory variables, the mean values for random locations will vary across years.

Order of graphs:

- Unburned land-covers: (Figs. H1-8)
- Burned lowlands and upland conifer (Figs. H9-16)
- Burned broadleaf forest and non-treed uplands (Figs. H17-24)
- Landscape context (Figs. H25-32)

- Distance-to variables (Figs. H33-40)
- Linear feature density (Figs. H41-48)

Within each section, the sequence of graphs is calving, summer, early fall, late fall, early winter, mid-winter, late winter, and all year.

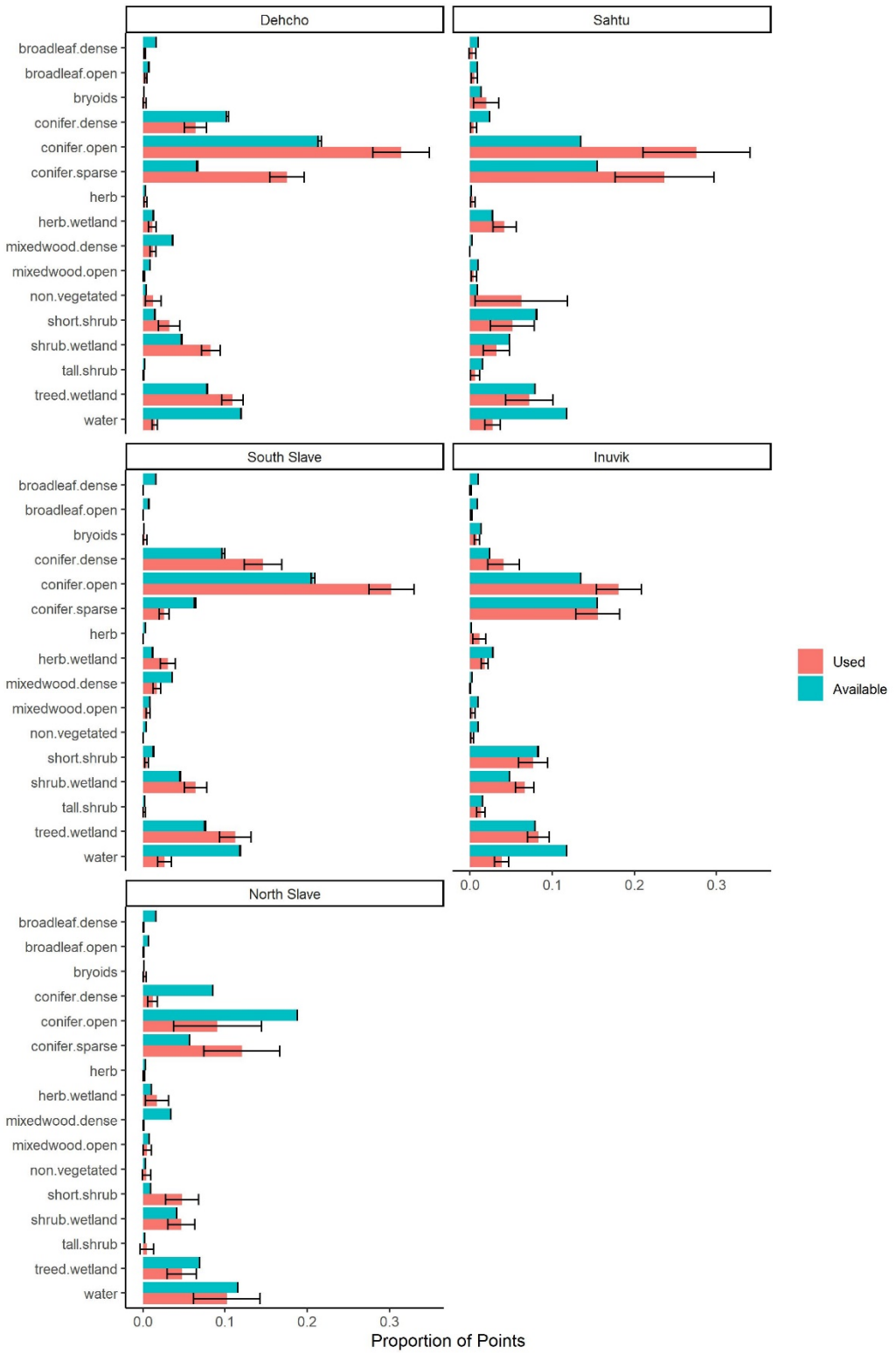


Figure H 1: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **calving**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

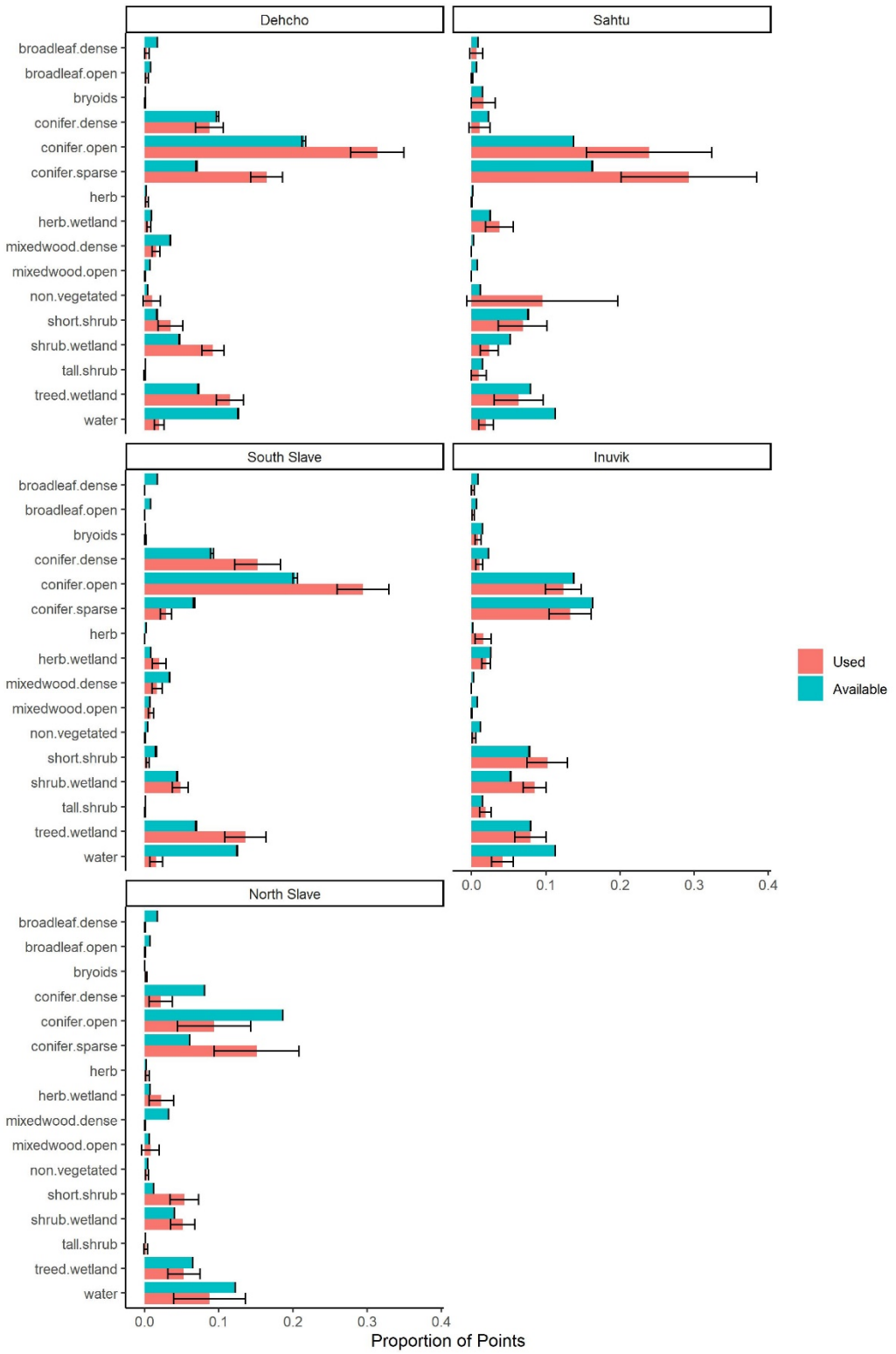


Figure H 2: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **summer**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

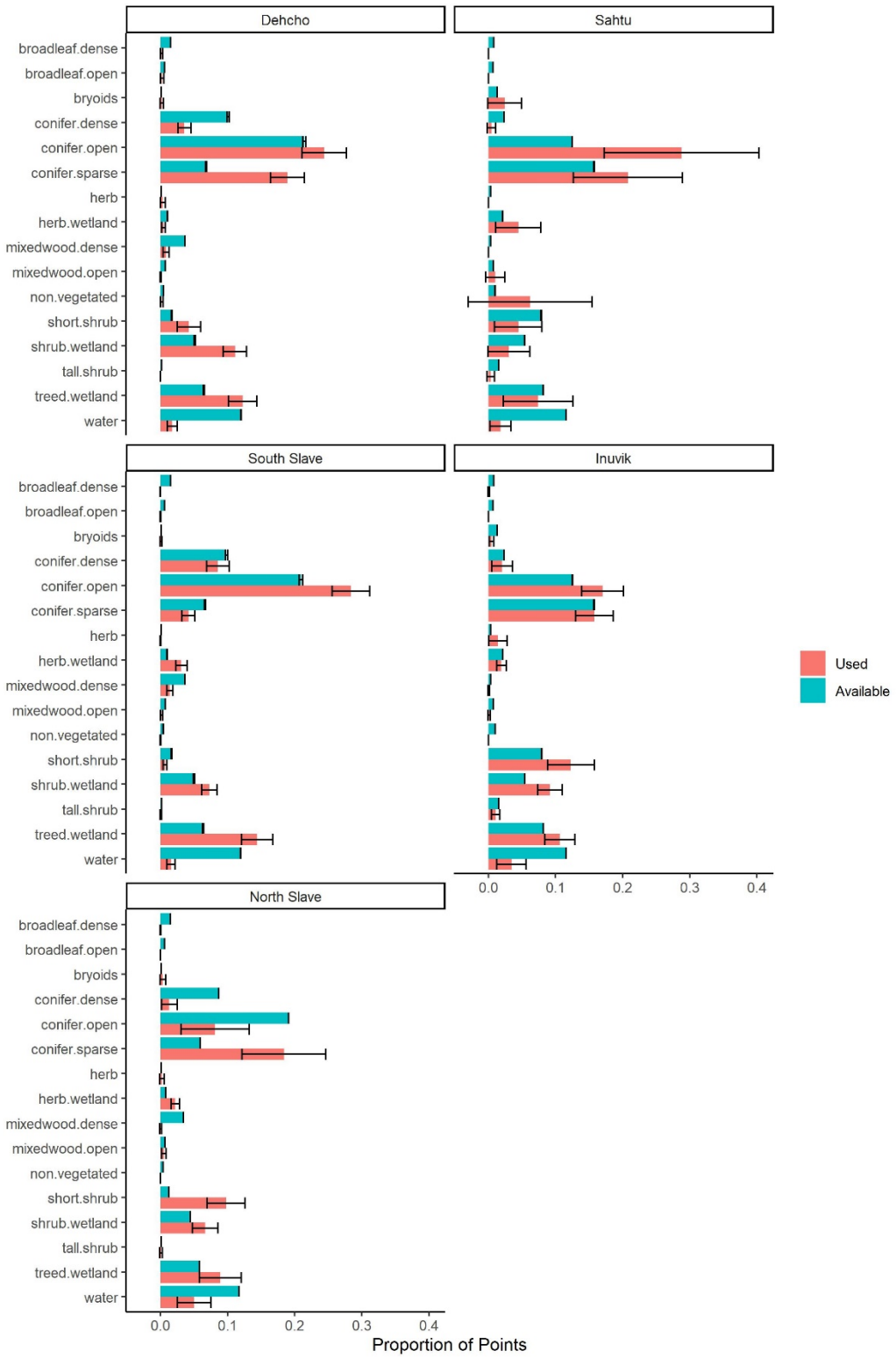


Figure H 3: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **early fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

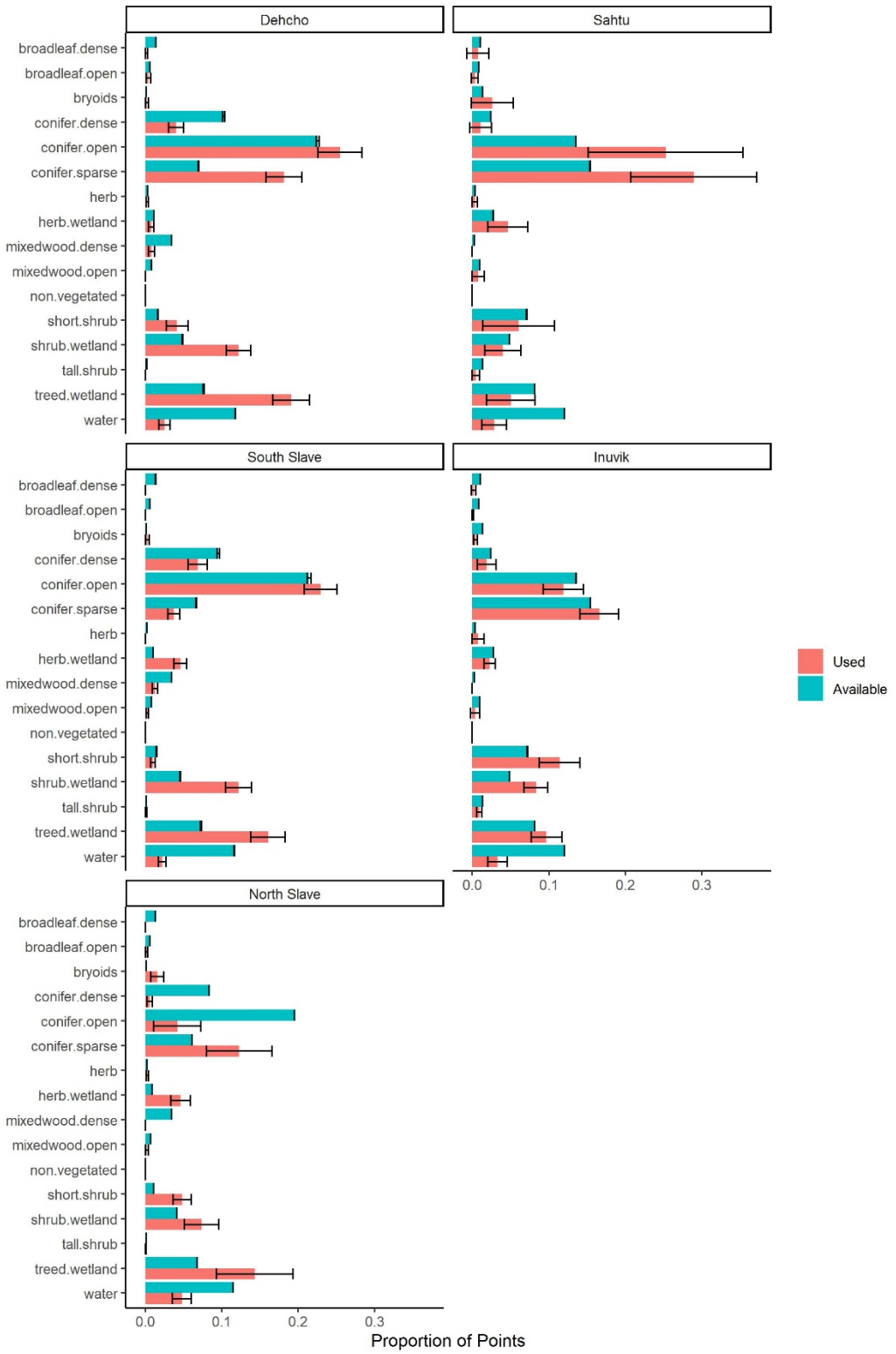


Figure H 4: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **late fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

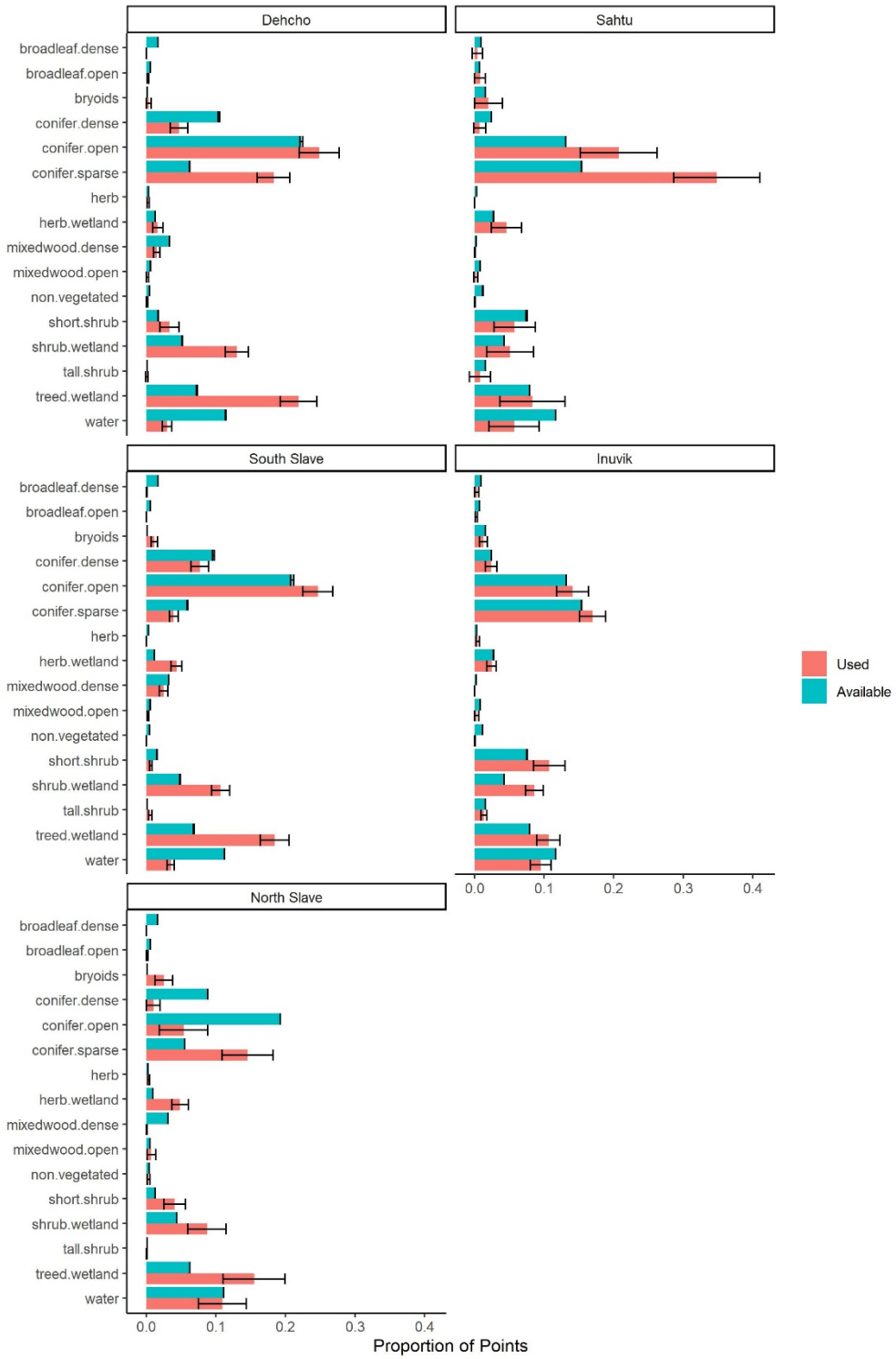


Figure H 5: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **early winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

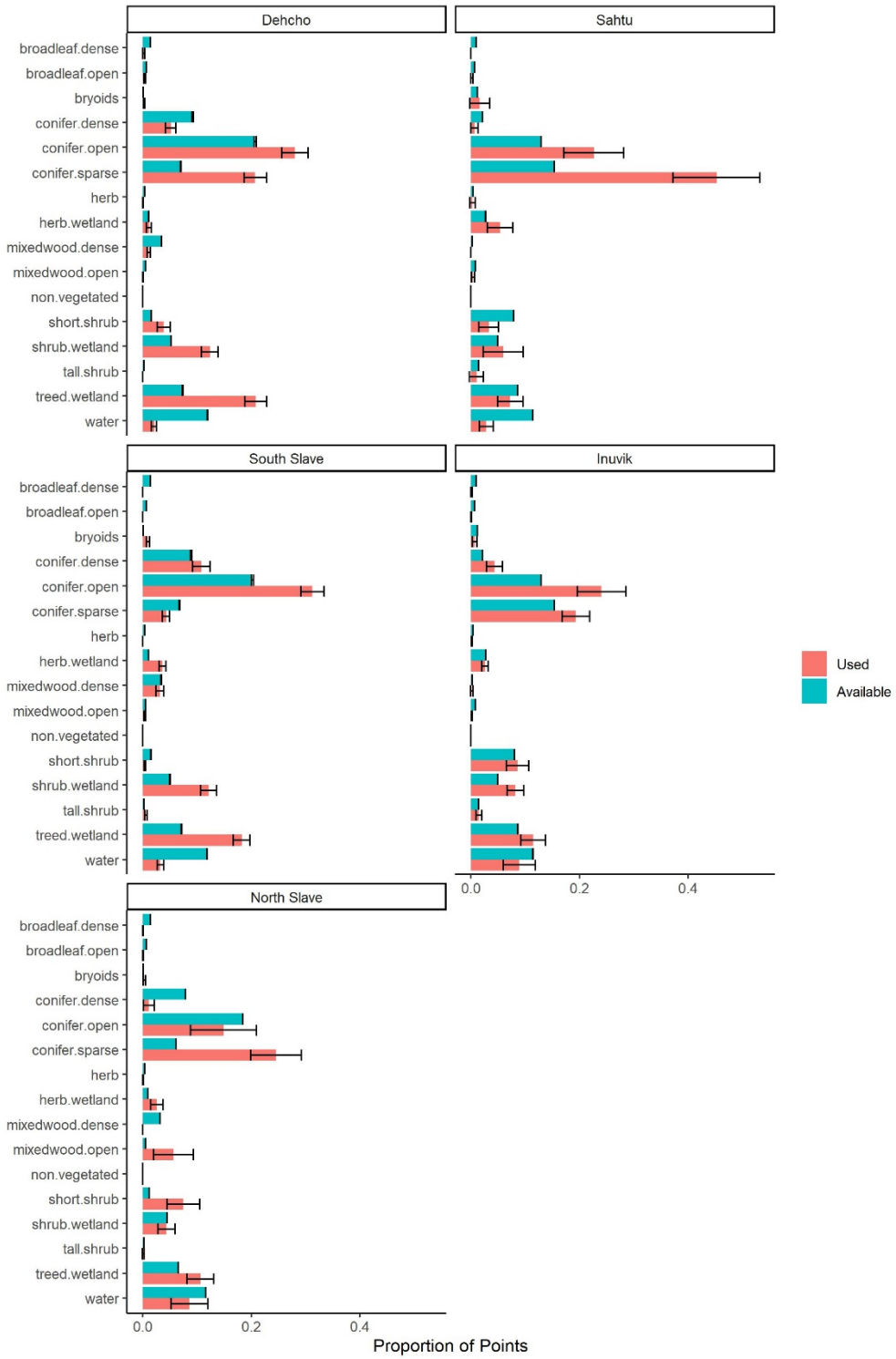


Figure H 6: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **mid-winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

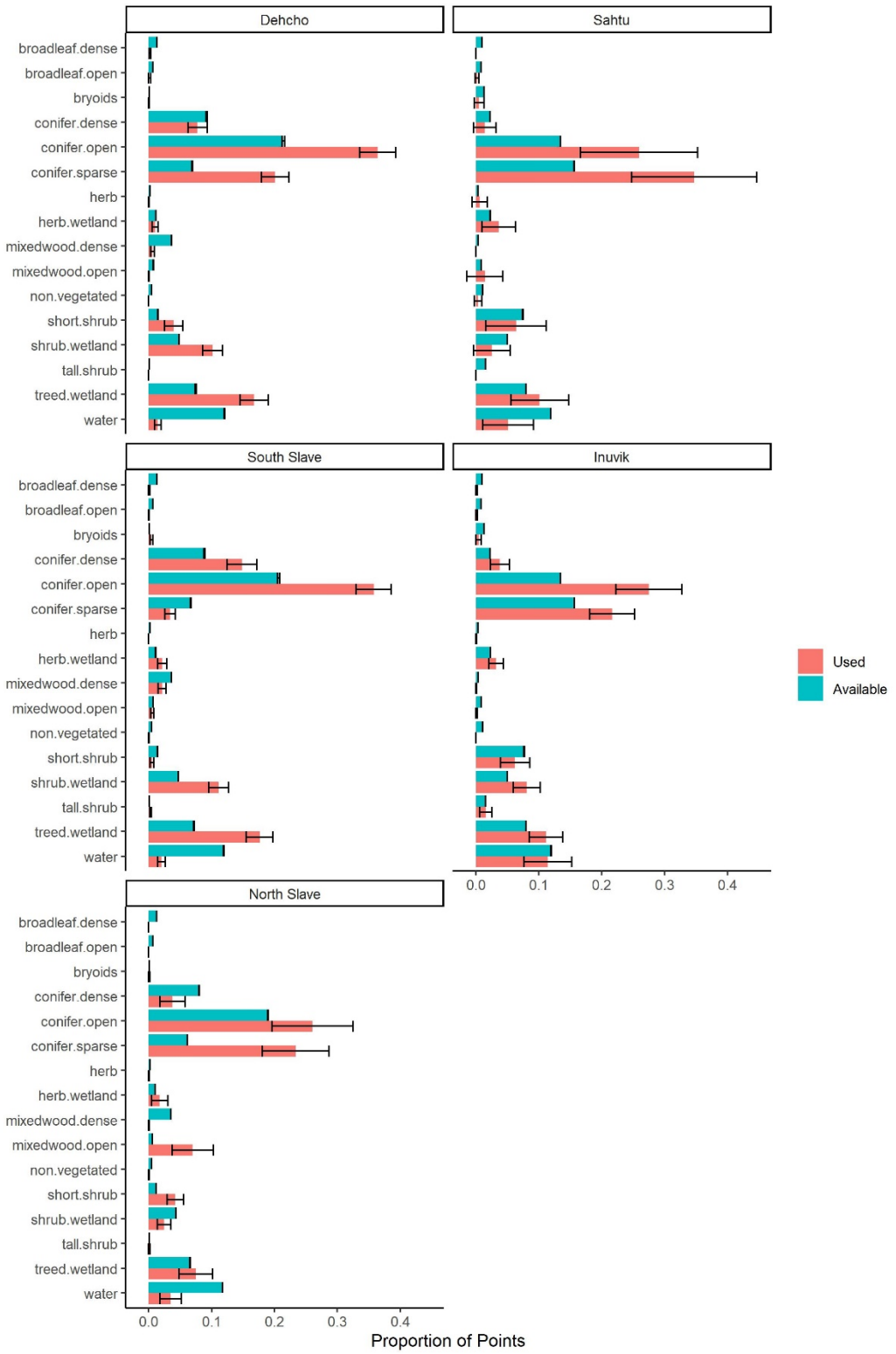


Figure H 7: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas during **late winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars

represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

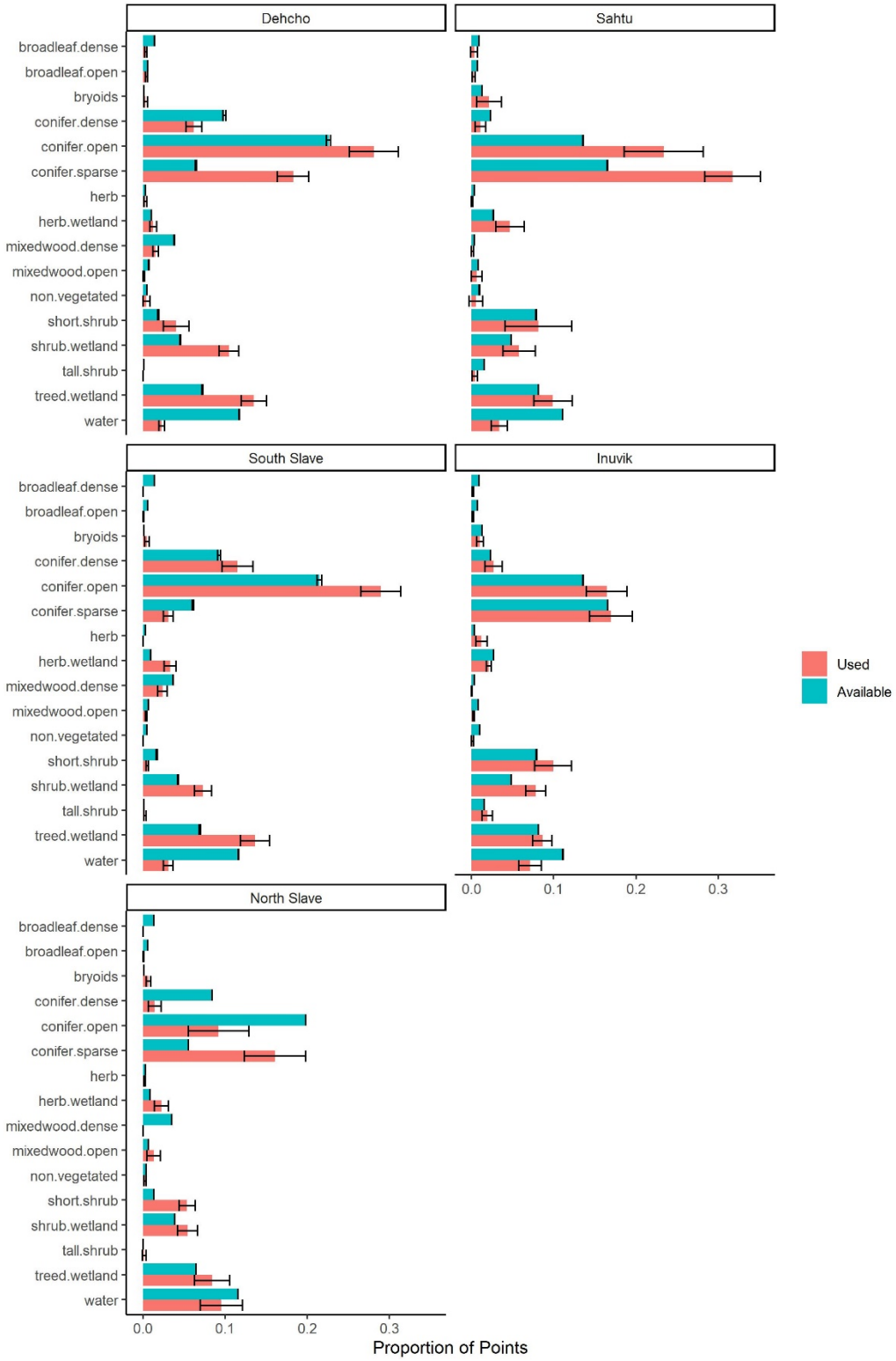


Figure H 8: The proportion of used (GPS) locations and available (or random) locations falling within various unburned land-cover types among the five regional monitoring areas on a **yearly** basis. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

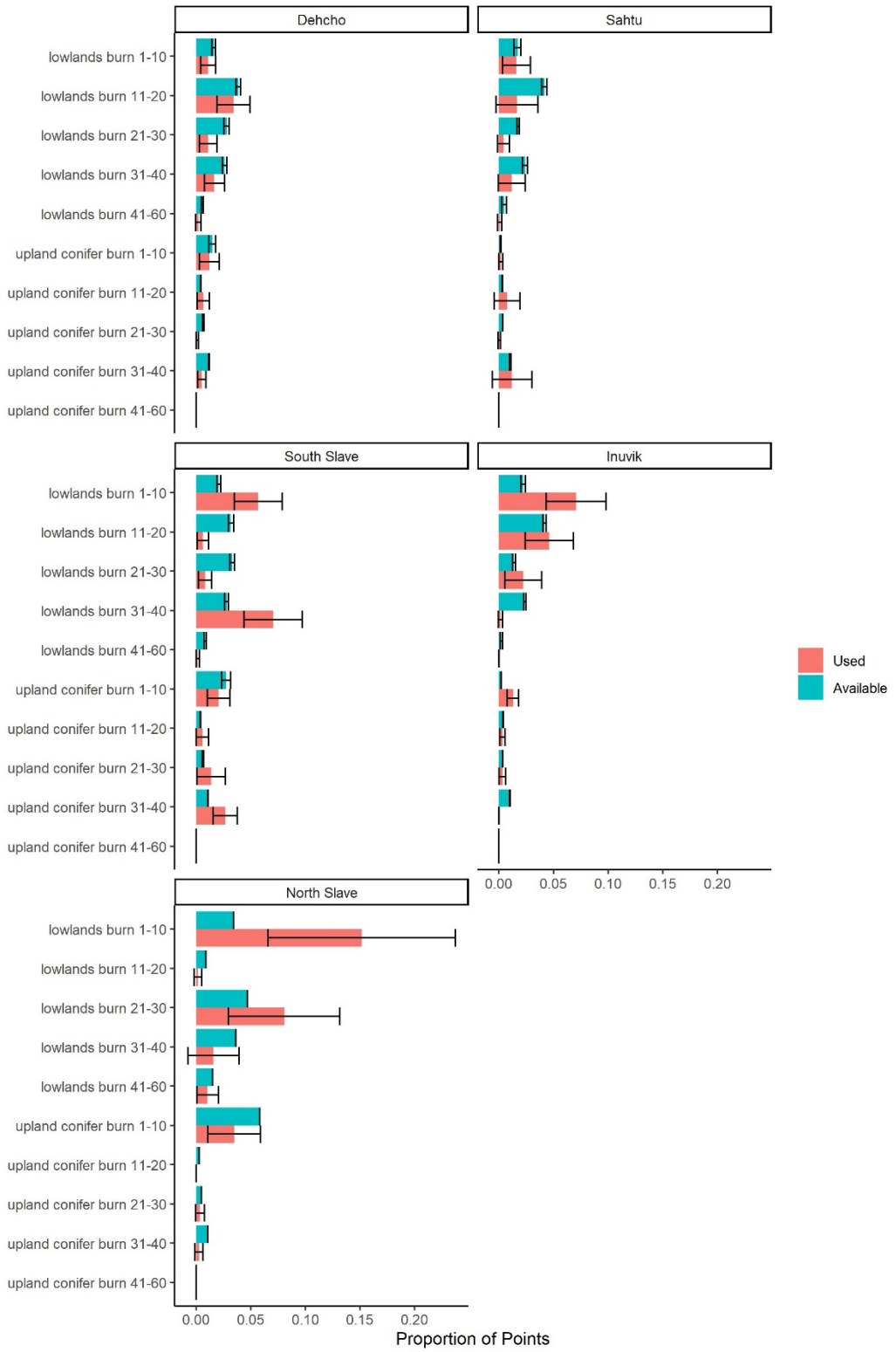


Figure H 9: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **calving**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

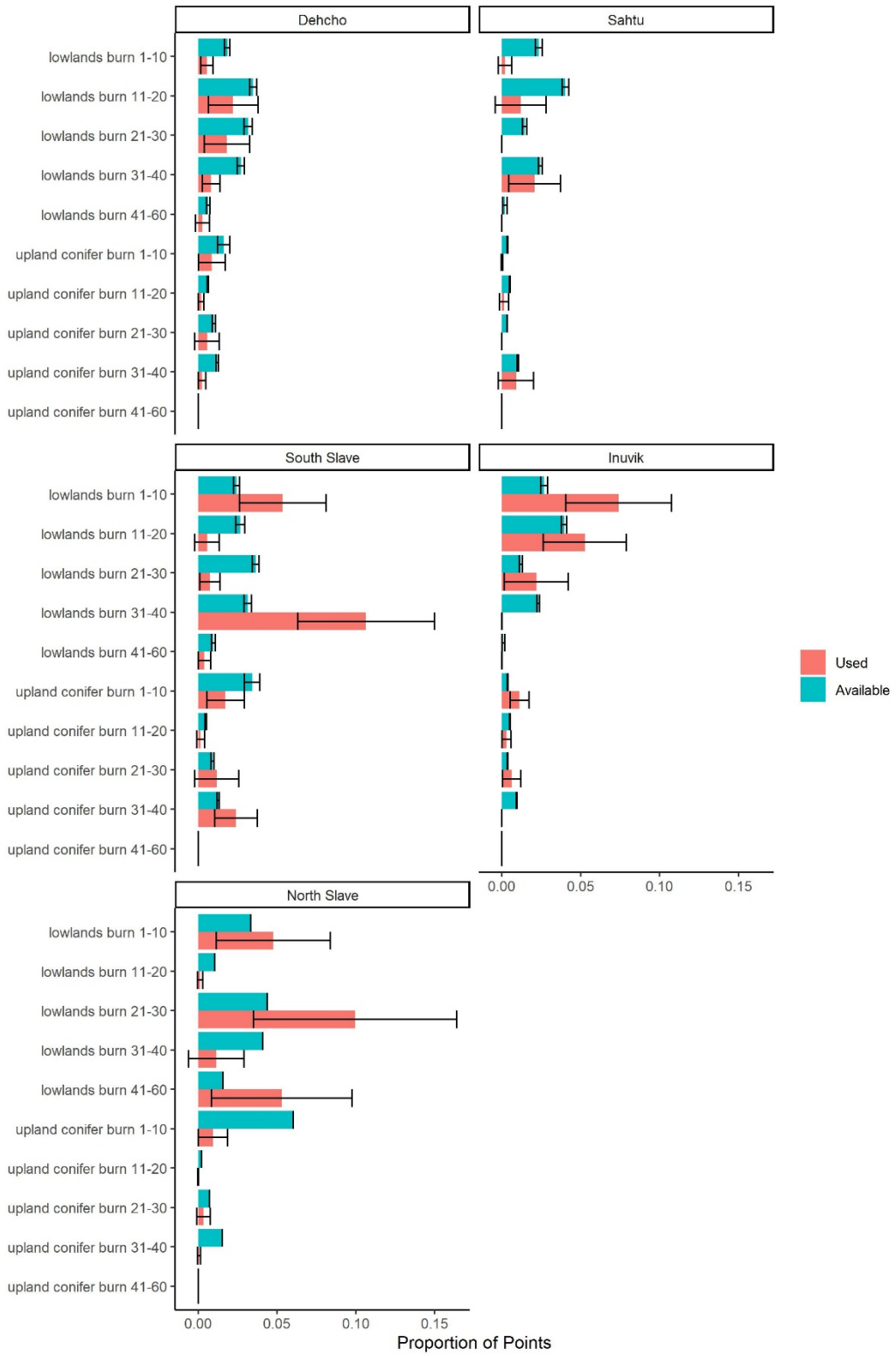


Figure H 10: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **summer**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

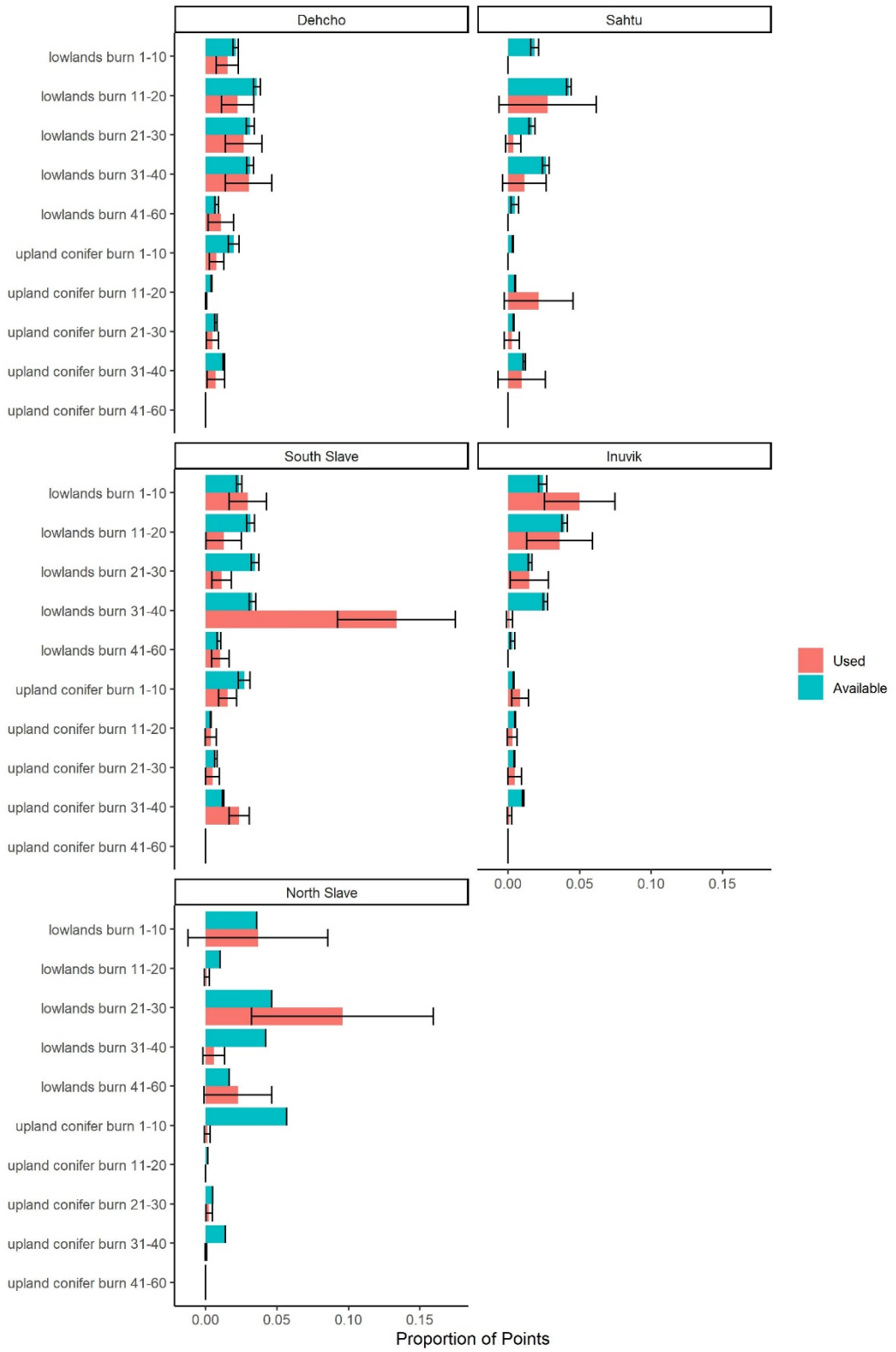


Figure H 11: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **early fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

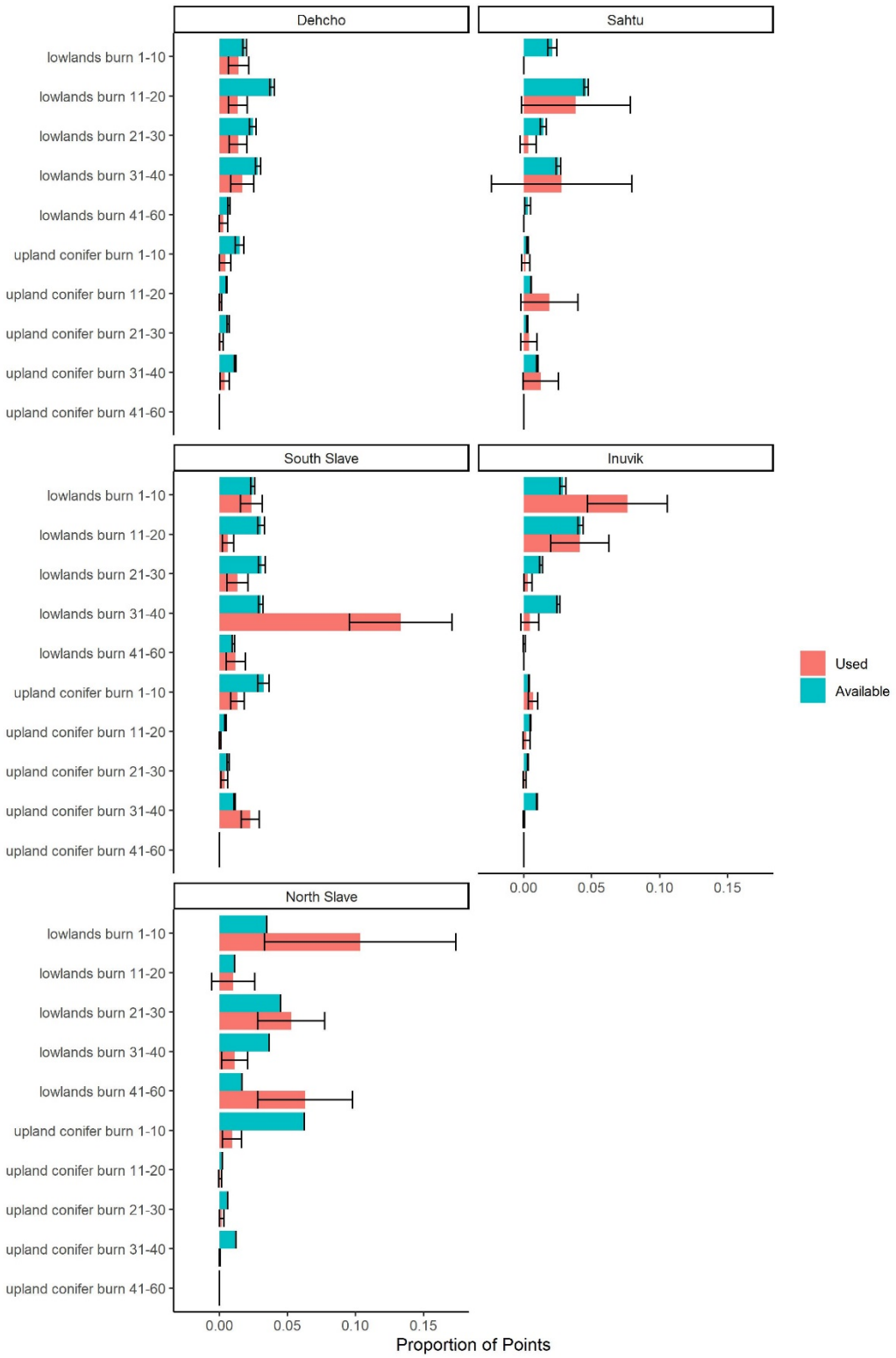


Figure H 12: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **late fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

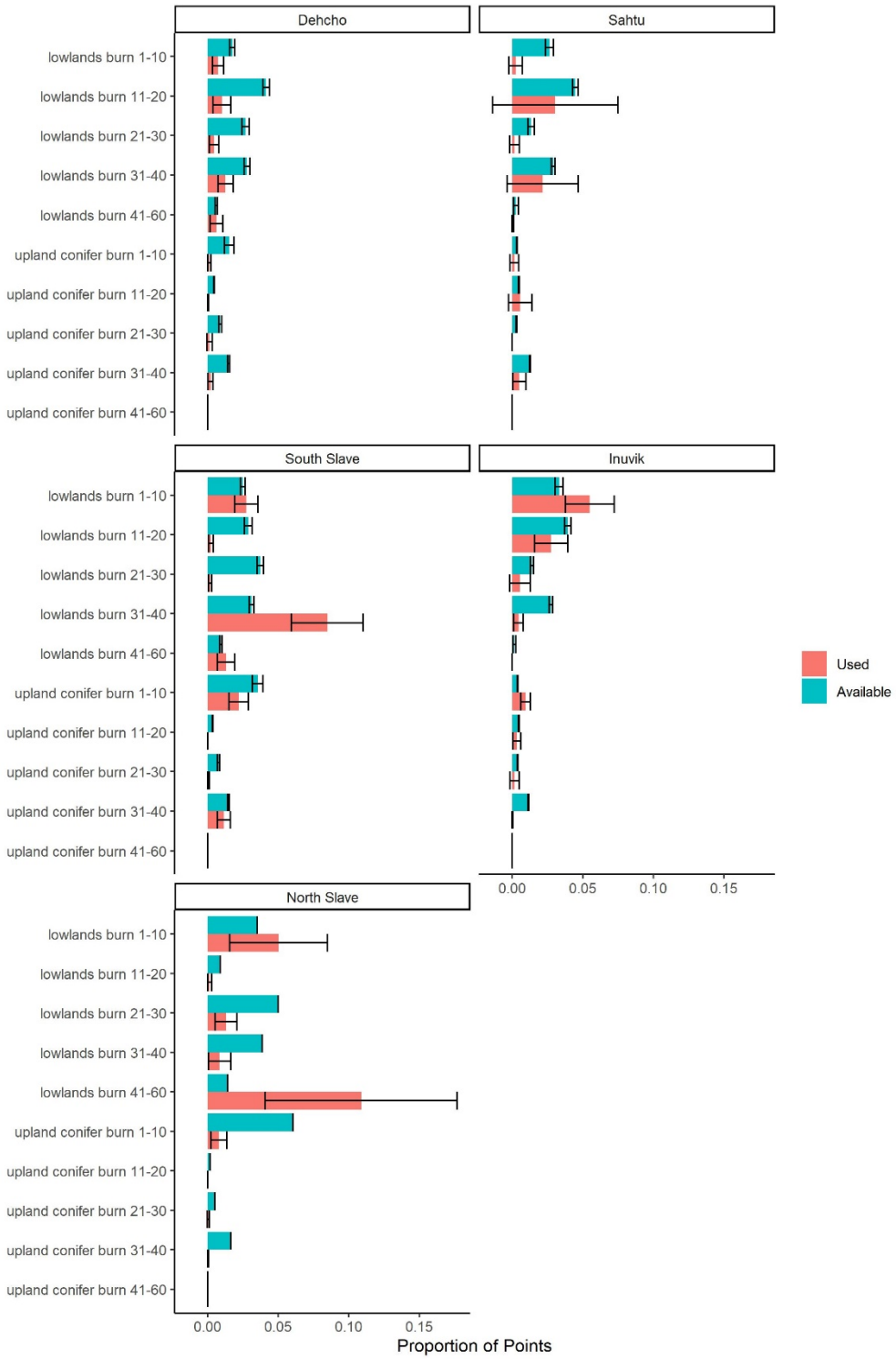


Figure H 13: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **early winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

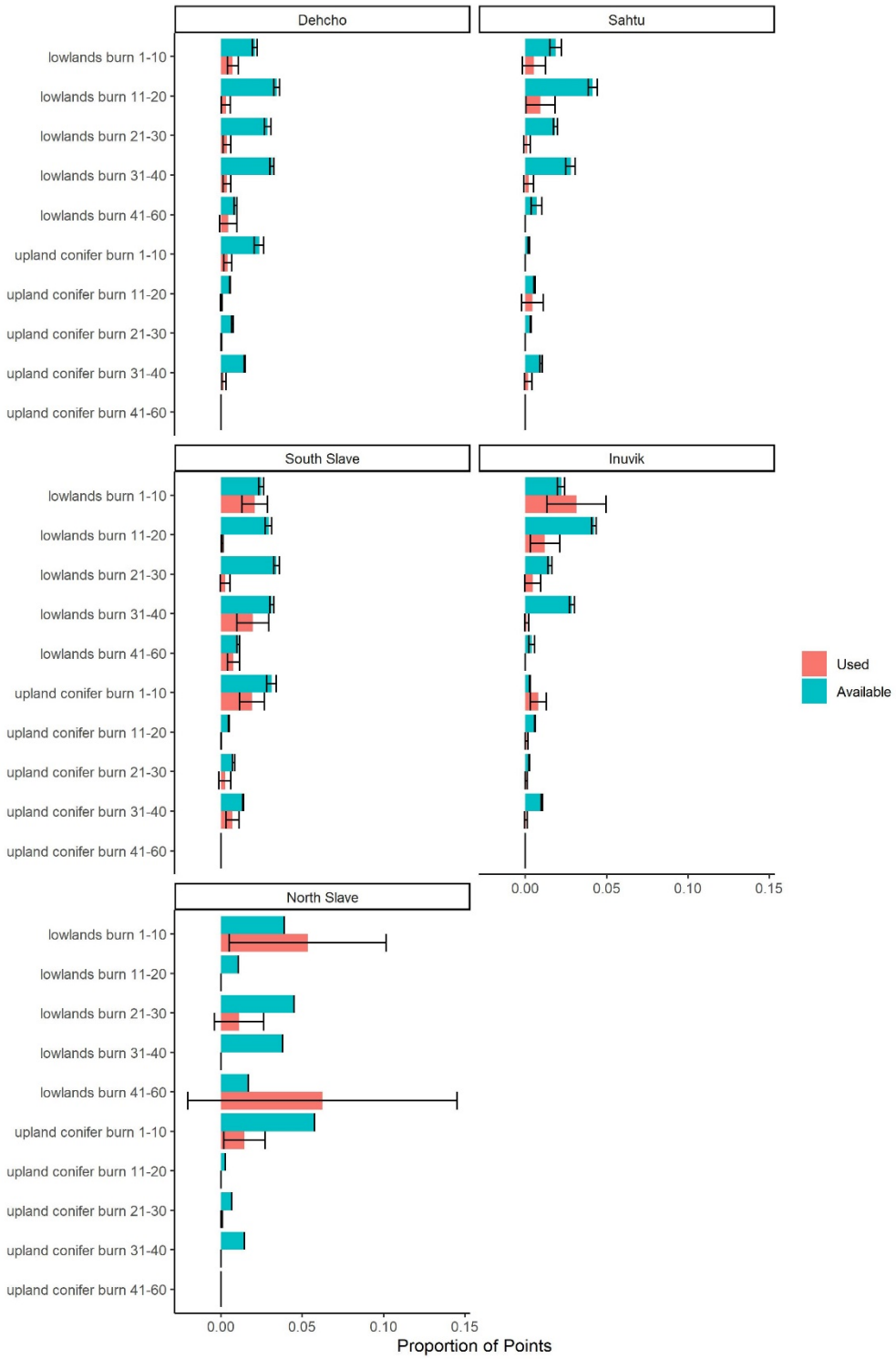


Figure H 14: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **mid-winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

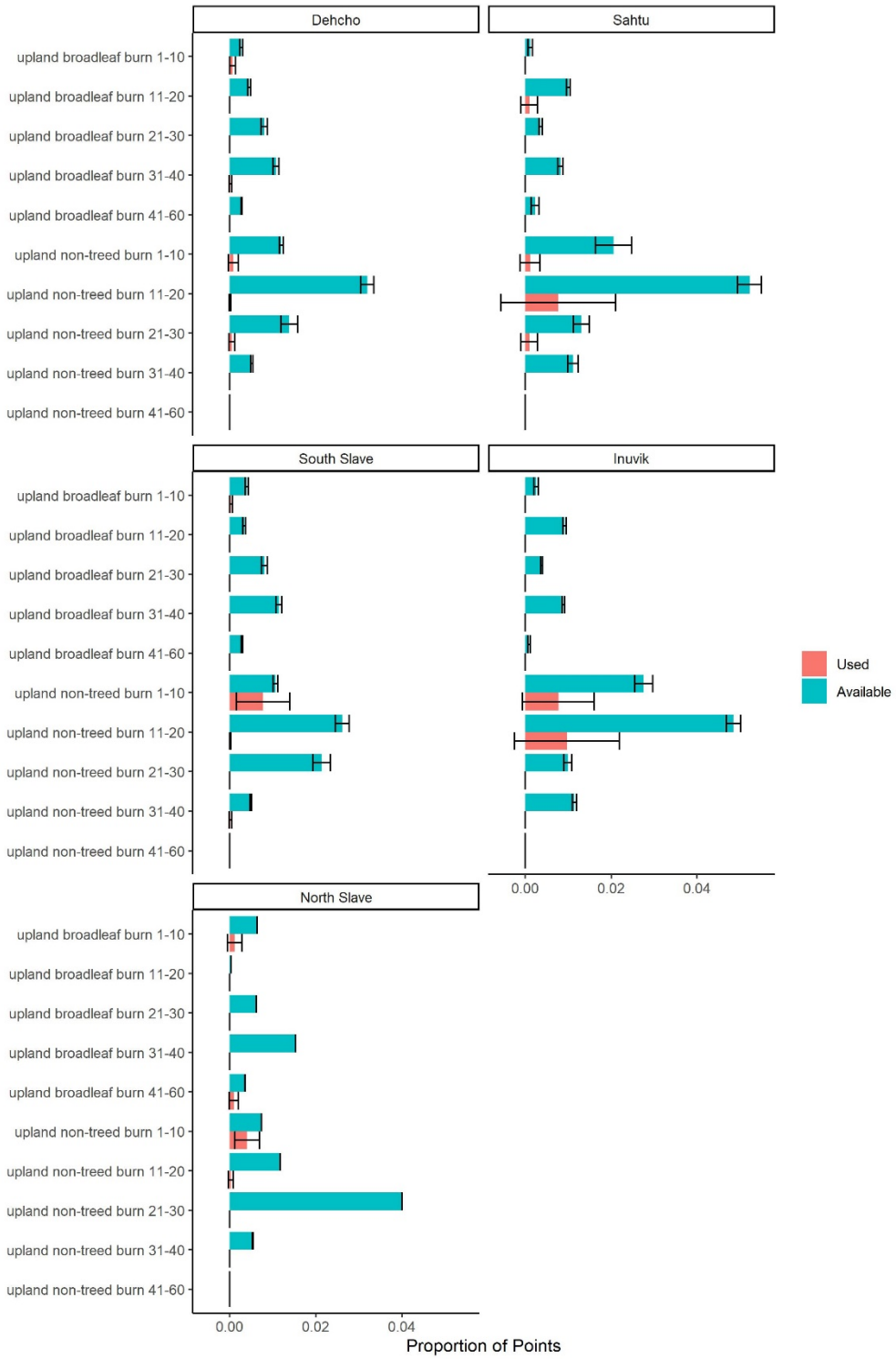


Figure H 15: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas during **late winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

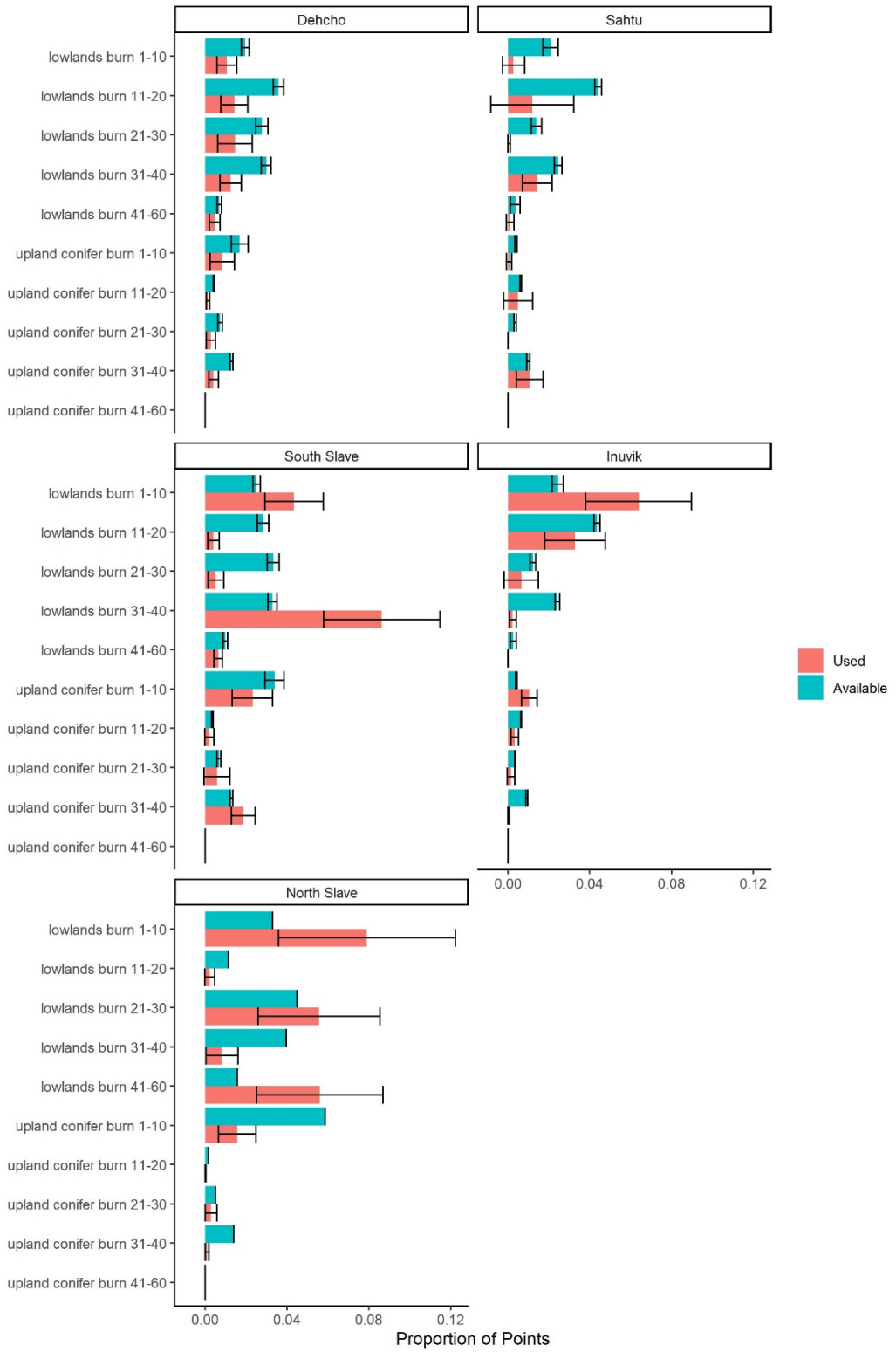


Figure H 16: The proportion of used (GPS) locations and available (or random) locations falling within burned lowlands and upland conifer among the five regional monitoring areas on a **yearly** basis. Random locations were sampled within the available area defined at a second-order scale. Error bars

represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

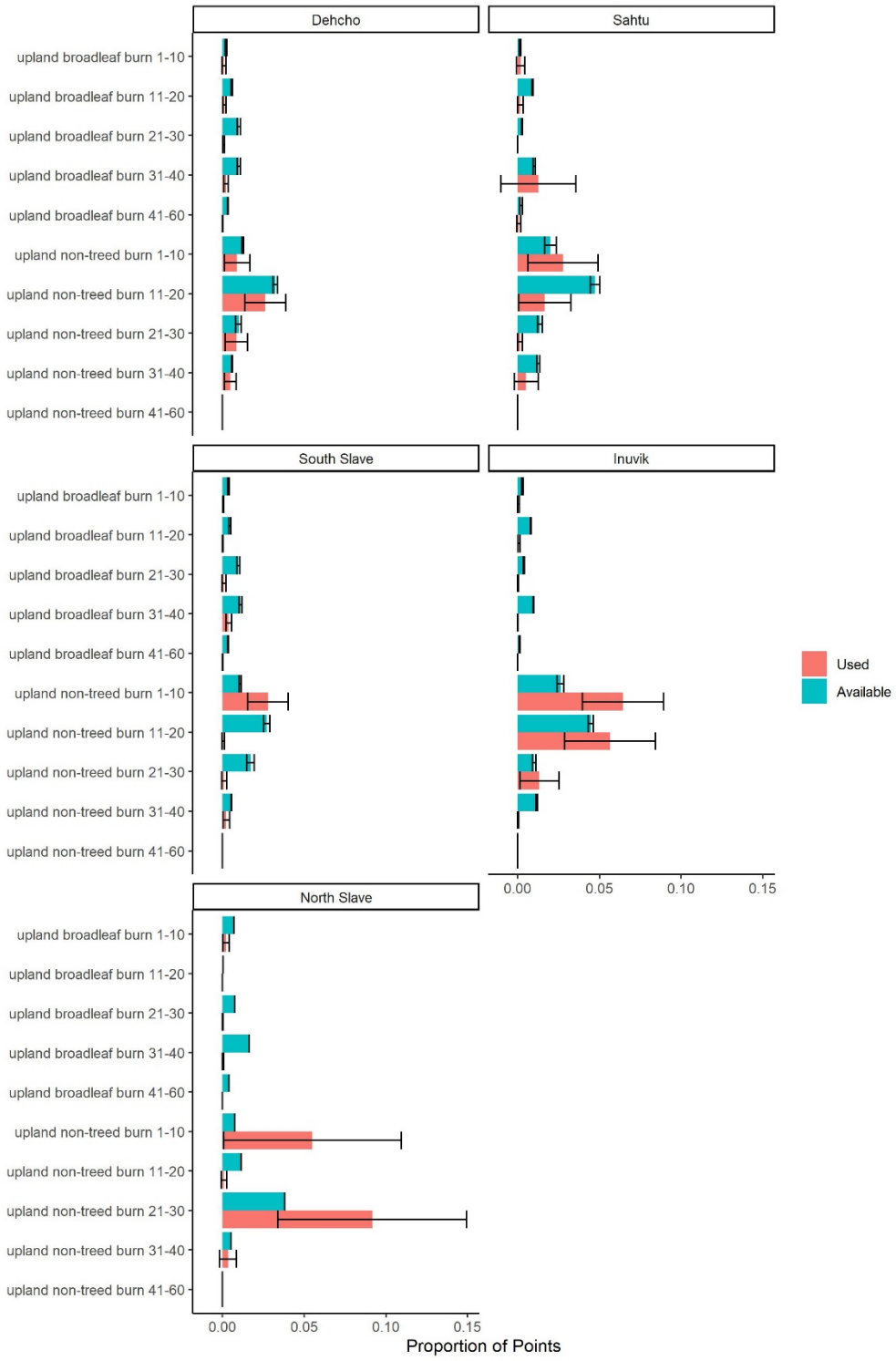


Figure H 17: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **calving**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

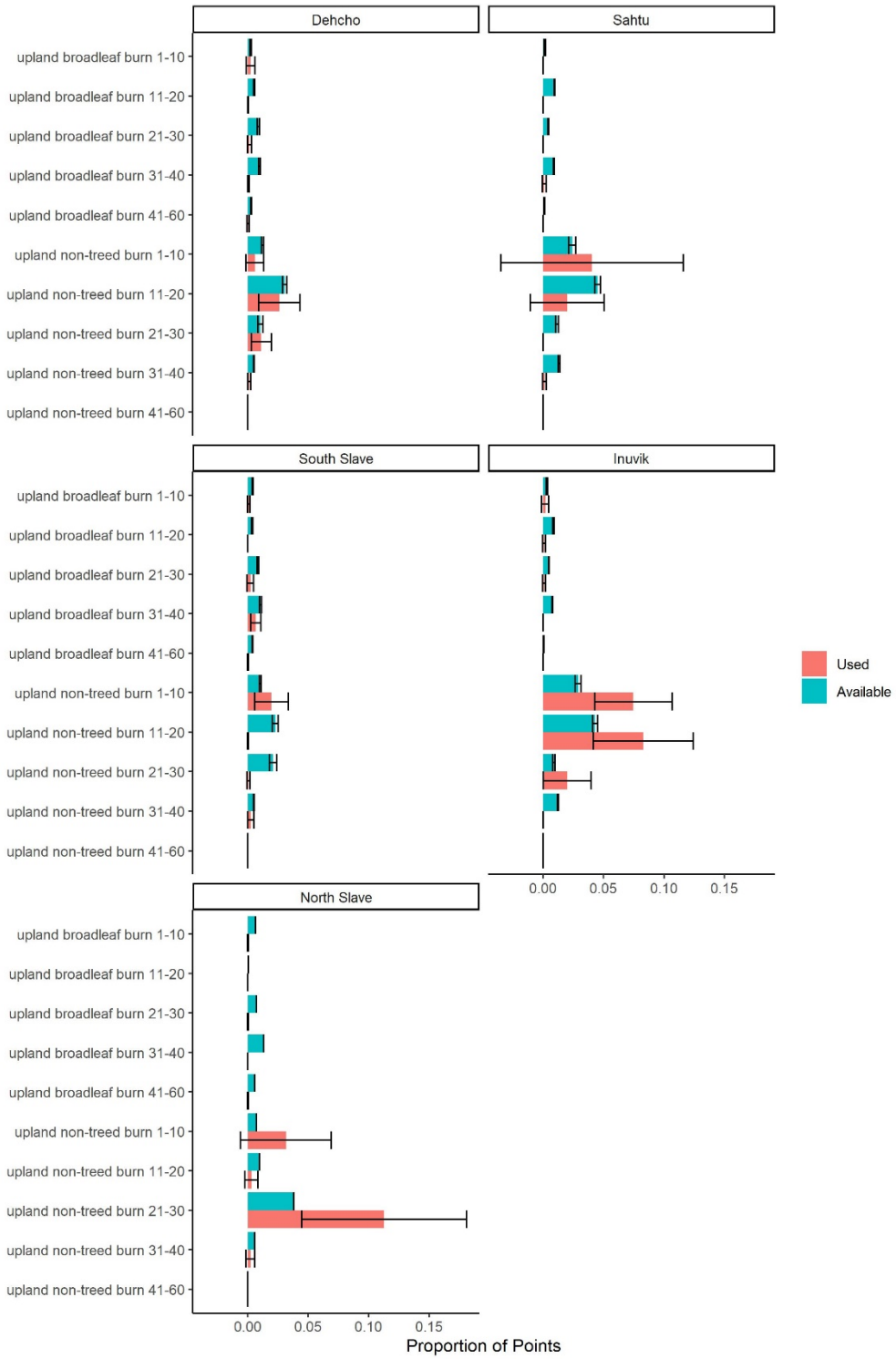


Figure H 18: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **summer**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

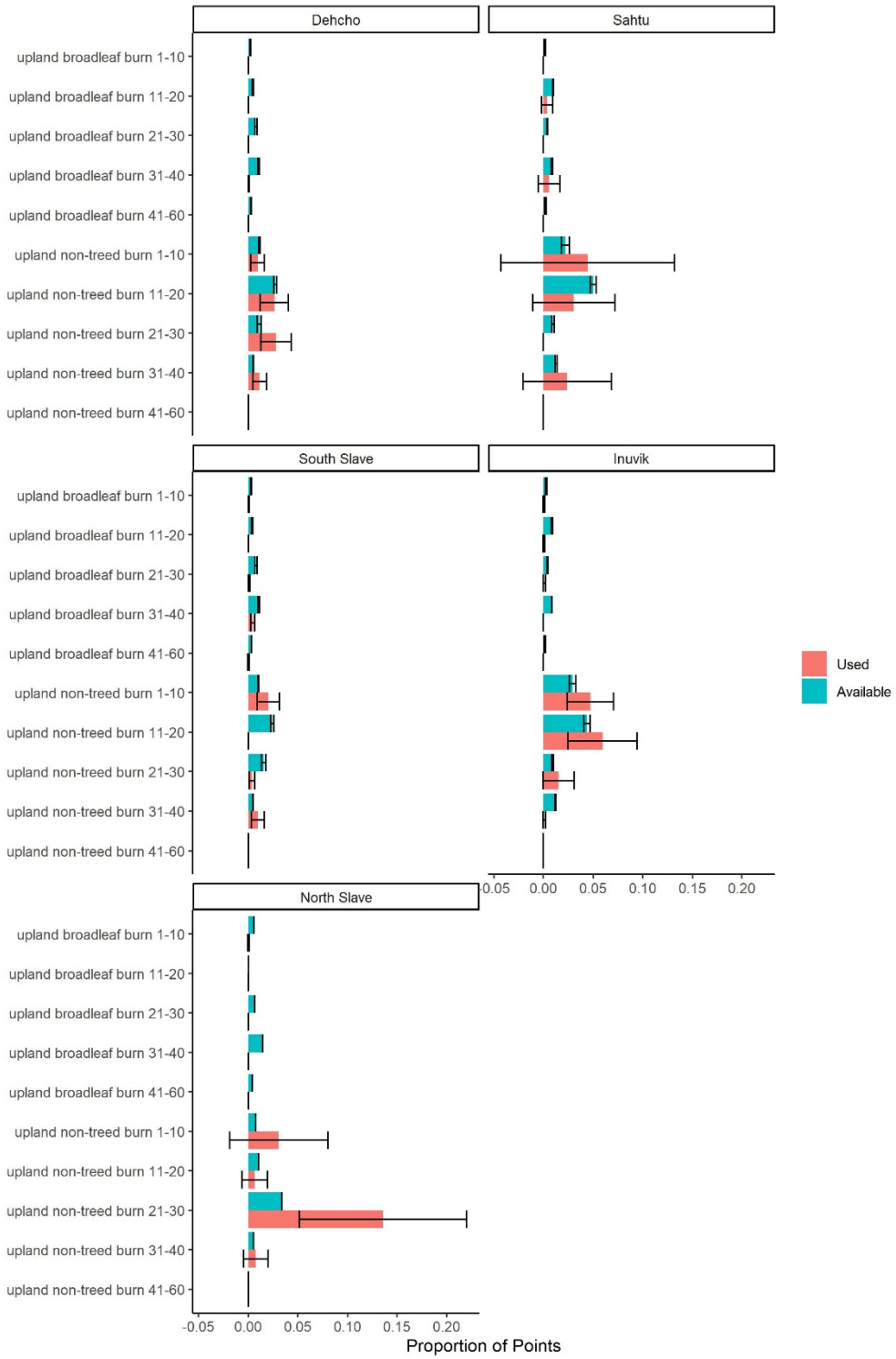


Figure H 19: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **early fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

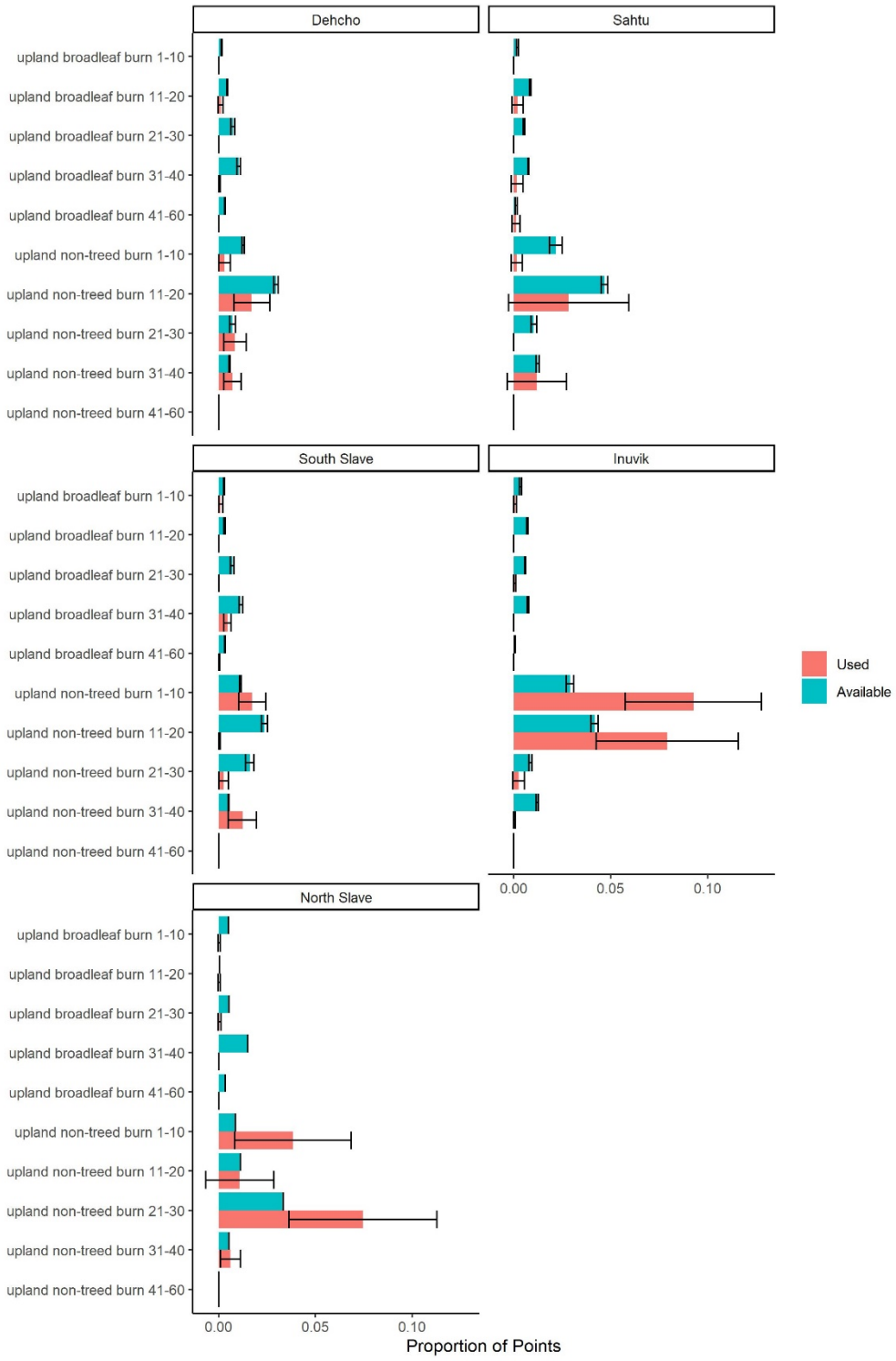


Figure H 20: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **late fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

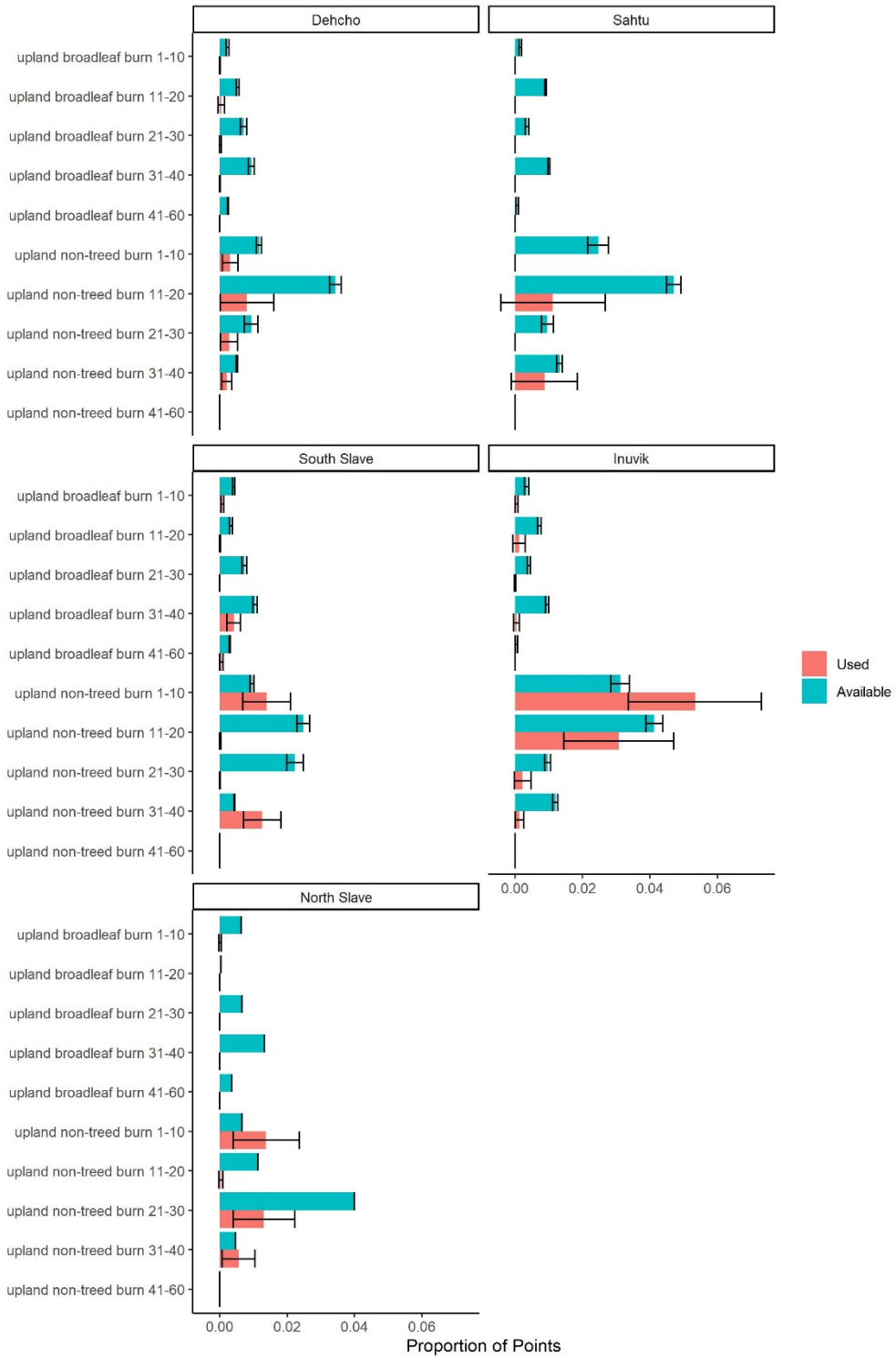


Figure H 21: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **early winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

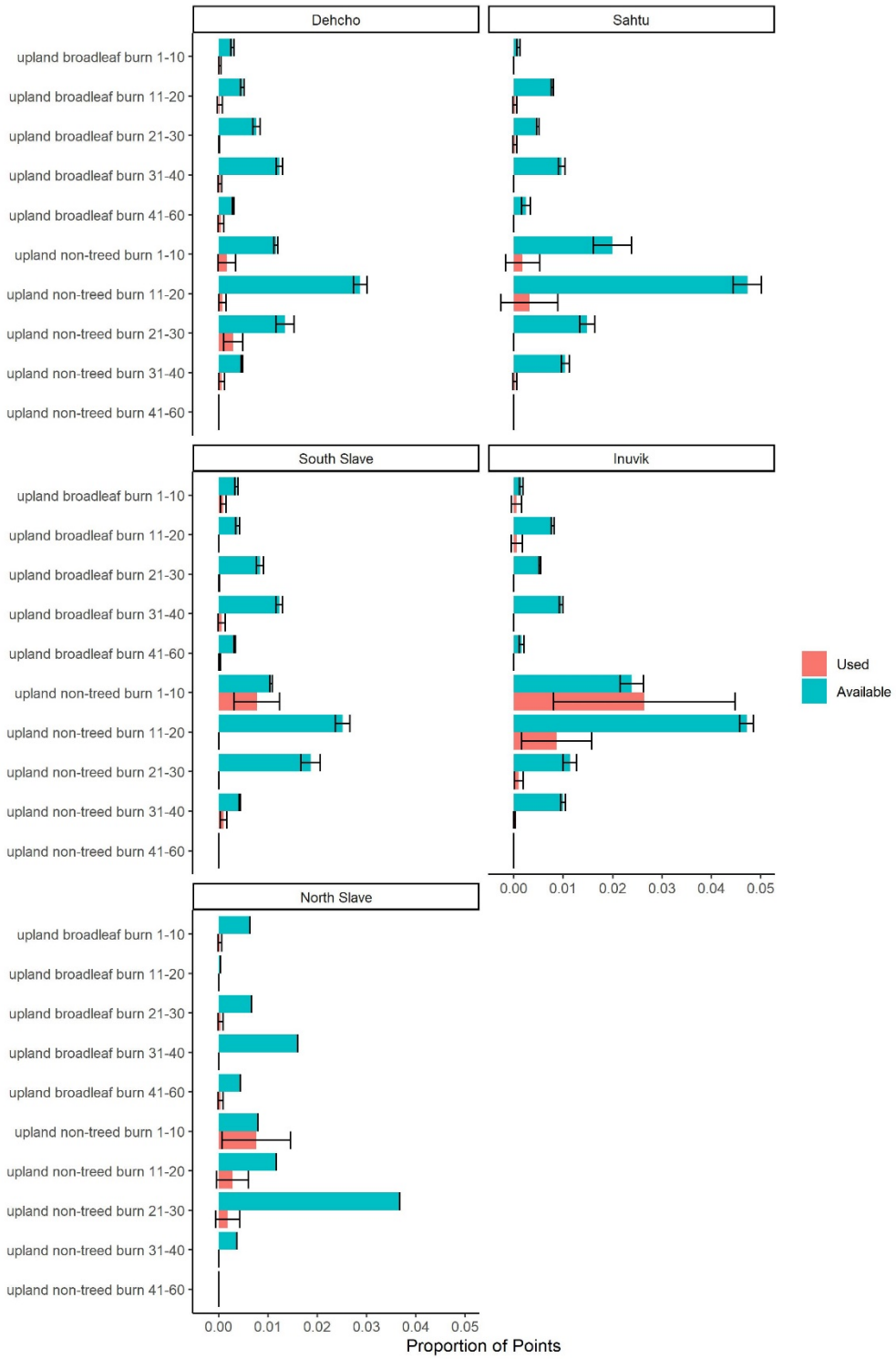


Figure H 22: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **mid-winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

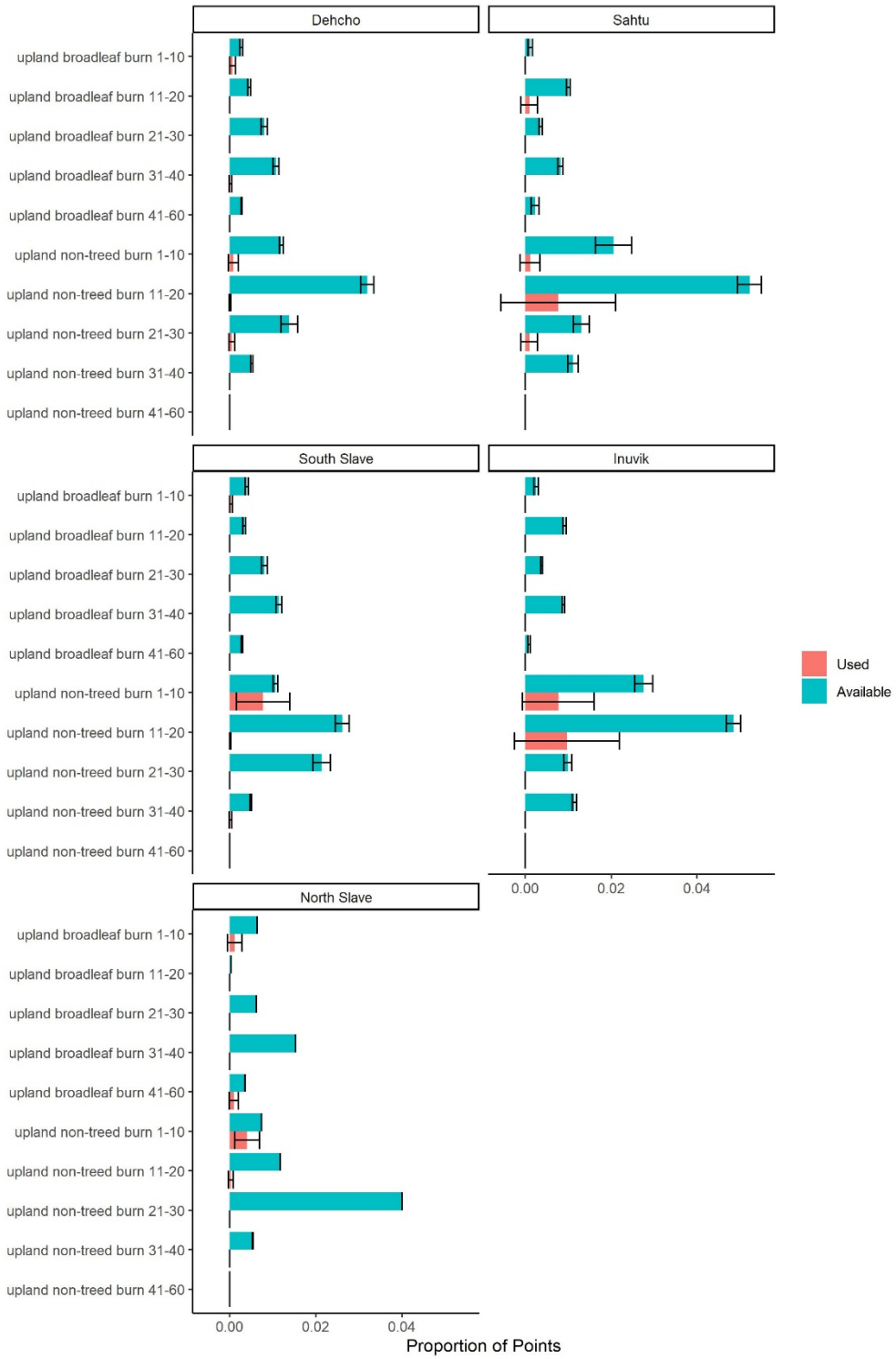


Figure H 23: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas during **late winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

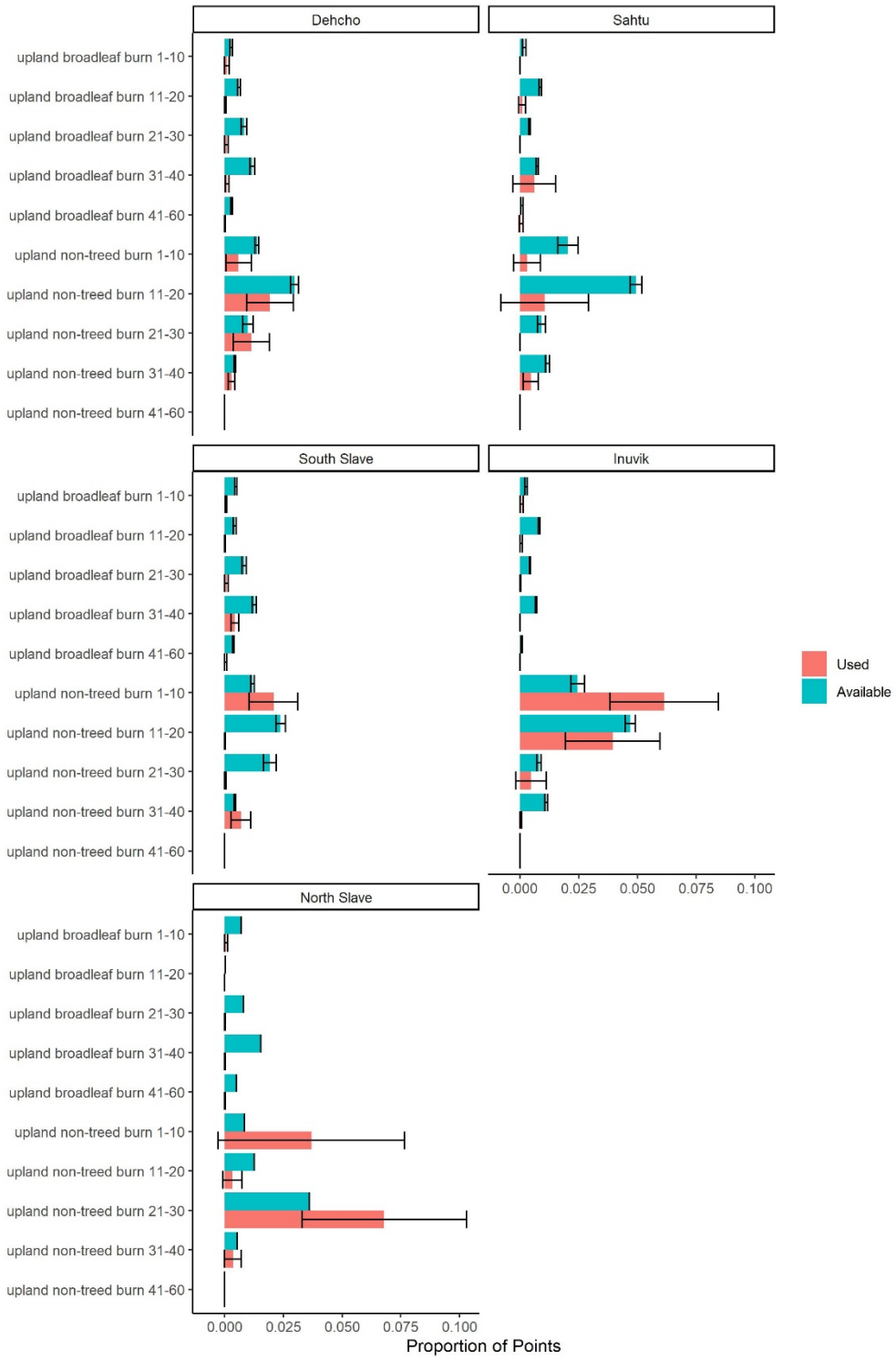


Figure H 24: The proportion of used (GPS) locations and available (or random) locations falling within burned upland broadleaf forest and non-treed uplands among the five regional monitoring areas on a **yearly** basis. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

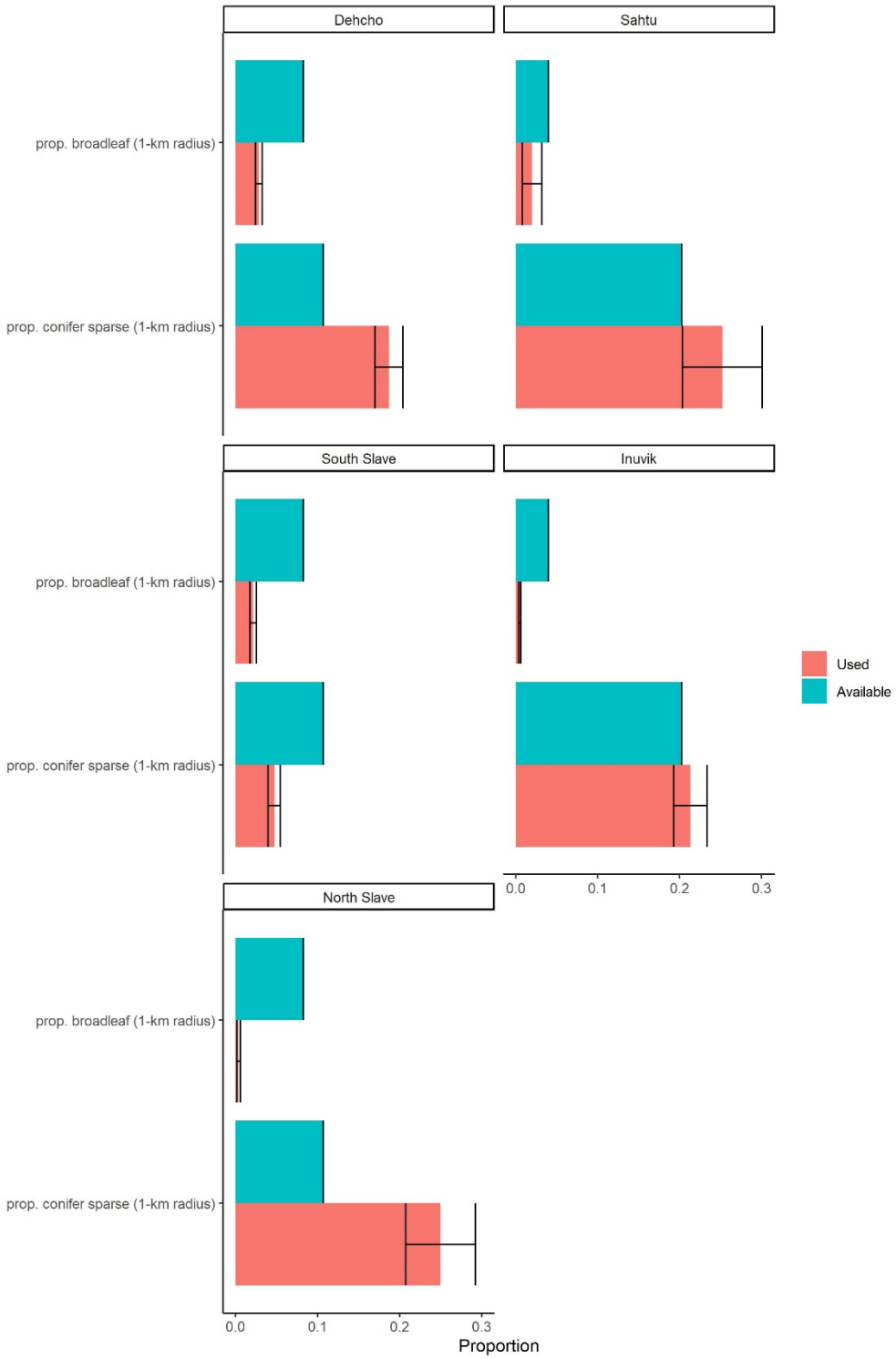


Figure H 25: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **calving**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

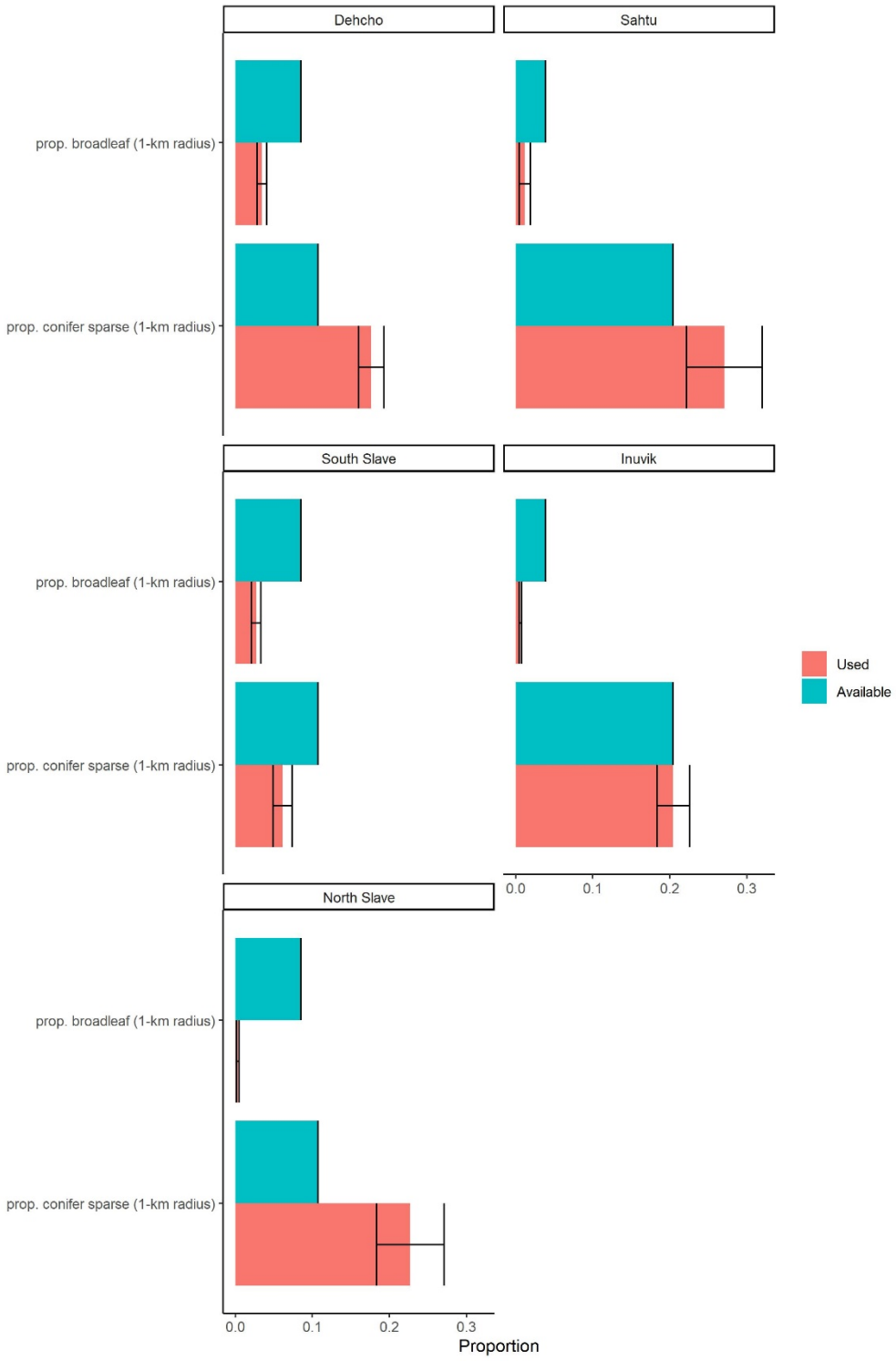


Figure H 26: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **summer**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

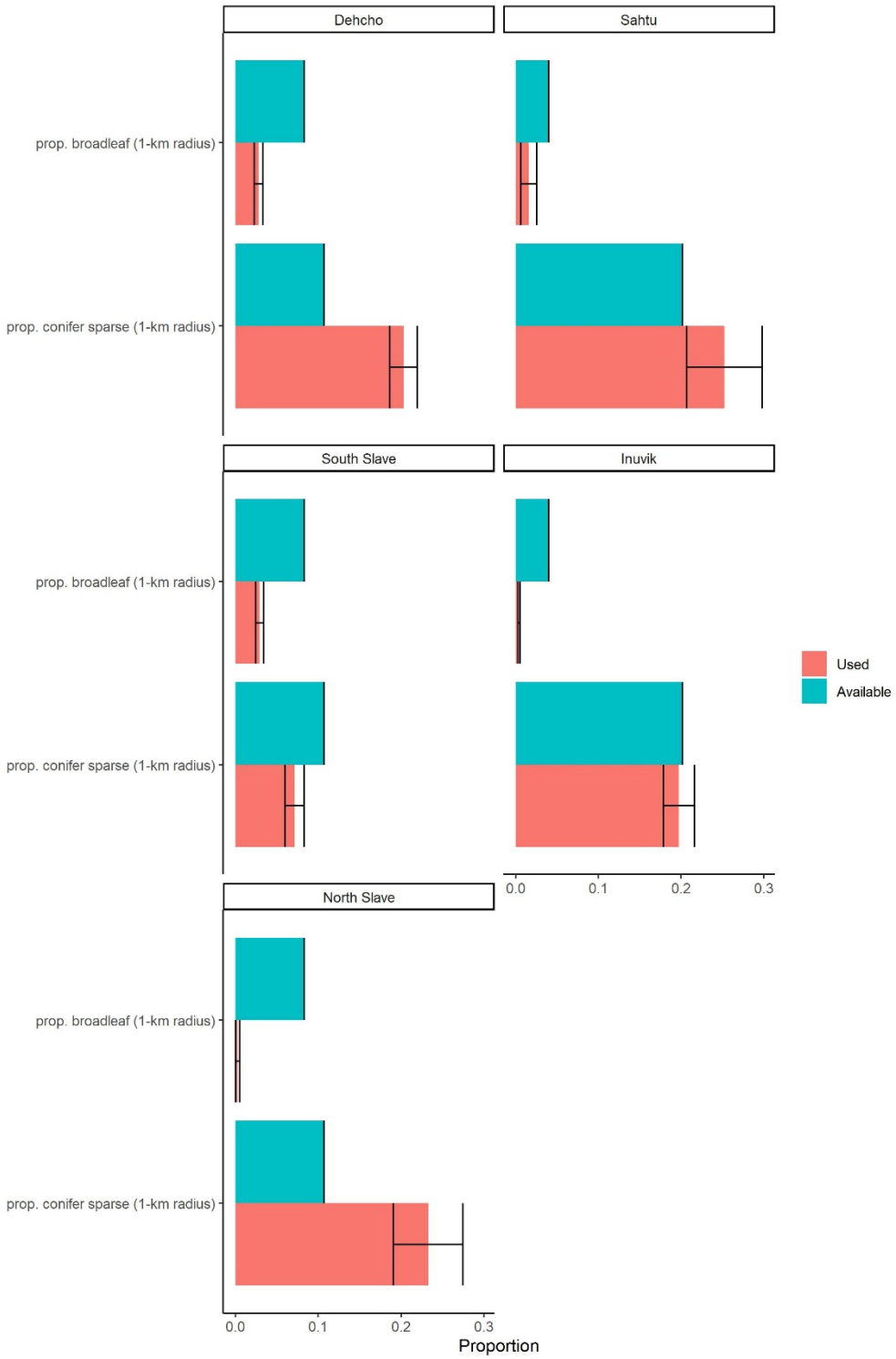


Figure H 27: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **early fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

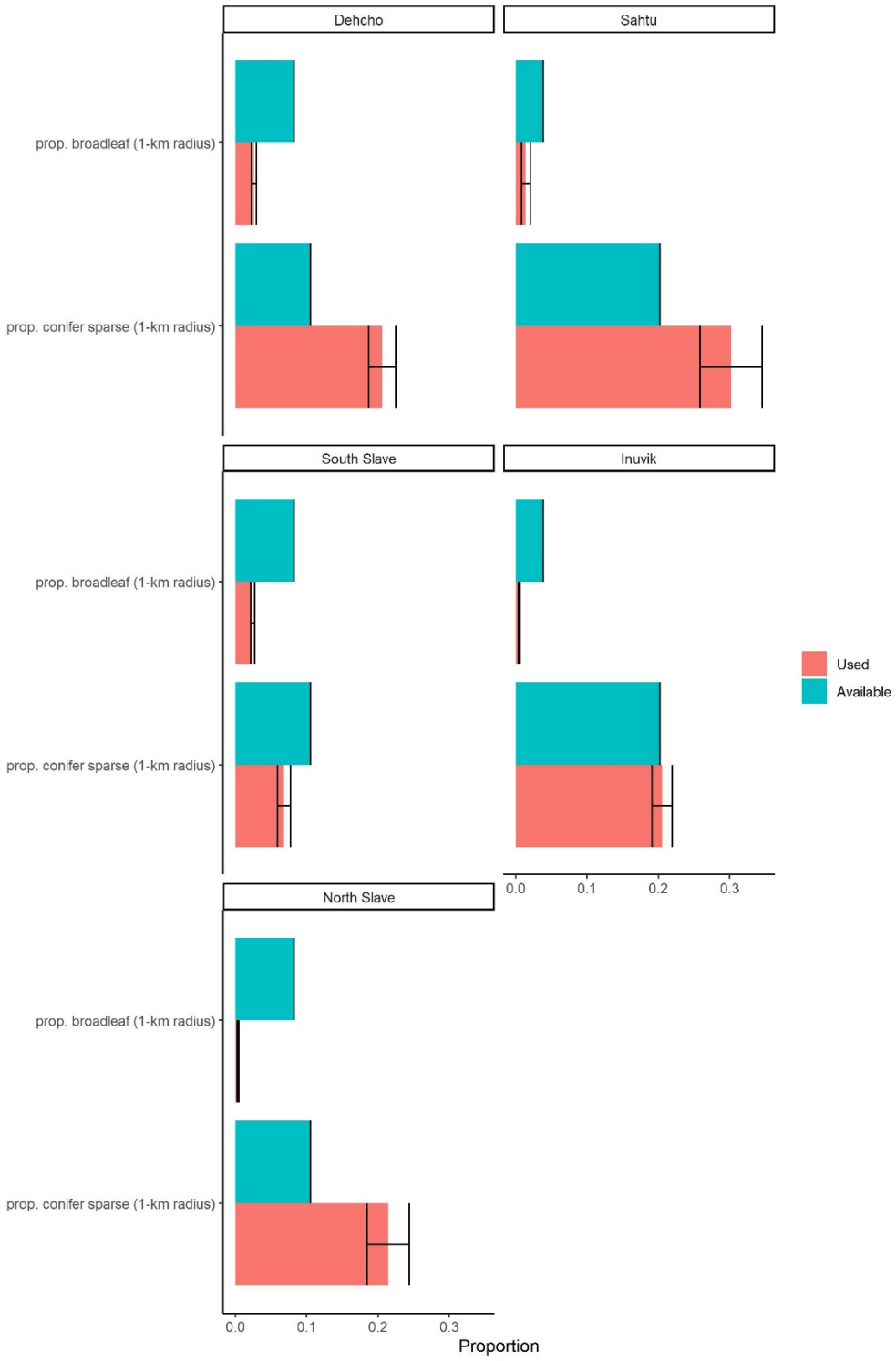


Figure H 28: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **late fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

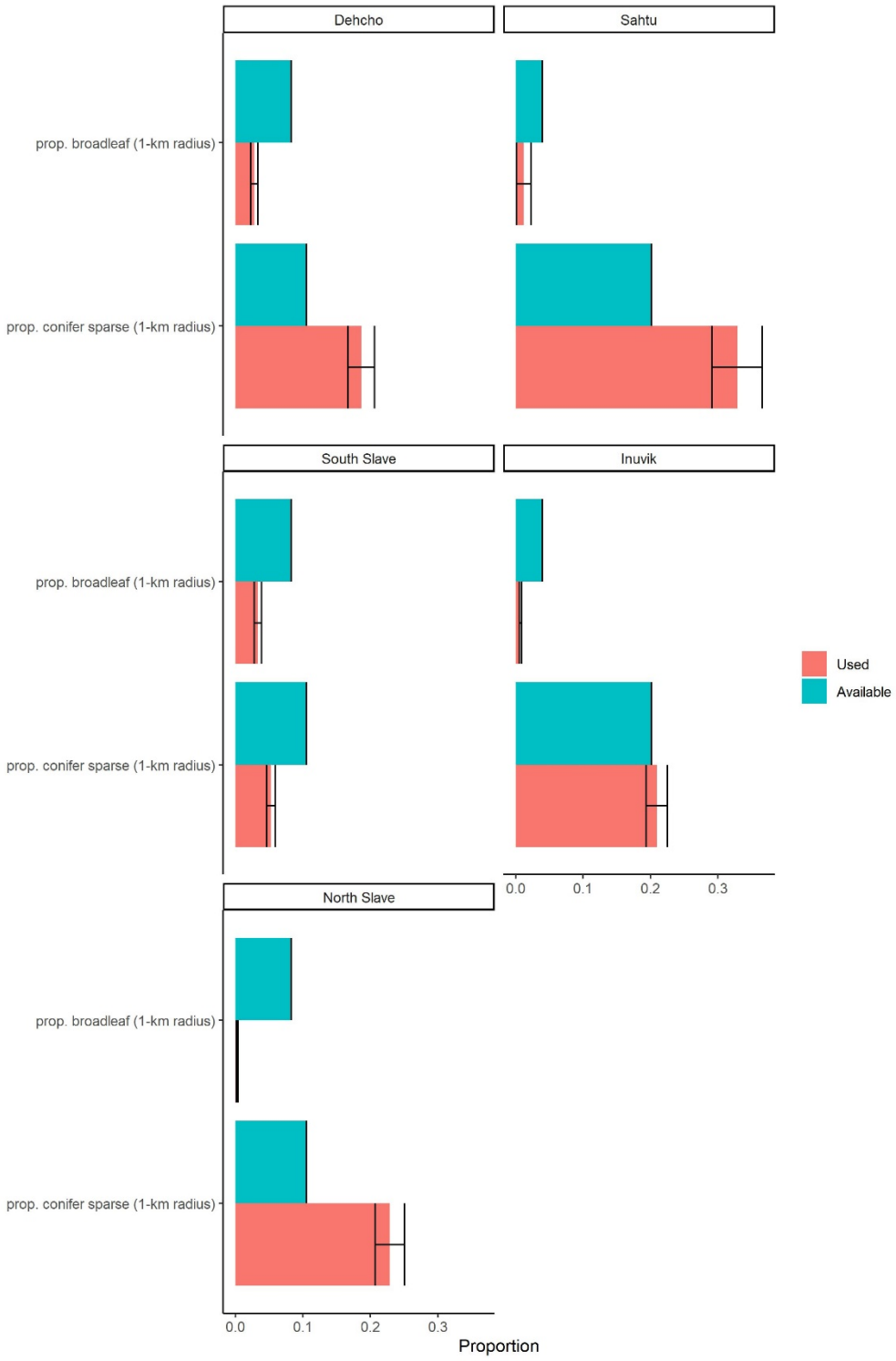


Figure H 29: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **early winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

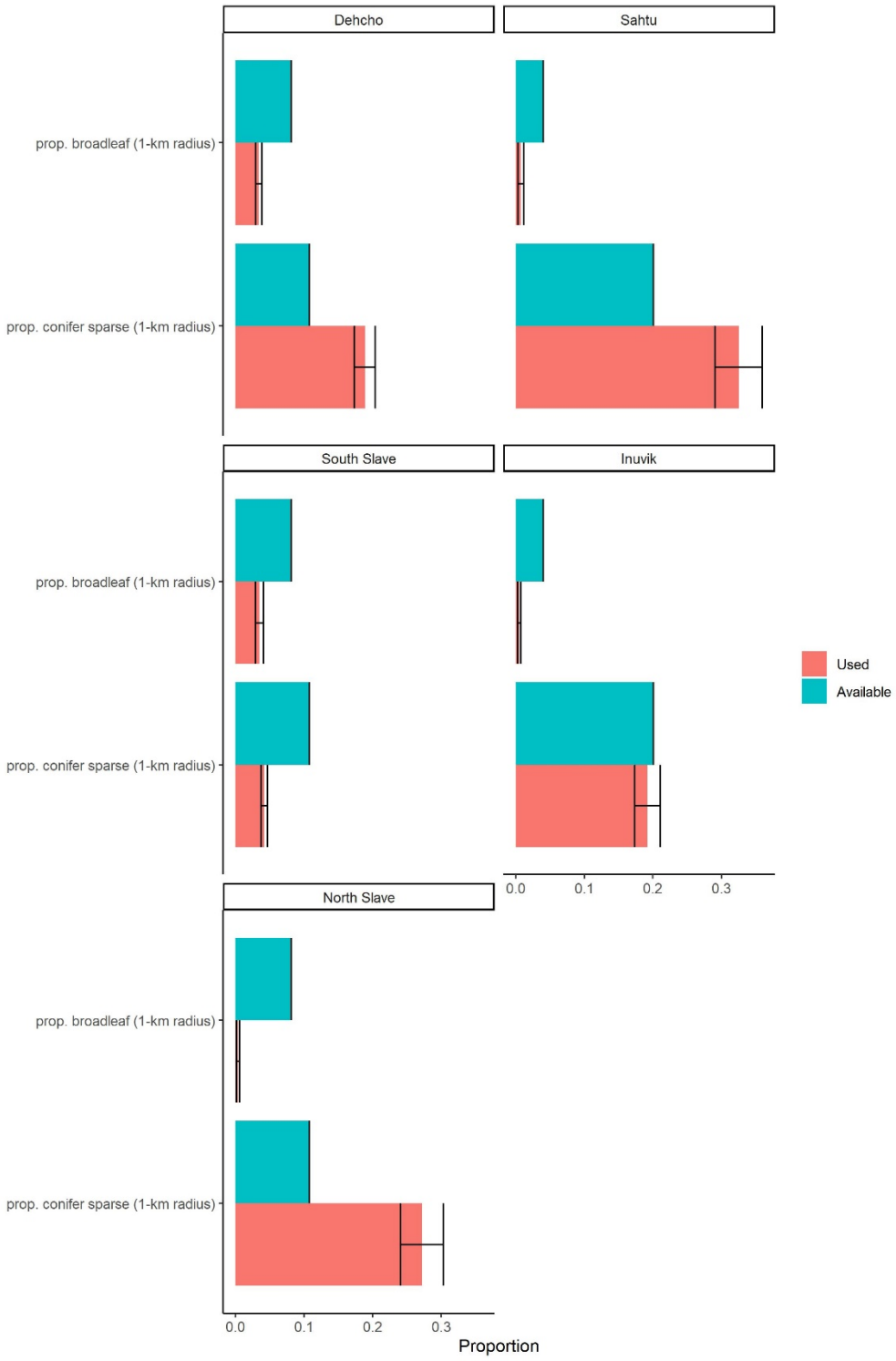


Figure H 30: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **mid-winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

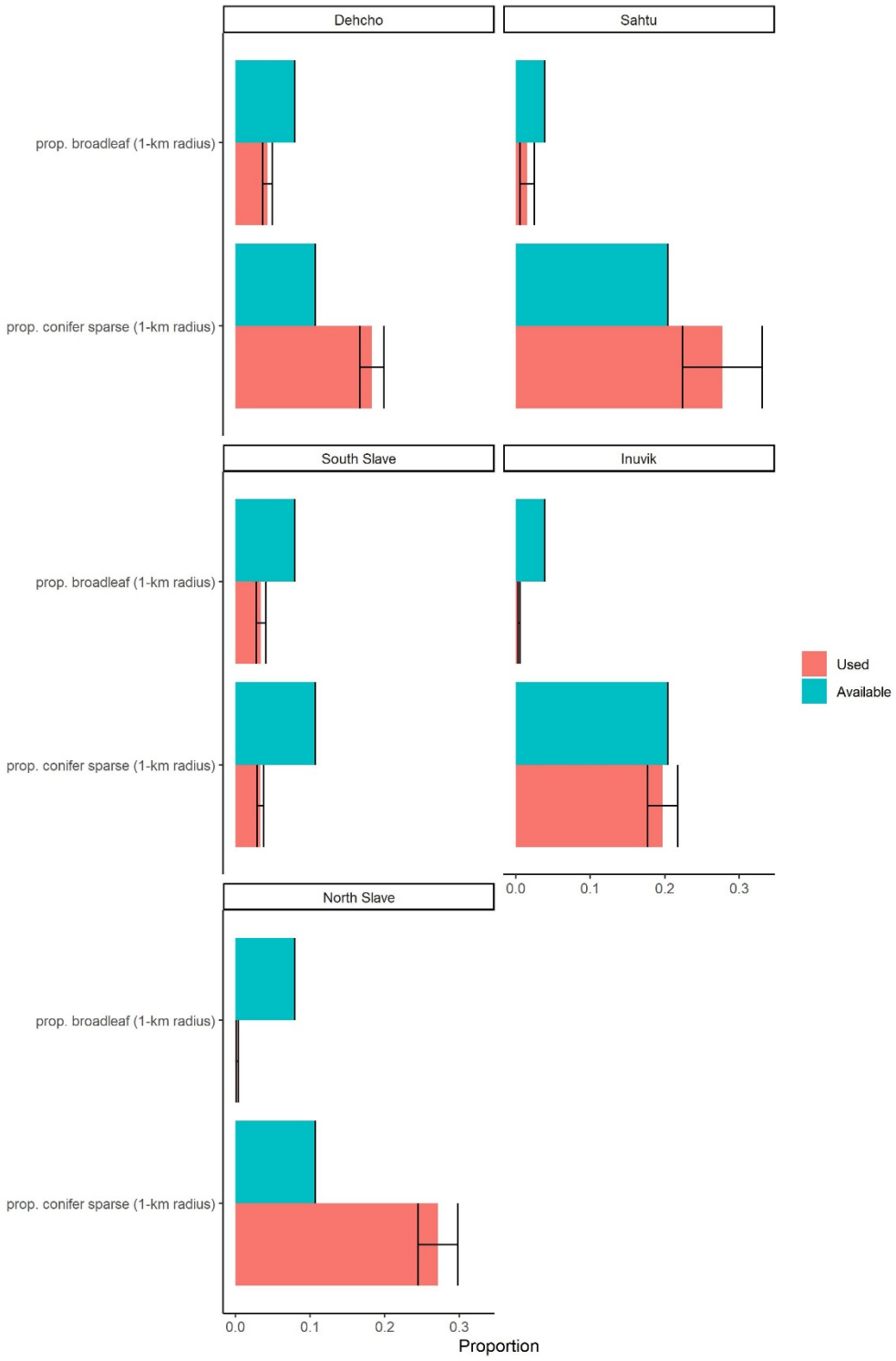


Figure H 31: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **late winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

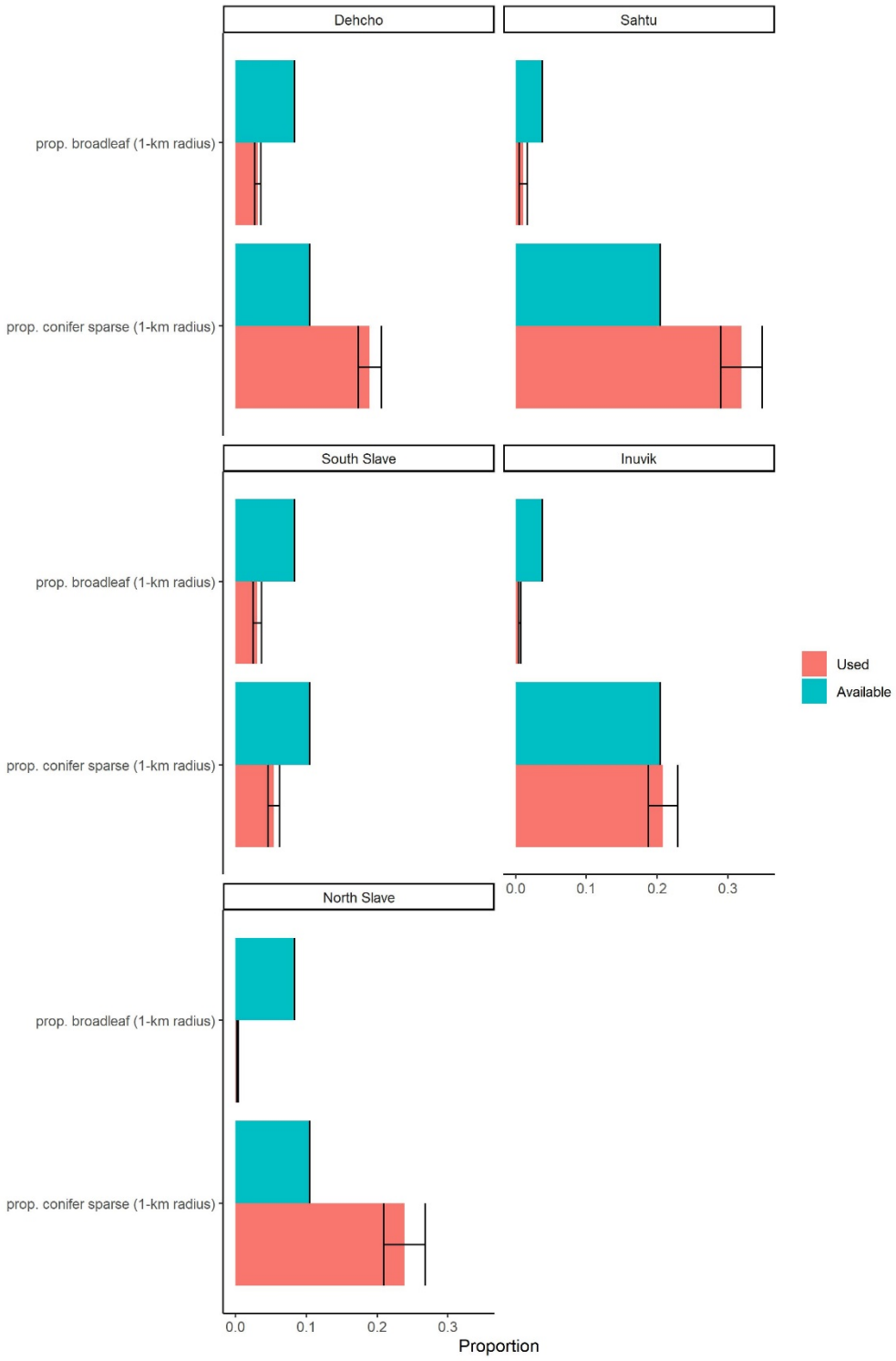


Figure H 32: The mean proportions of broadleaf forest and sparse conifer forest in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas on a **yearly** basis. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean proportion calculated across individual caribou-years.

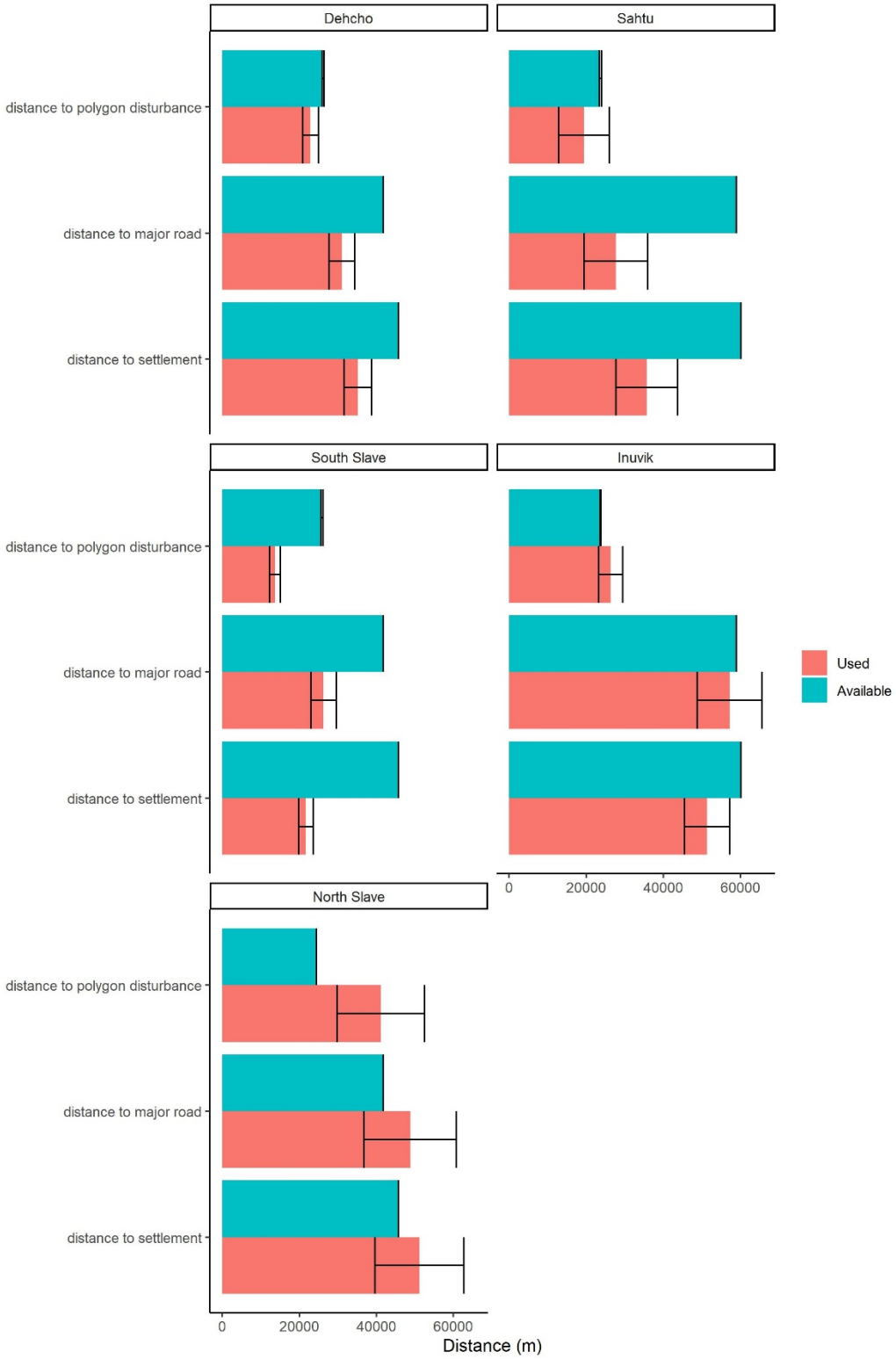


Figure H 33: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **calving**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

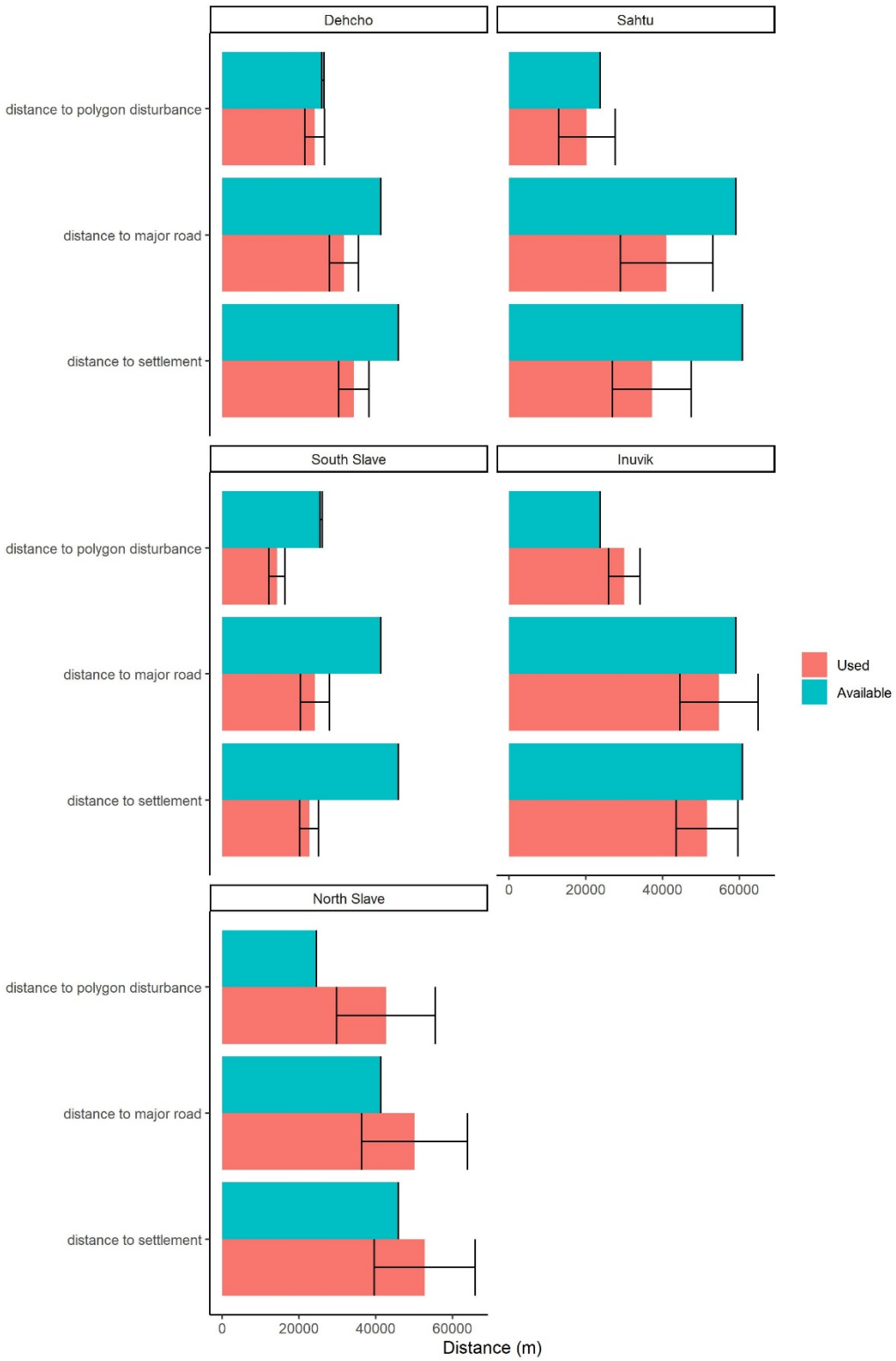


Figure H 34: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **summer**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

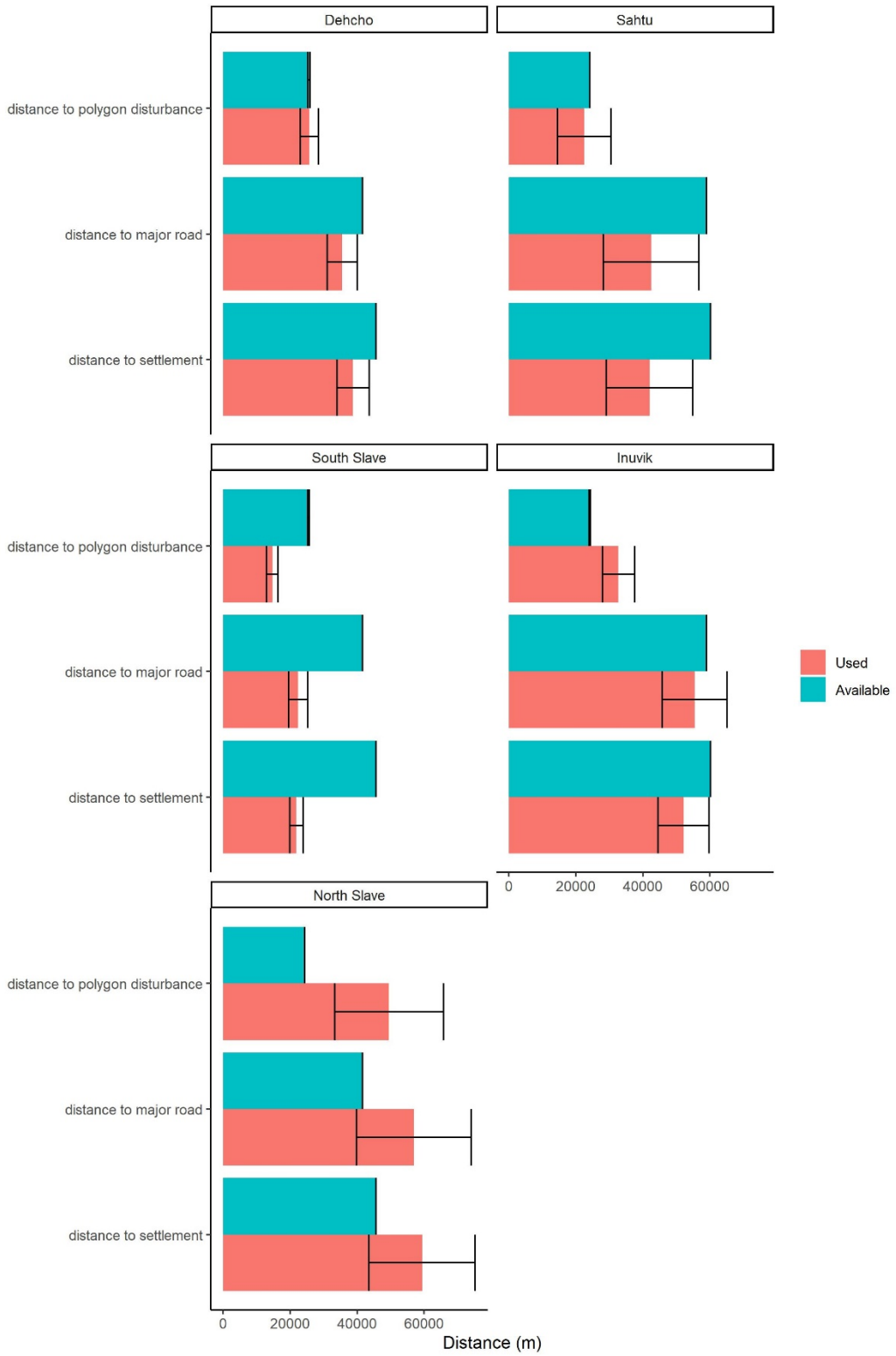


Figure H 35: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **early fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

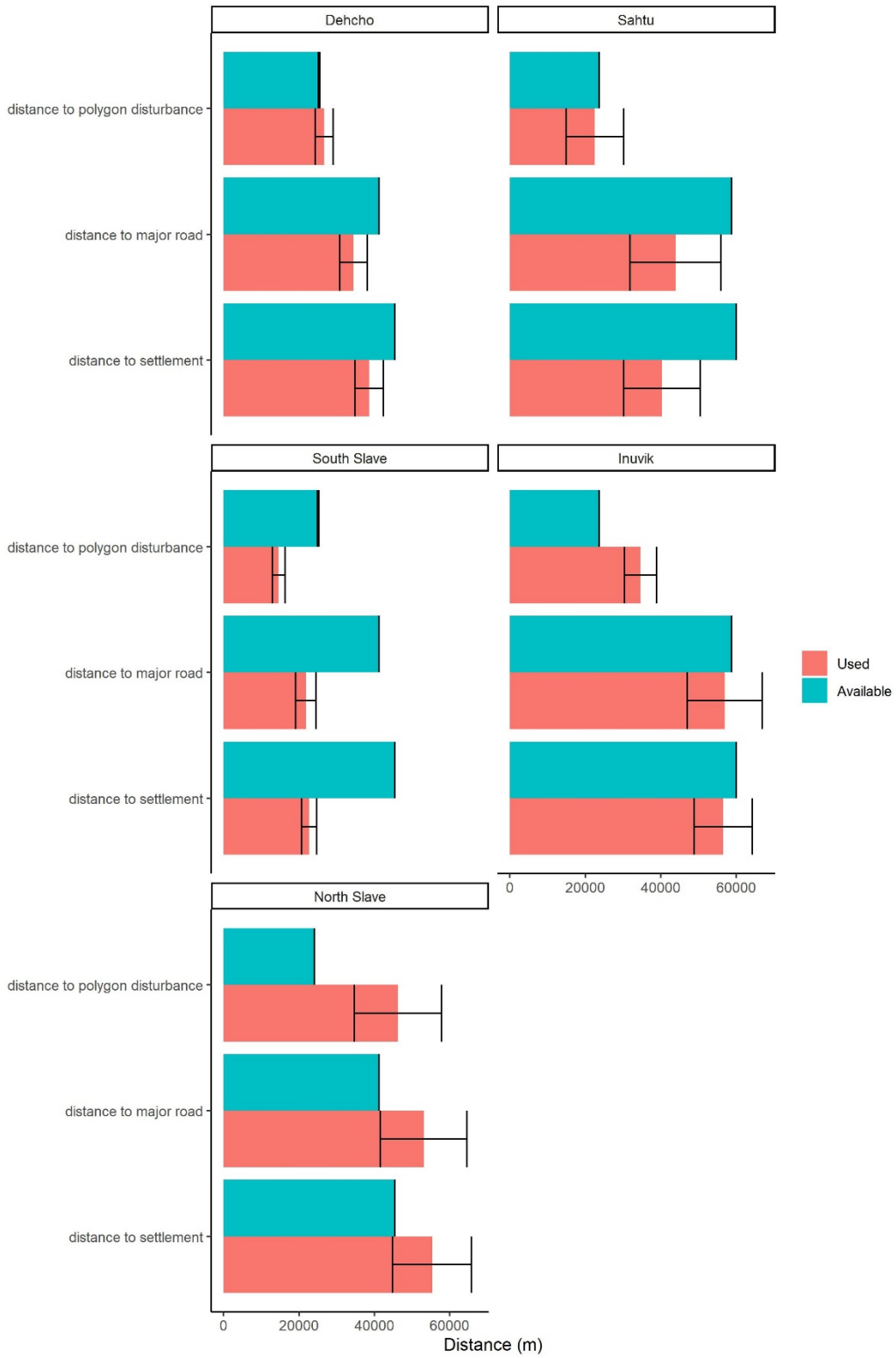


Figure H 36: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **late fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

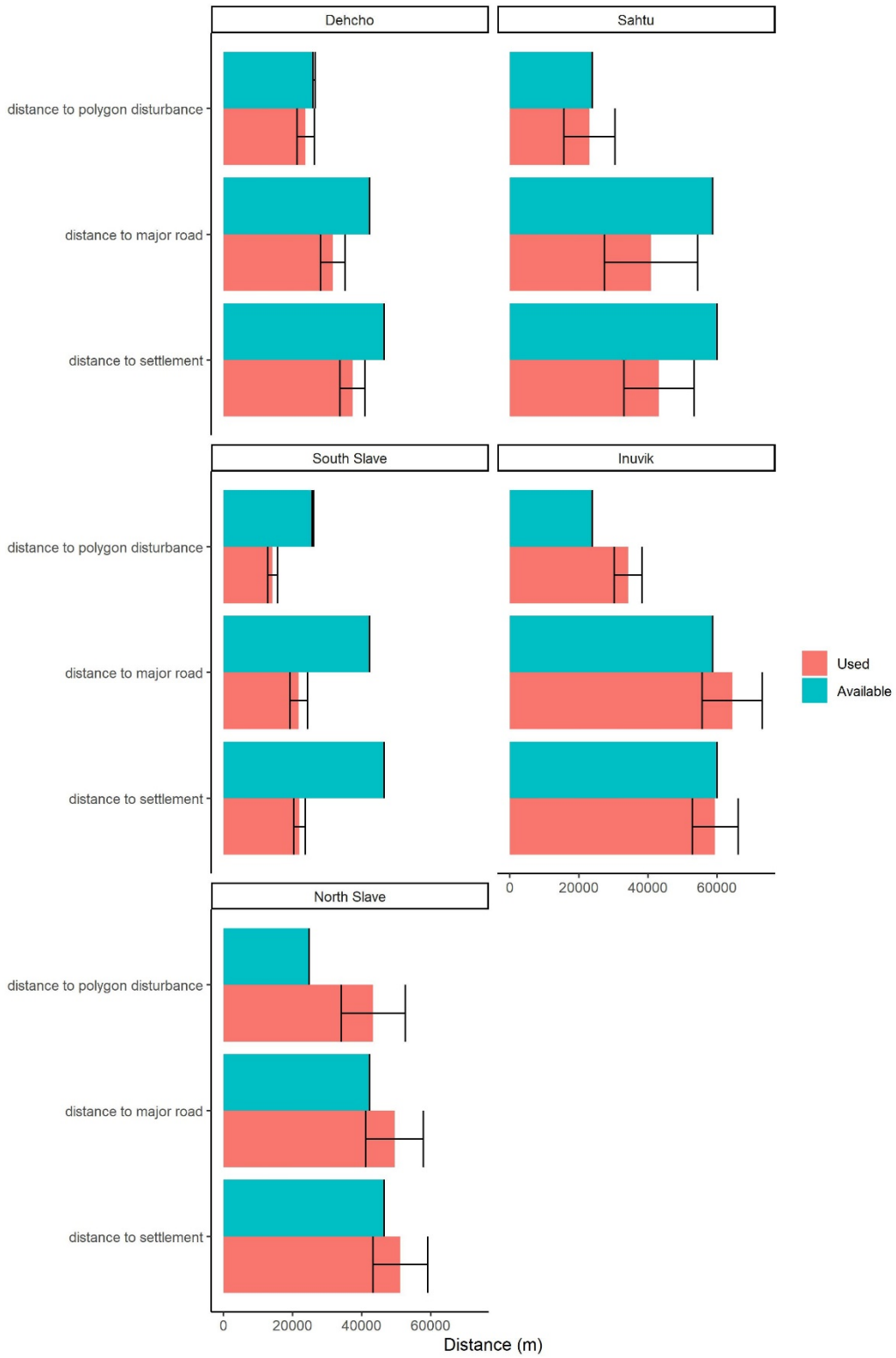


Figure H 37: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **early winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

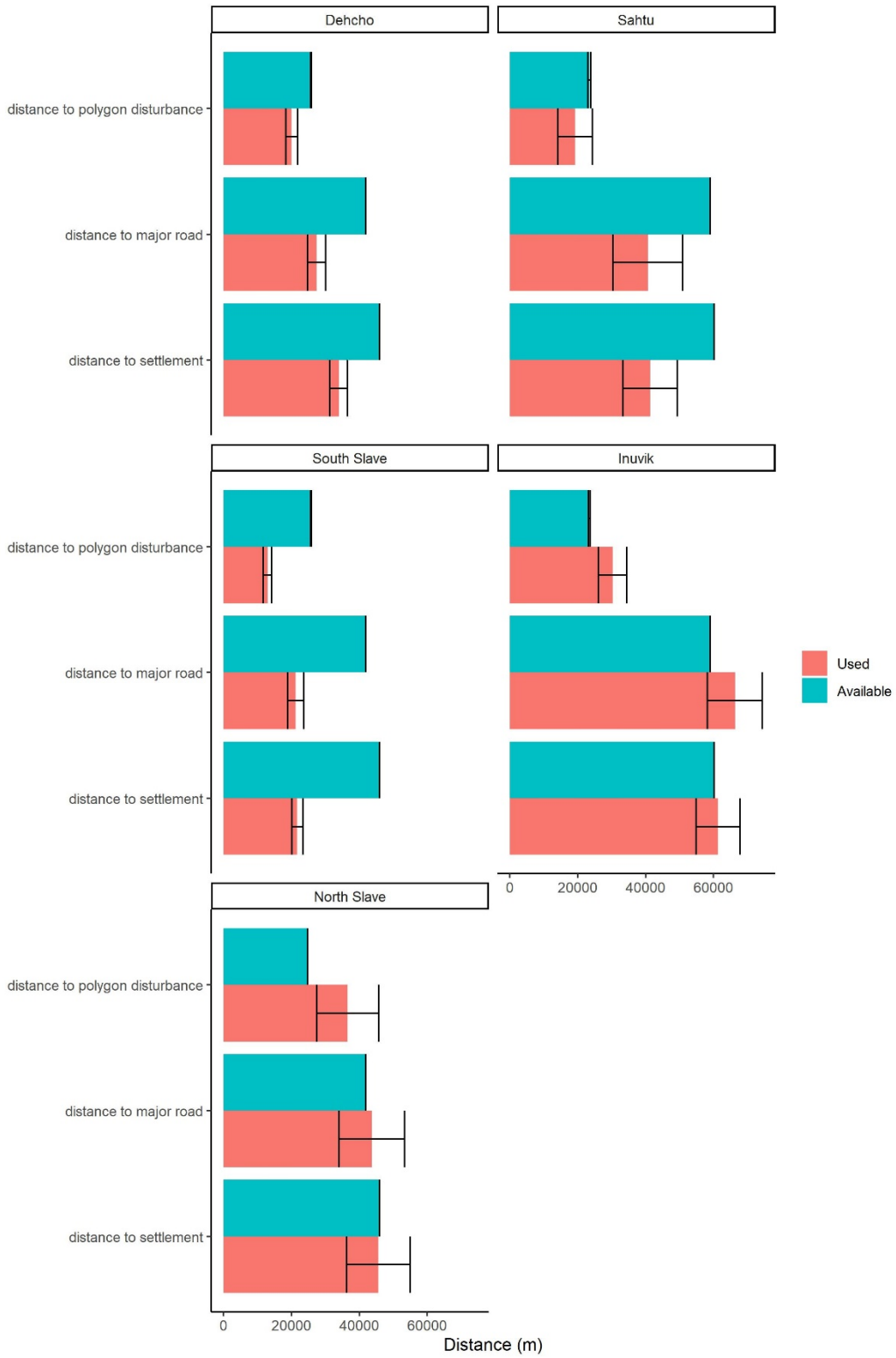


Figure H 38: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **mid-winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

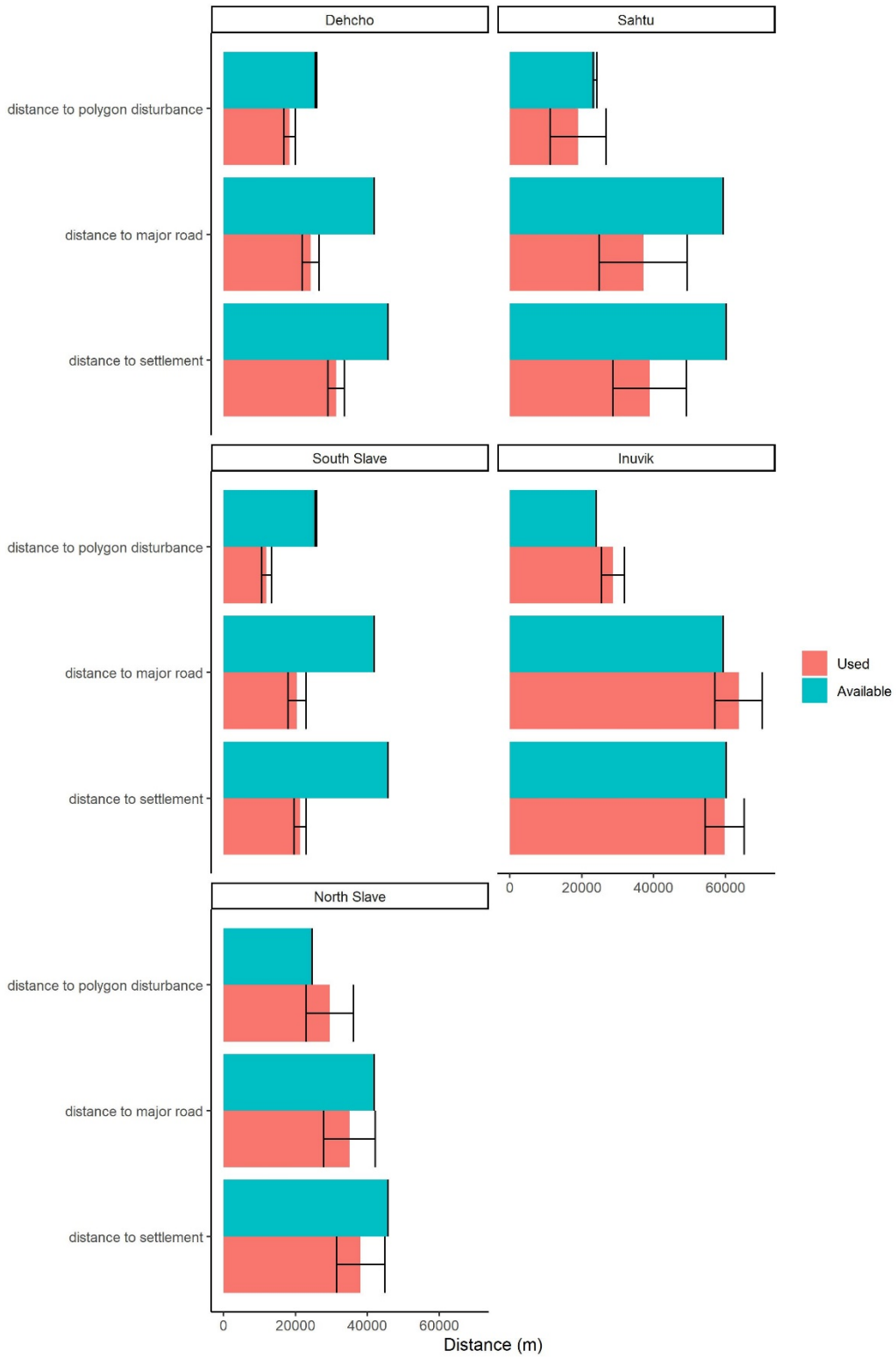


Figure H 39: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **late winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

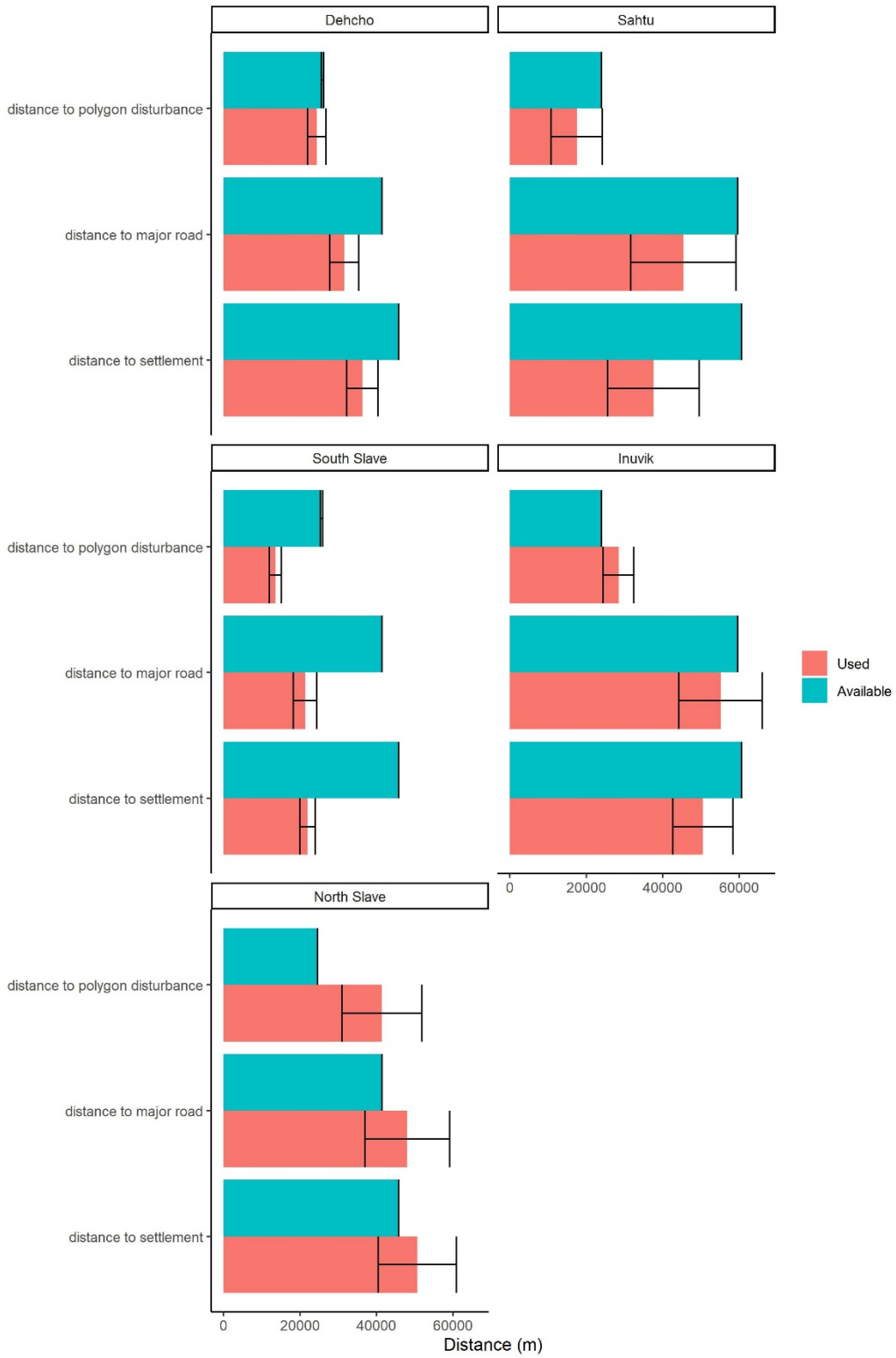


Figure H 40: The mean distances to various anthropogenic disturbances for used (GPS) locations and available (or random) locations among the five regional monitoring areas on a **yearly** basis. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean distance calculated across individual caribou-years.

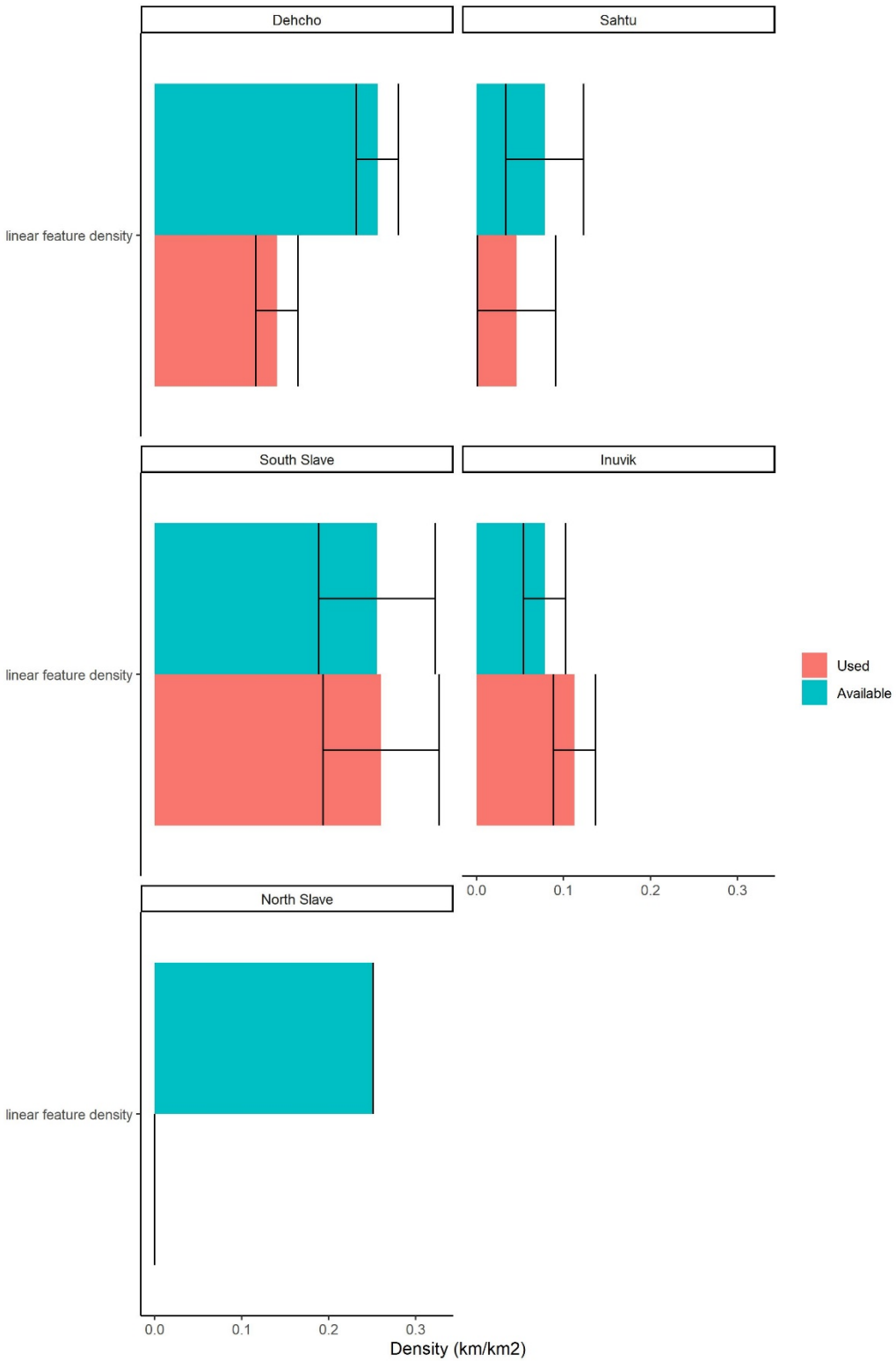


Figure H 41: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **calving**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

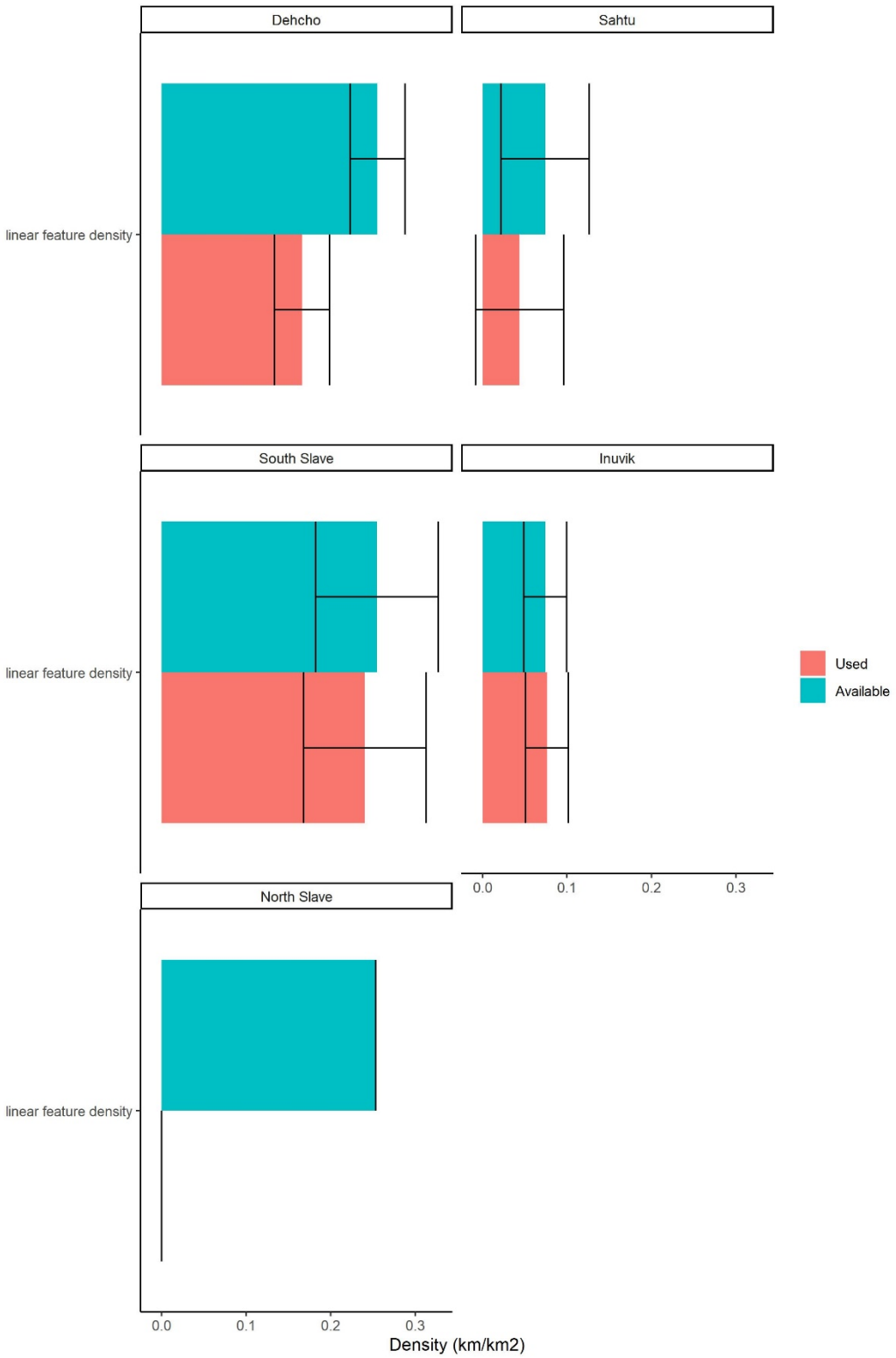


Figure H 42: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **summer**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

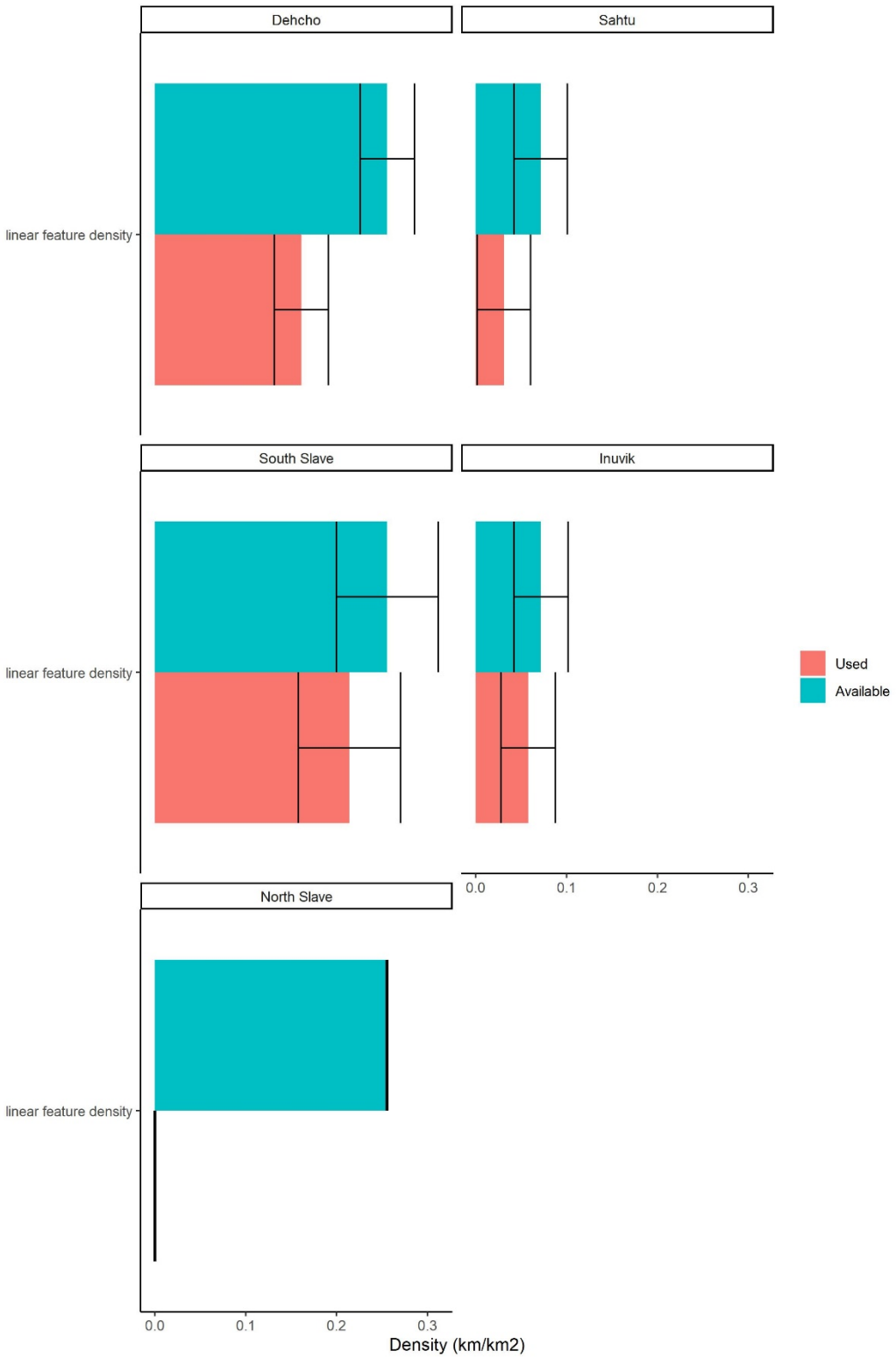


Figure H 43: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **early fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

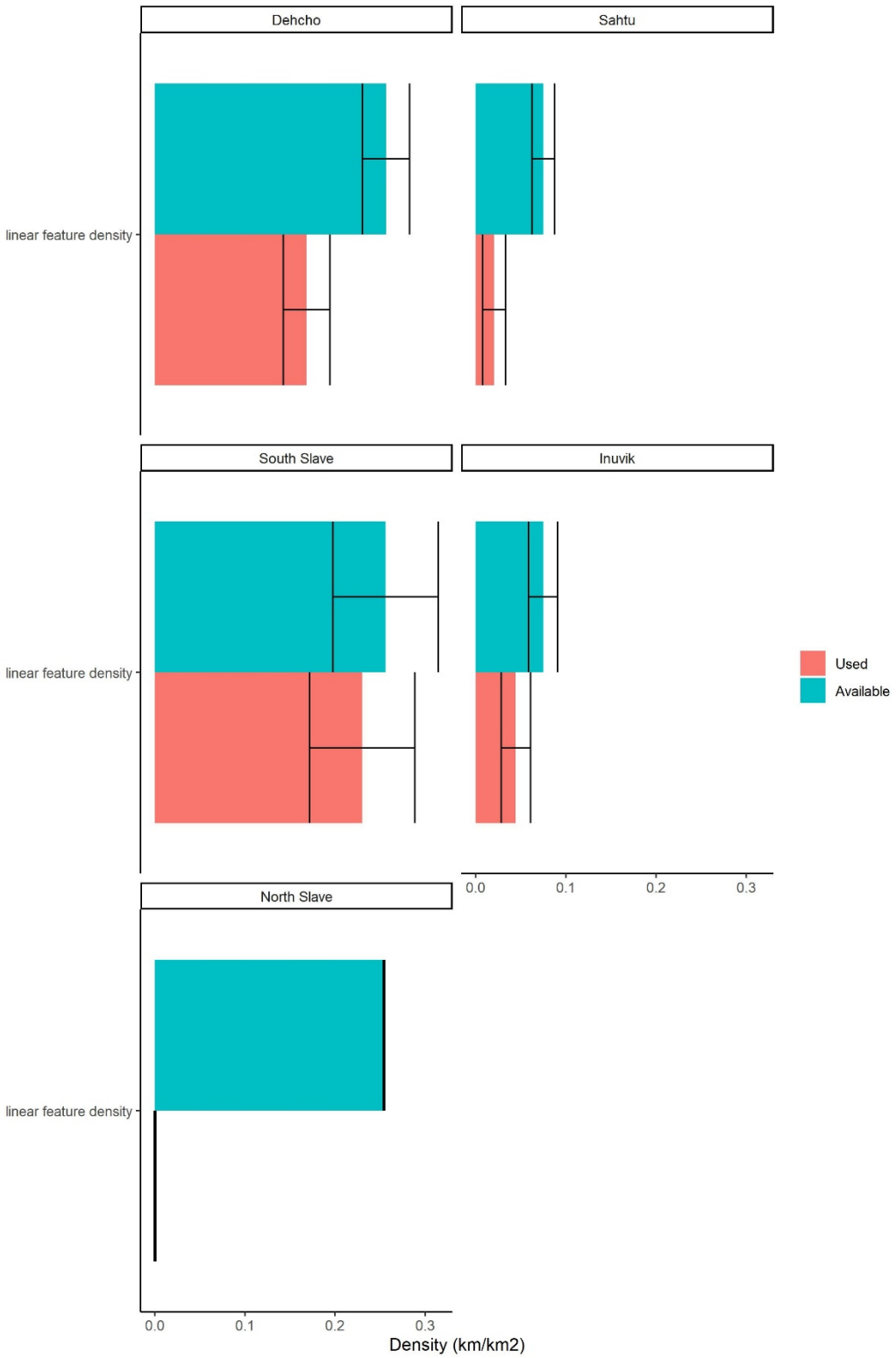


Figure H 44: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **late fall**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

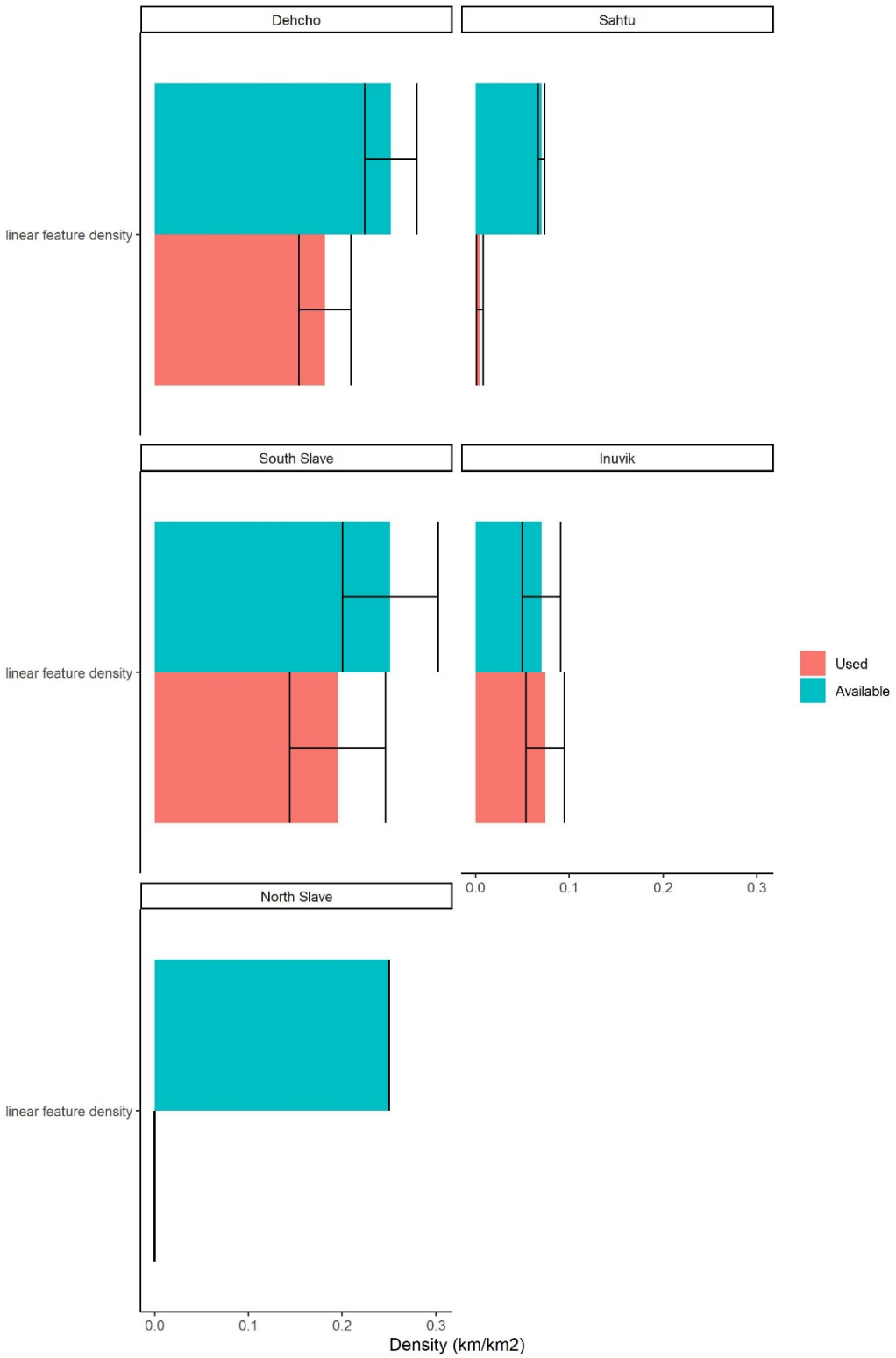


Figure H 45: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **early winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

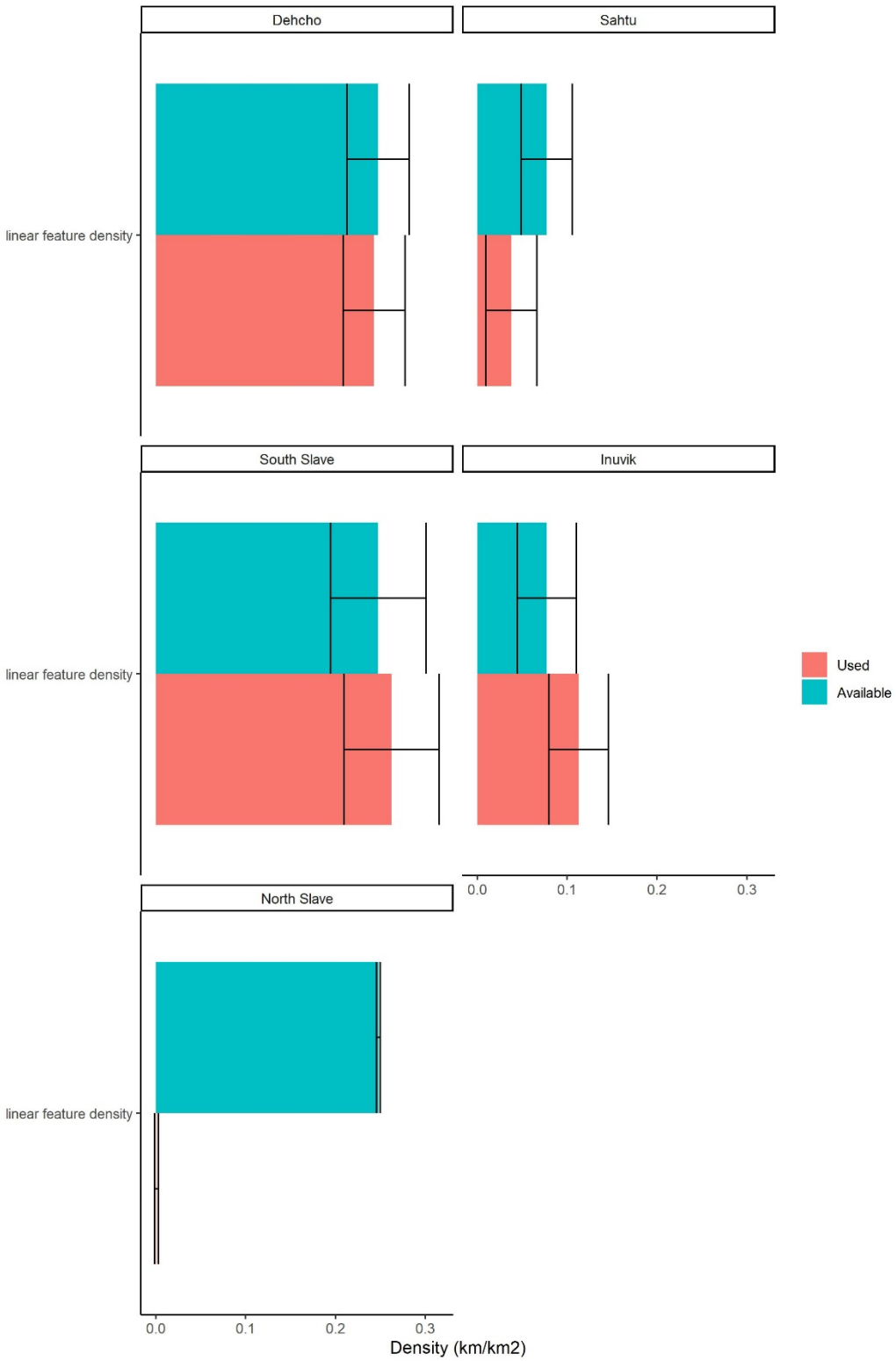


Figure H 46: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **mid-winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

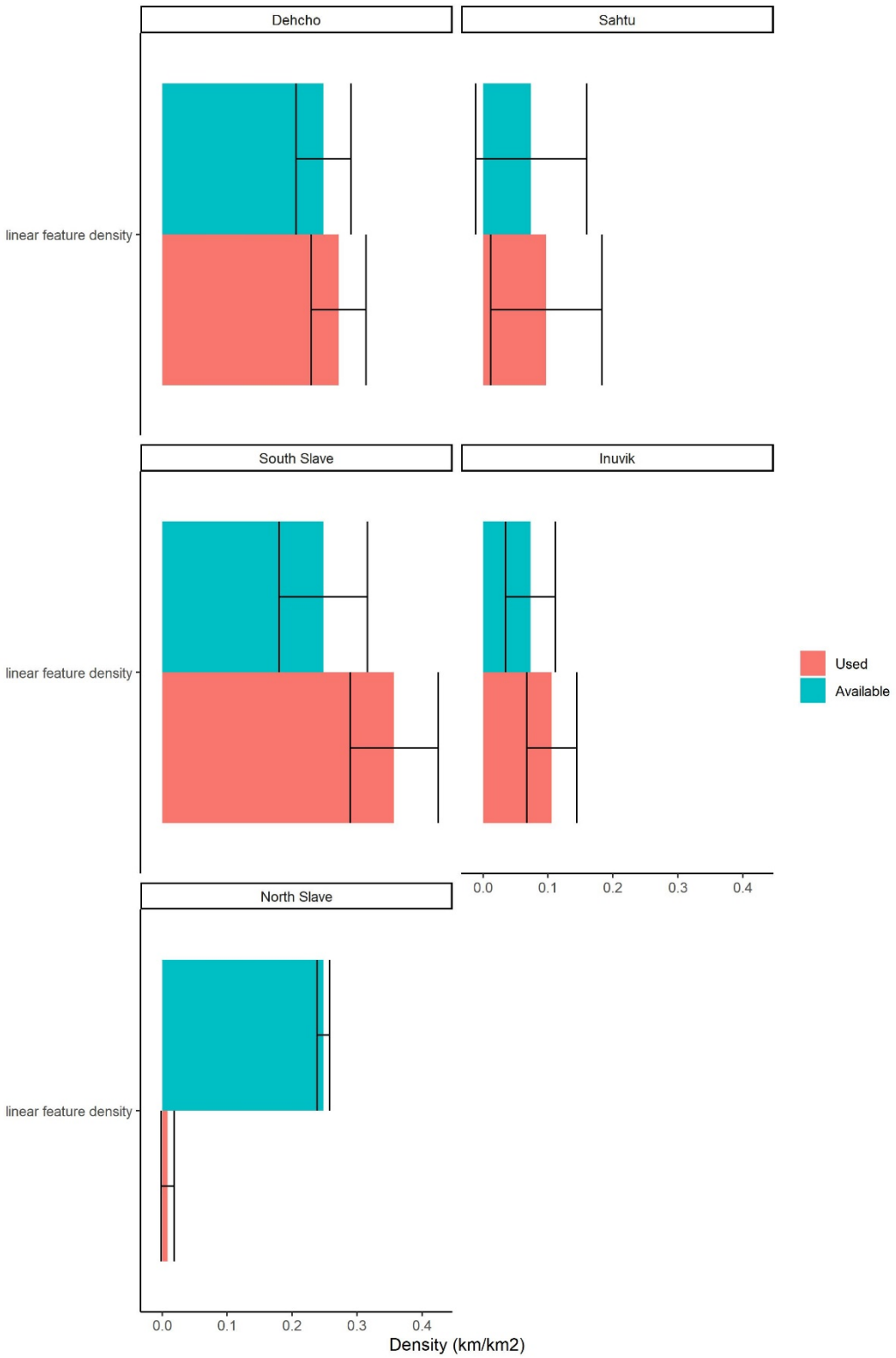


Figure H 47: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas during **late winter**. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

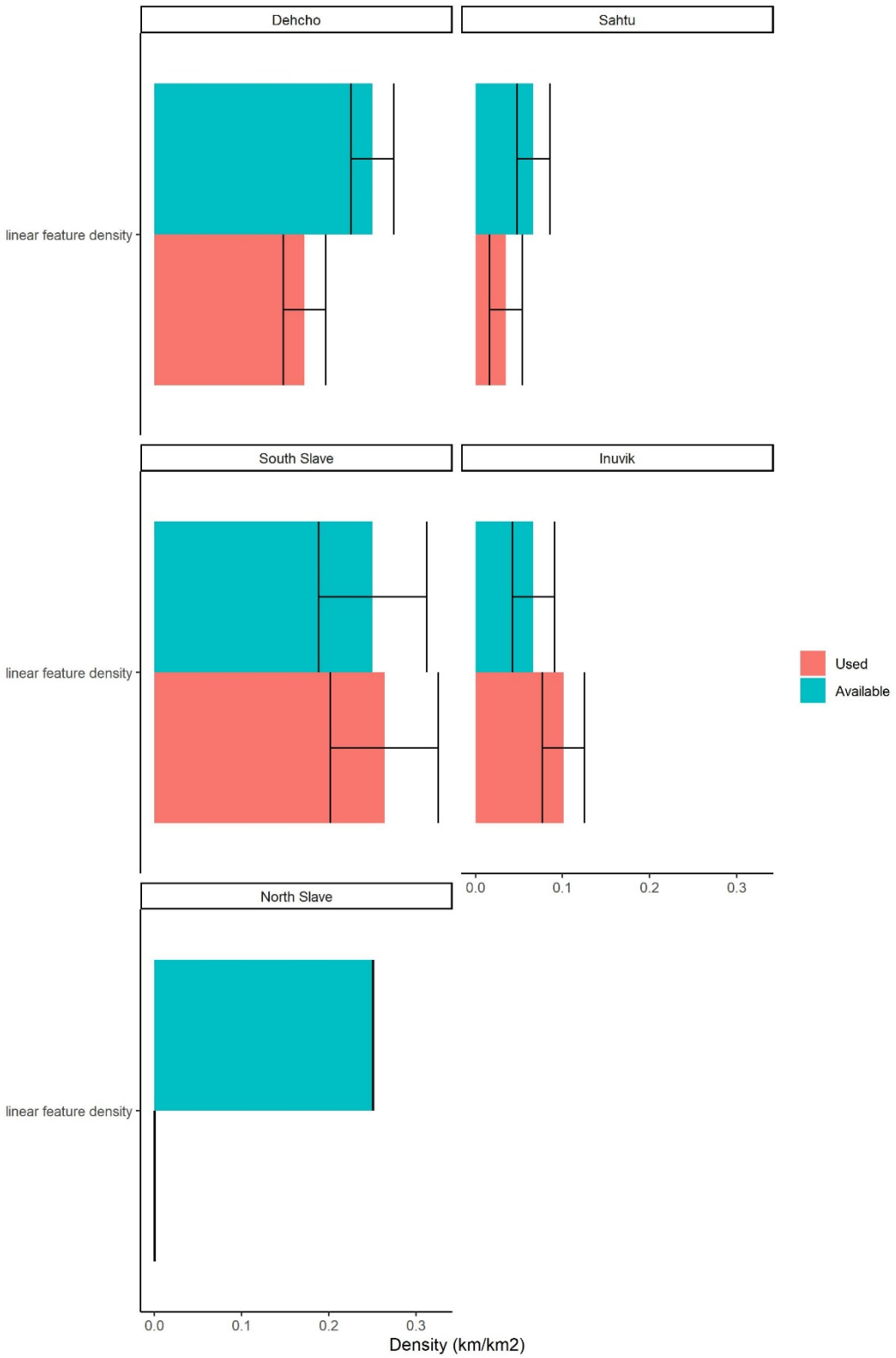


Figure H 48: The mean densities of linear features in a 1-km radius for used (GPS) locations and available (or random) locations among the five regional monitoring areas on a **yearly** basis. Random locations were sampled within the available area defined at a second-order scale. Error bars represent the 95% confidence intervals of the mean densities calculated across individual caribou-years.

APPENDIX I: PREDICTIVE SEASONAL AND ALL-YEAR RESOURCE SELECTION FUNCTION MAPS

The fixed-effect (or population-level) coefficients from each of the 2nd order sand 3rd order seasonal and all-year resource selection function (RSF) models were used to generate predictive maps of habitat selection within the project's study area. The maps represent the predicted relative likelihood of habitat selection based on landscape conditions current to 2017 (i.e. including fires occurring up to 2017). For each map, we partitioned the predicted RSF values for pixels (30-m resolution) into 10 bins to improve visual interpretation of seasonal resource selection by caribou. Cut points between bins were delineated using the same approach as for k-fold cross validation. Specifically, coefficients from a given RSF model were used to predict values for the random locations (n = 40,000) sampled within the combined North and South MCPs used in 2nd order RSF models, and the predicted values for these locations were partitioned into decile bins (i.e., 10 bins with each bin having an equal number of points, which equates to an equal-area binning approach). Note that extrapolating the RSF model to the full study area and binning RSF values based on the above approach causes some inequality in the number of map pixels contained in each category. Bin 1 (dark red) represents the most strongly avoided habitat and Bin 10 (dark blue) represents the most highly selected habitat. Each map includes the outlines for the North and South minimum convex polygons (buffered by 15-km), which were used to define availability for 2nd order RSF models. Any areas outside of these two polygons represent areas where RSF model predictions have been extrapolated beyond the extent of the collar data and inferences about habitat selection in these areas should be treated with greater caution. The NT1 range boundary is included on each of the maps to illustrate where they RSF model has been extrapolated beyond the NT1 range. Inferences about habitat suitability beyond the NT1 range boundary (with the exception of areas south of the NWT/AB/BC border) should similarly be treated with caution as there is less certainty about whether boreal caribou occur in these areas.

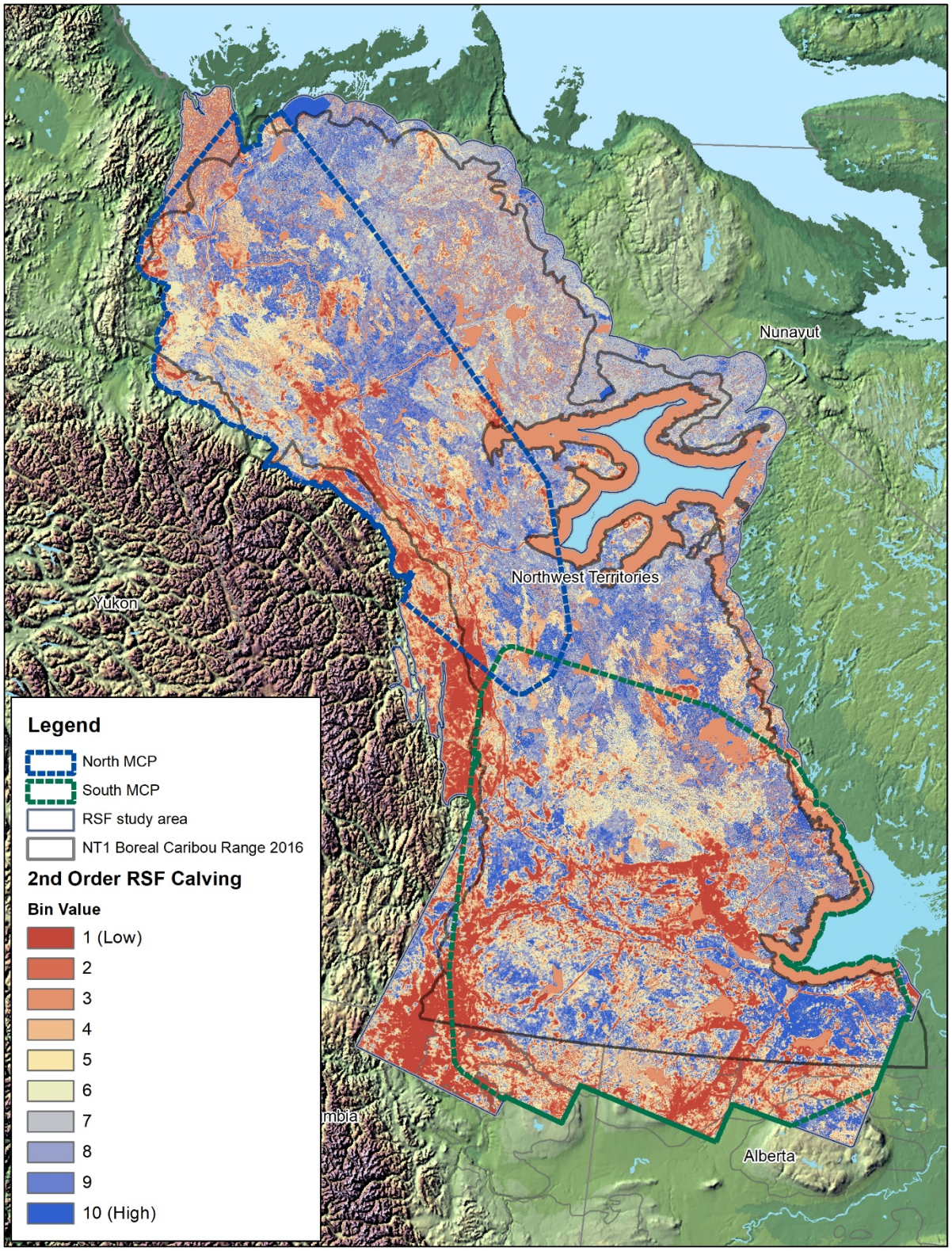


Figure I 1: Map of predicted RSF values at the 2nd order scale during the **Calving** season partitioned into 10 equal area bins.

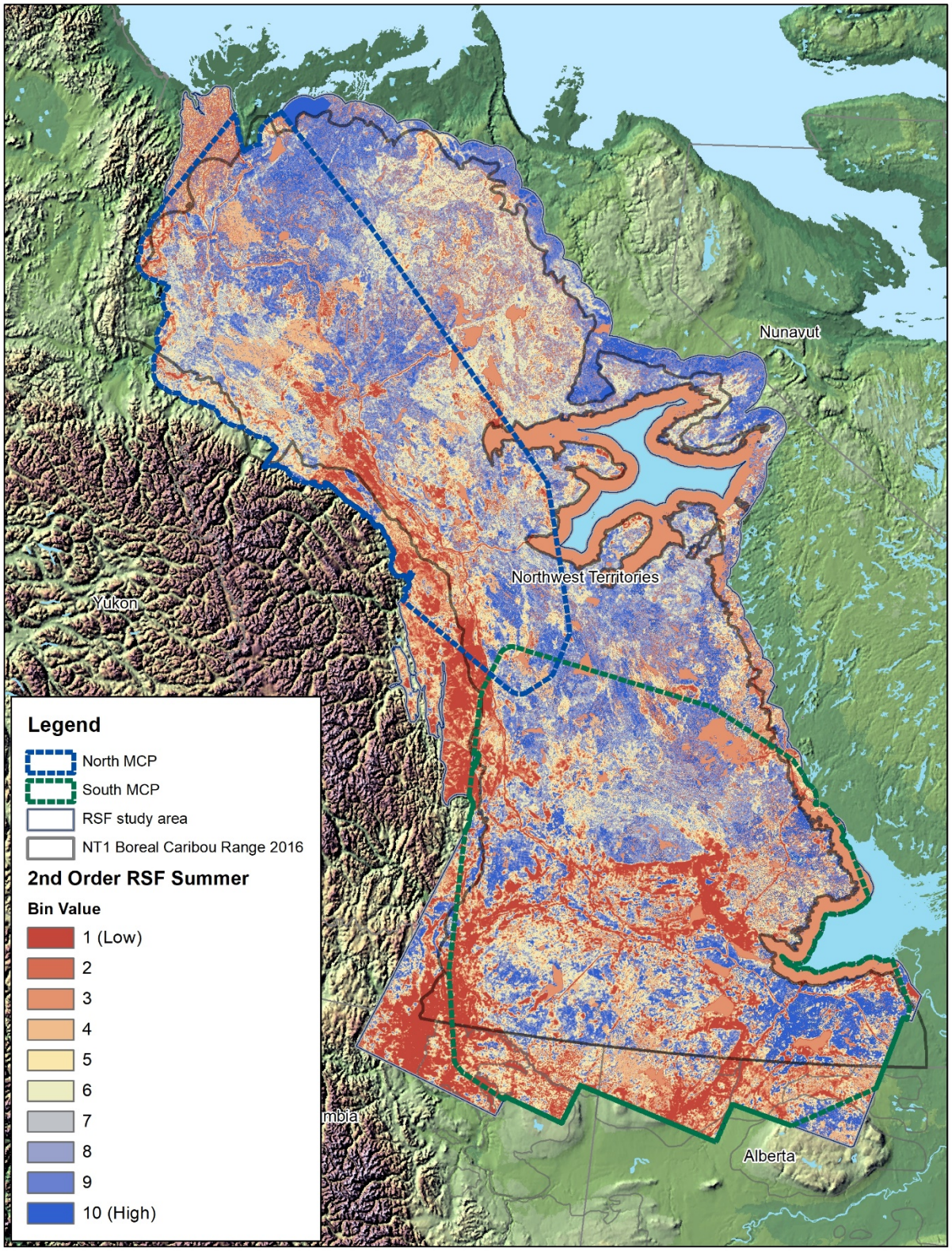


Figure I 2: Map of predicted RSF values at the 2nd order scale during the **Summer** season partitioned into 10 equal area bins.

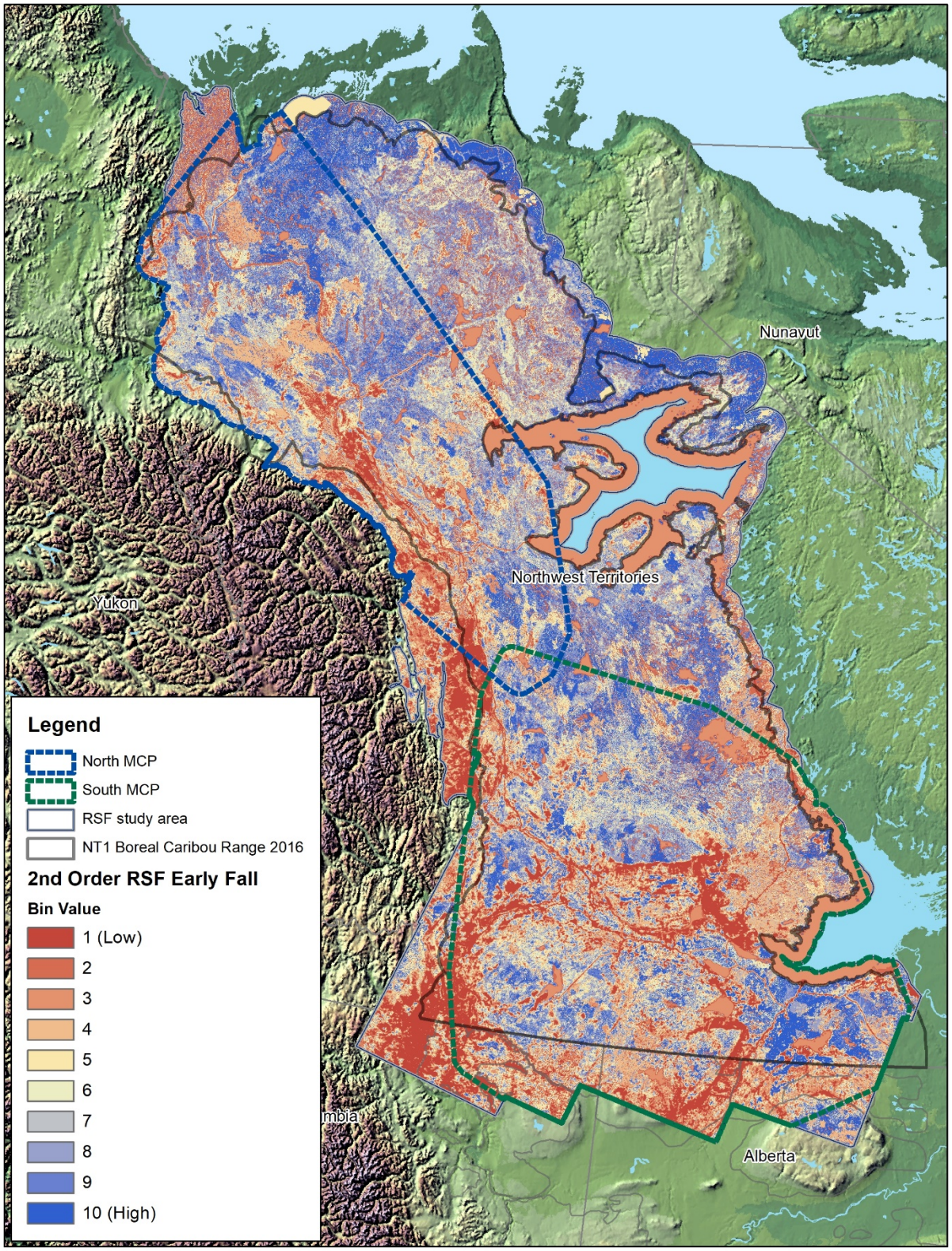


Figure I 3: Map of predicted RSF values at the 2nd order scale during the **Early Fall** season partitioned into 10 equal area bins.

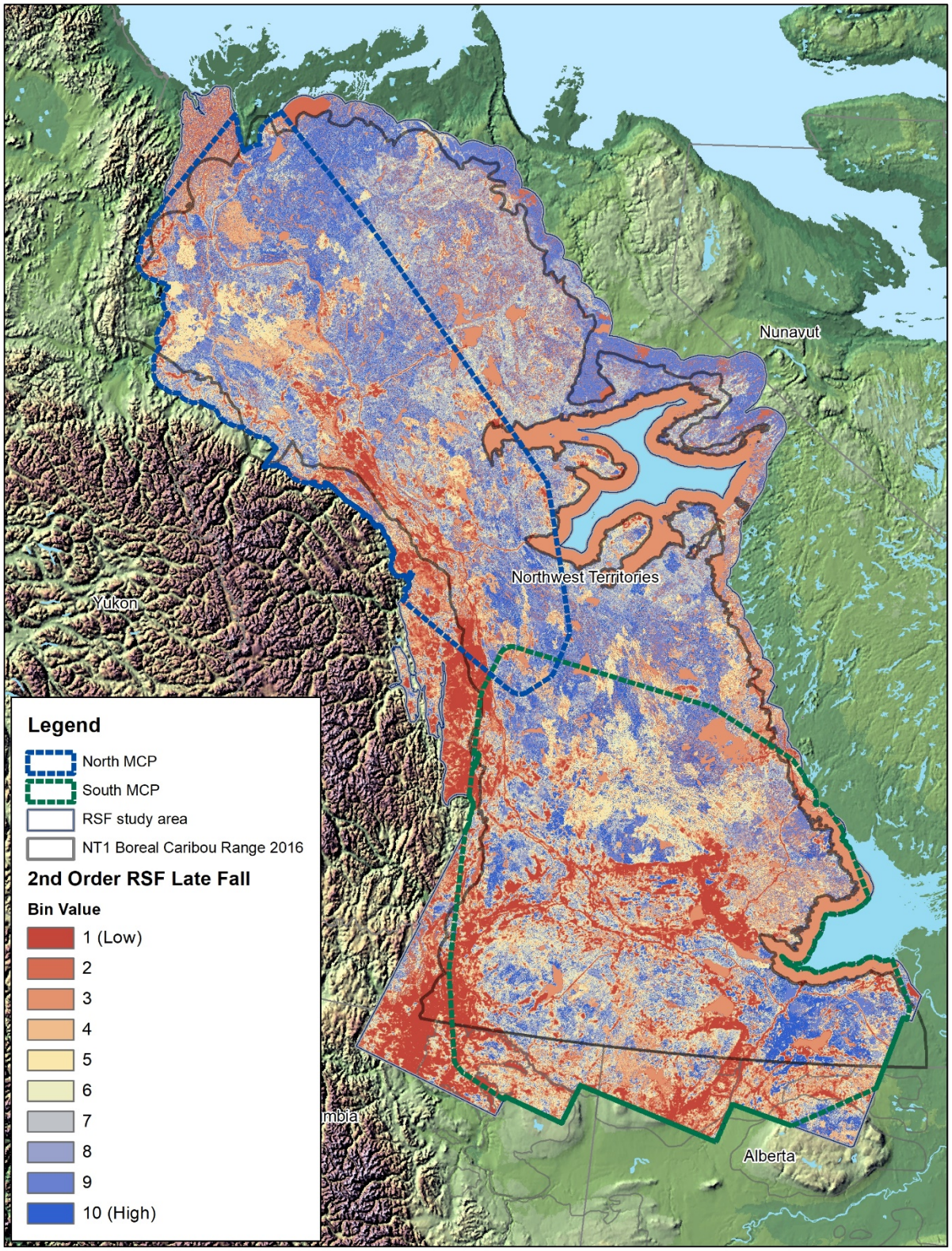


Figure I 4: Map of predicted RSF values at the 2nd order scale during the **Late Fall** season partitioned into 10 equal area bins.

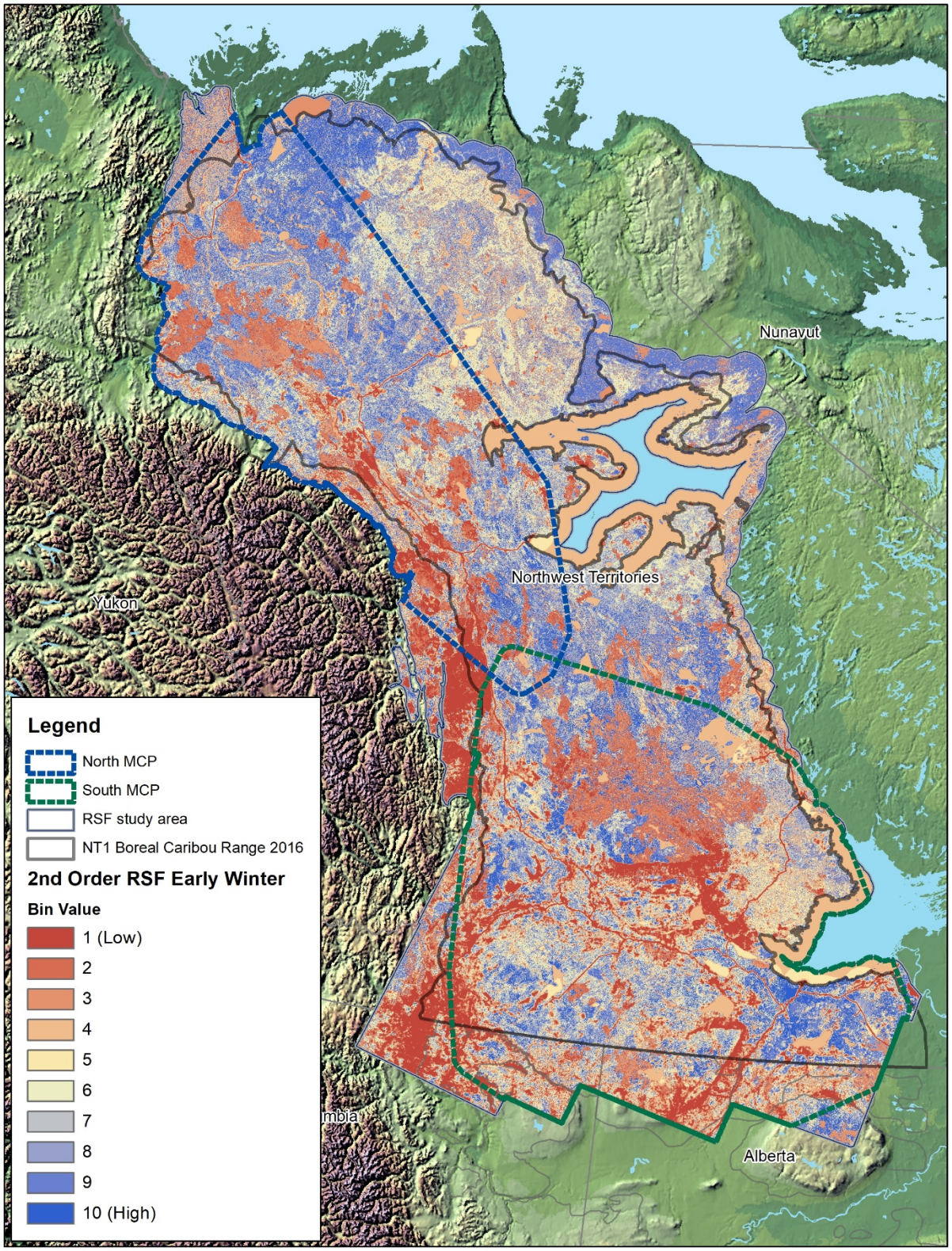


Figure I 5: Map of predicted RSF values at the 2nd order scale during the **Early Winter** season partitioned into 10 equal area bins.

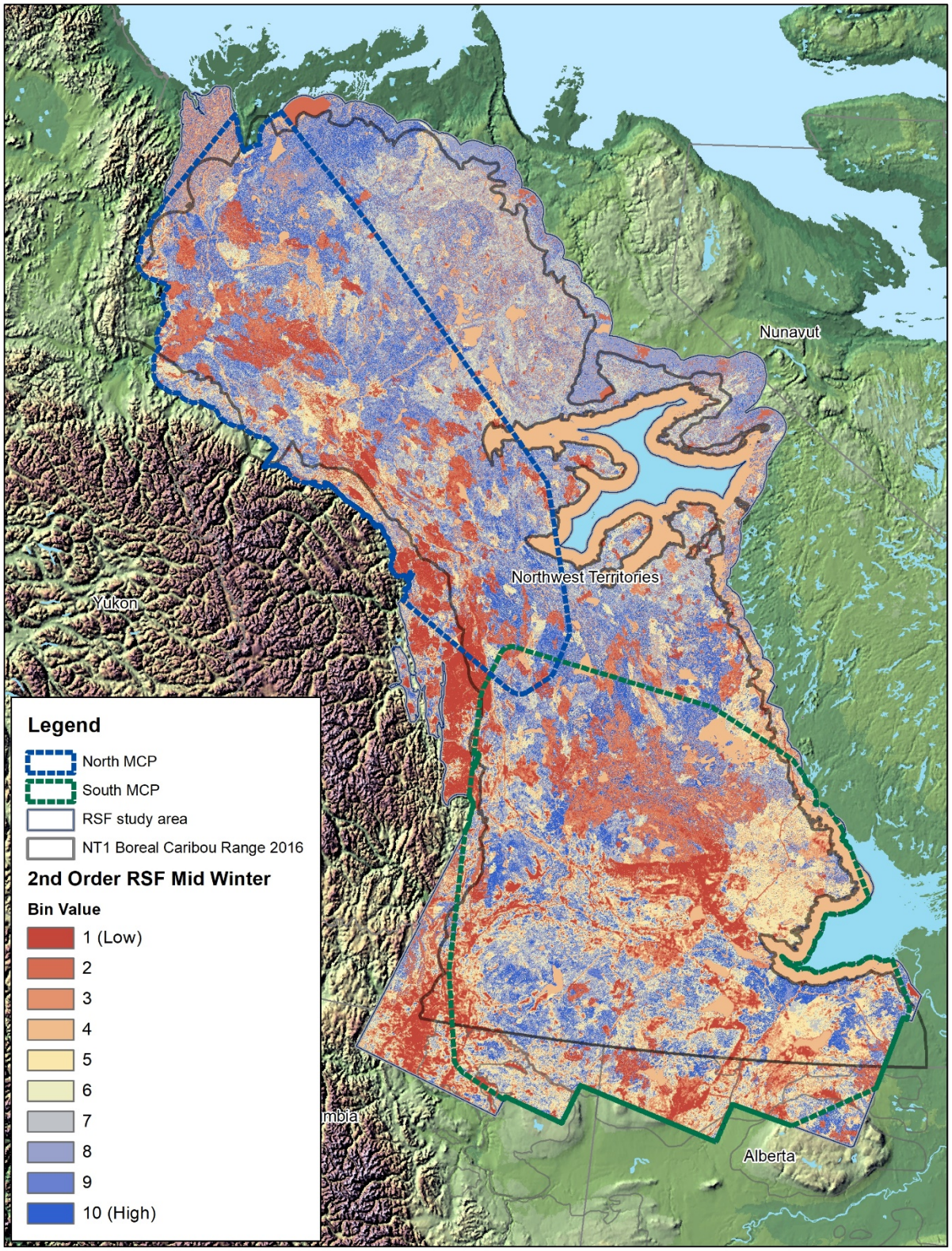


Figure I 6: Map of predicted RSF values at the 2nd order scale during the **Mid Winter** season partitioned into 10 equal area bins.

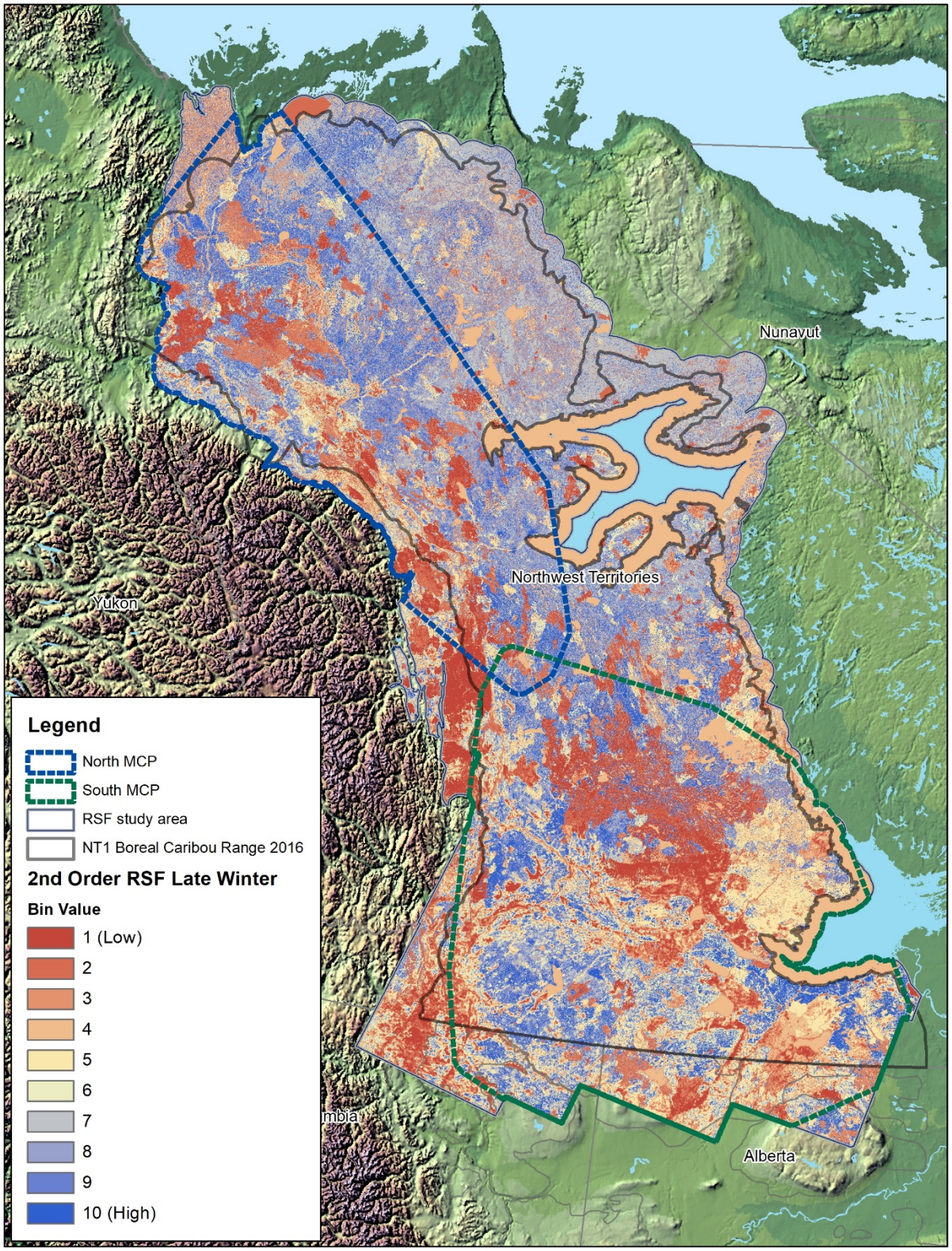


Figure I 7: Map of predicted RSF values at the 2nd order scale during the **Late Winter** season partitioned into 10 equal area bins.

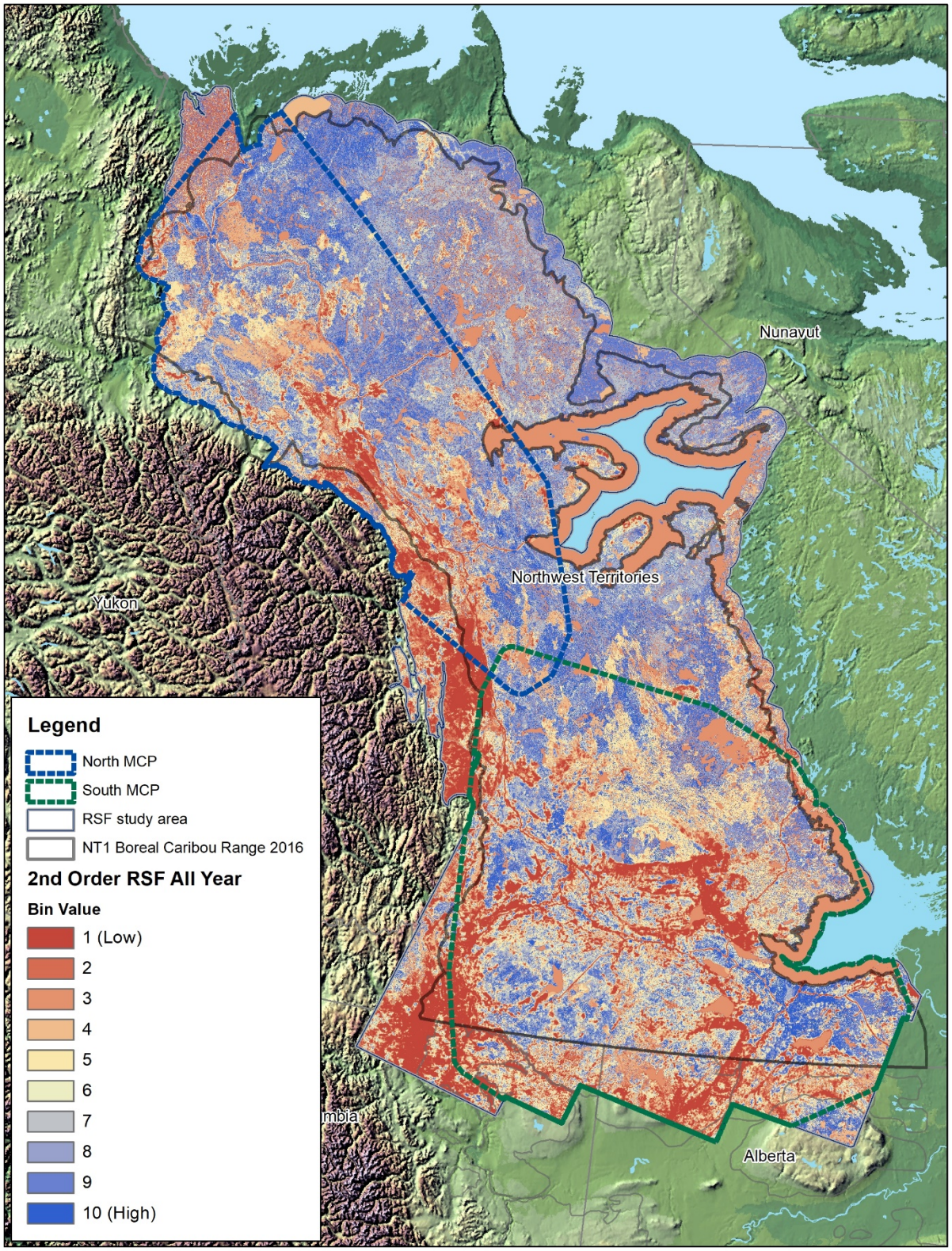


Figure I 8: Map of predicted RSF values at the 2nd order scale from the **All Year** model partitioned into 10 equal area bins.

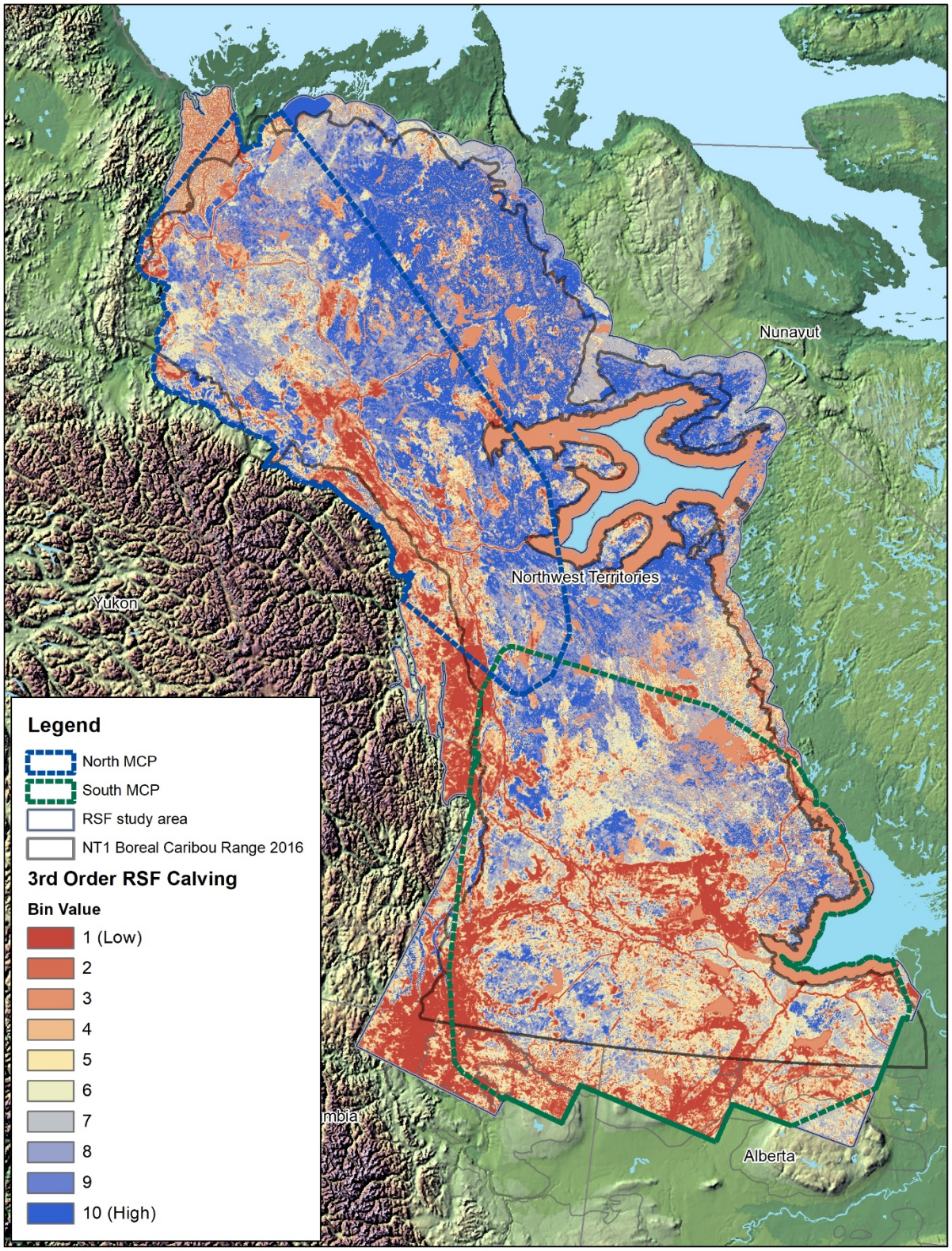


Figure I 9: Map of predicted RSF values at the 3rd order scale during the **Calving** season partitioned into 10 equal area bins.

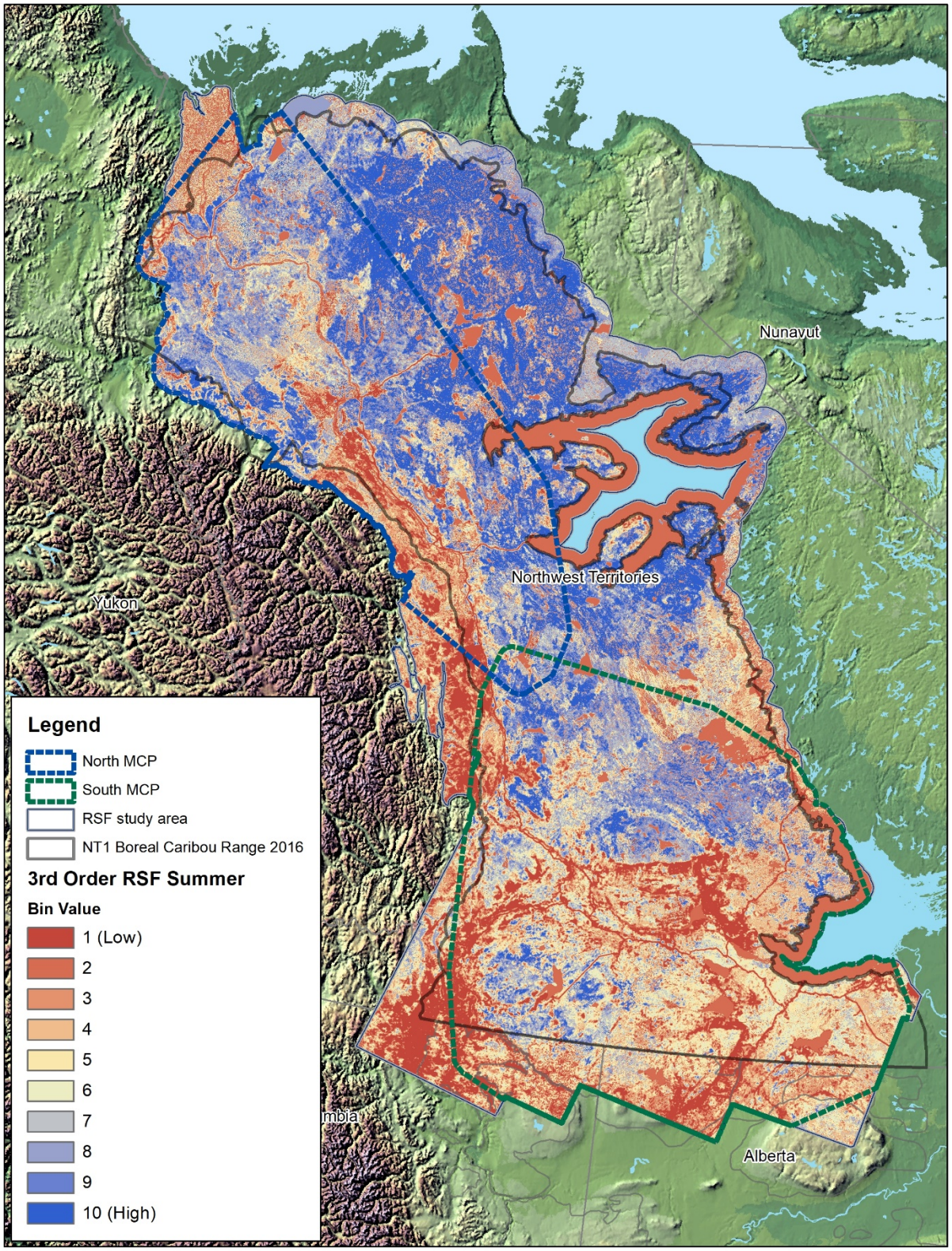


Figure I 10: Map of predicted RSF values at the 3rd order scale during the **Summer** season partitioned into 10 equal area bins.

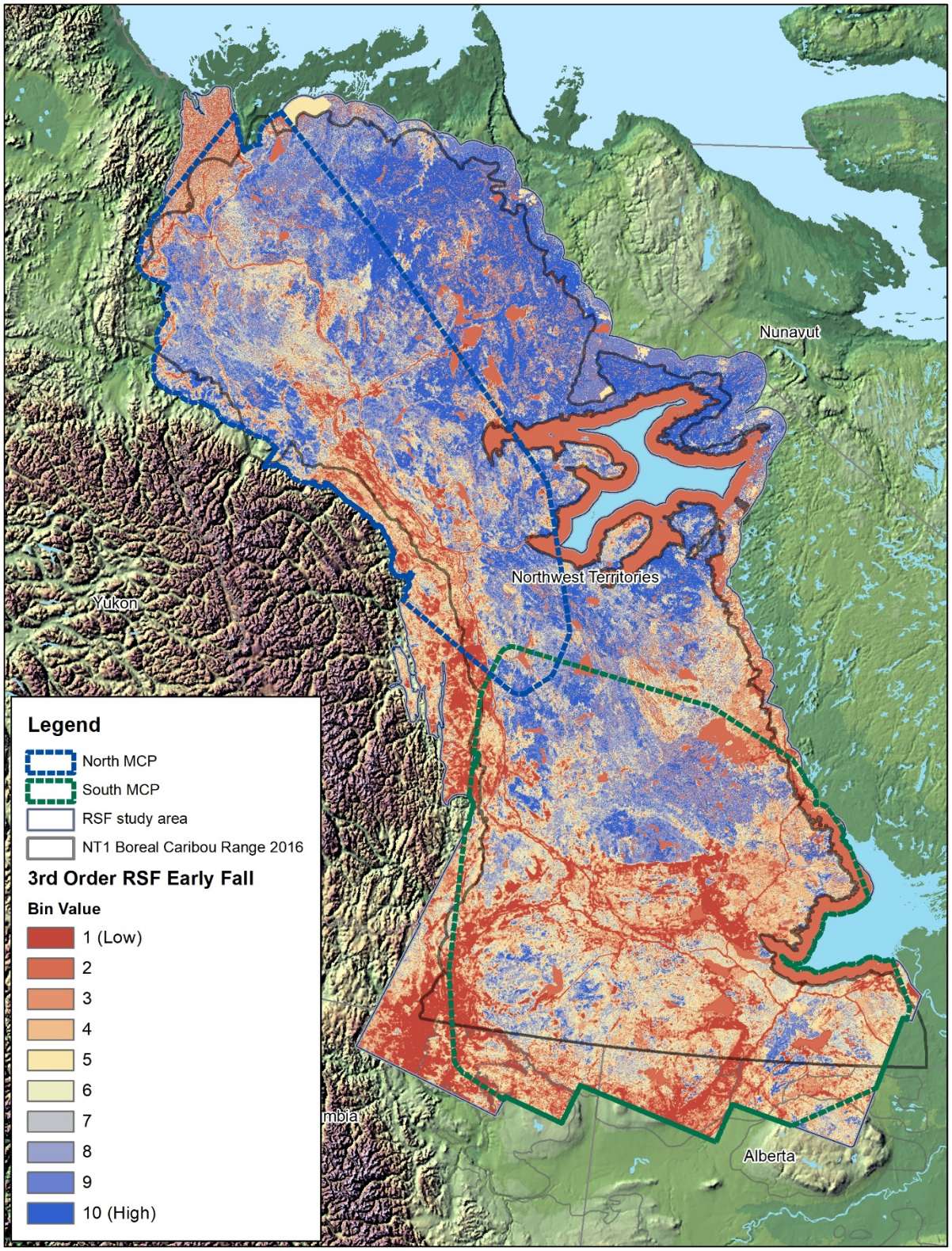


Figure I 11: Map of predicted RSF values at the 3rd order scale during the **Early Fall** season partitioned into 10 equal area bins.

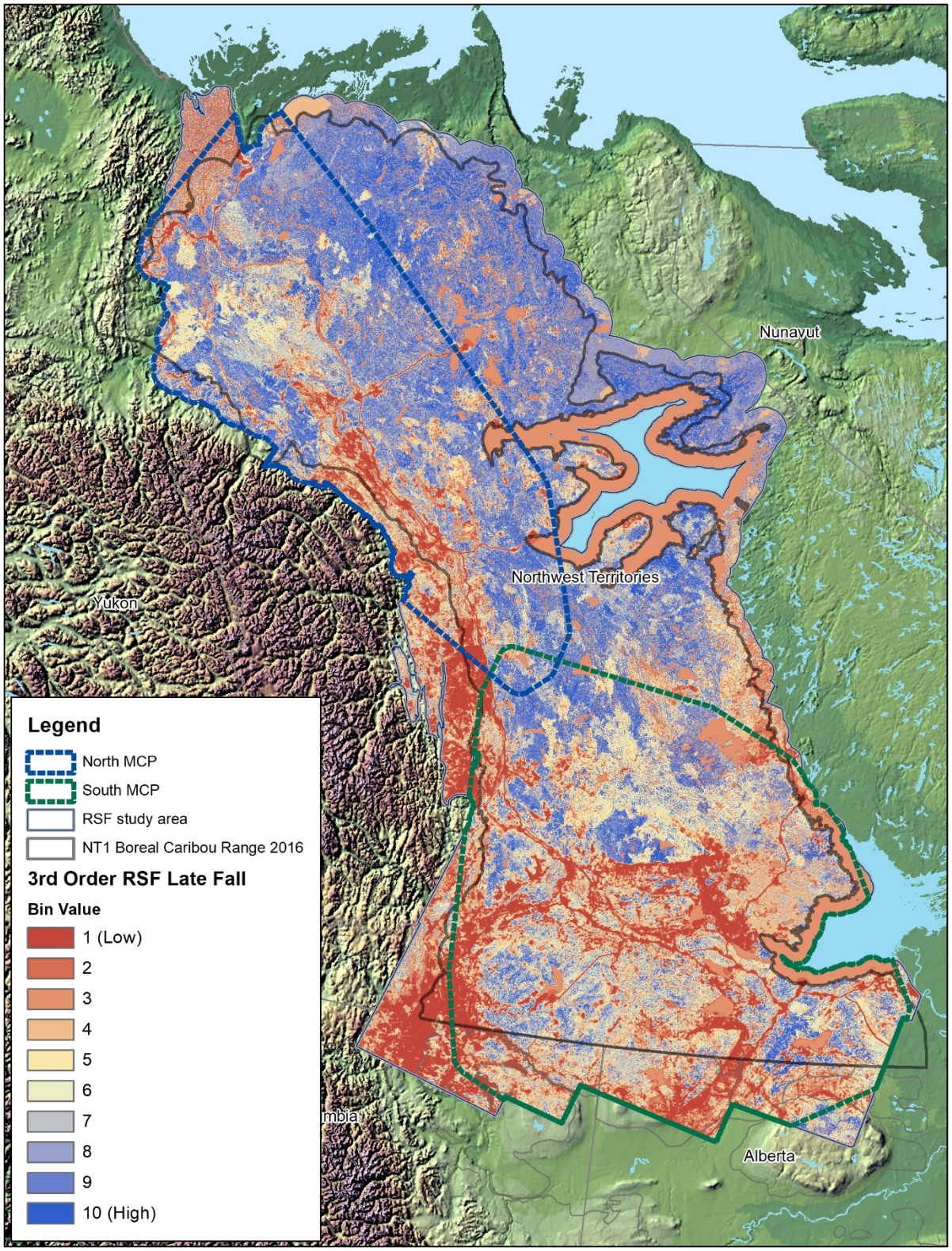


Figure I 12: Map of predicted RSF values at the 3rd order scale during the **Late Fall** season partitioned into 10 equal area bins.

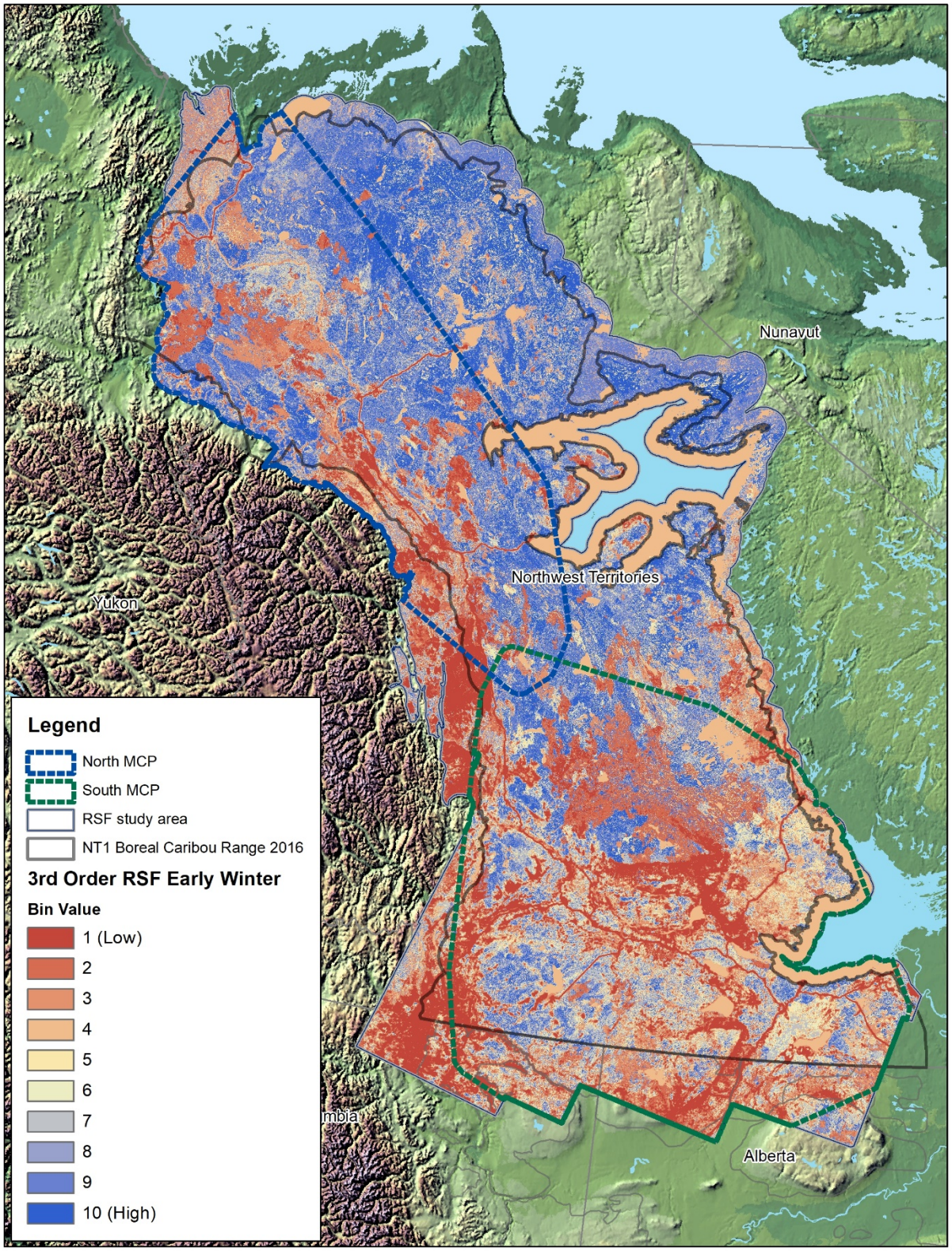


Figure I 13: Map of predicted RSF values at the 3rd order scale during the **Early Winter** season partitioned into 10 equal area bins.

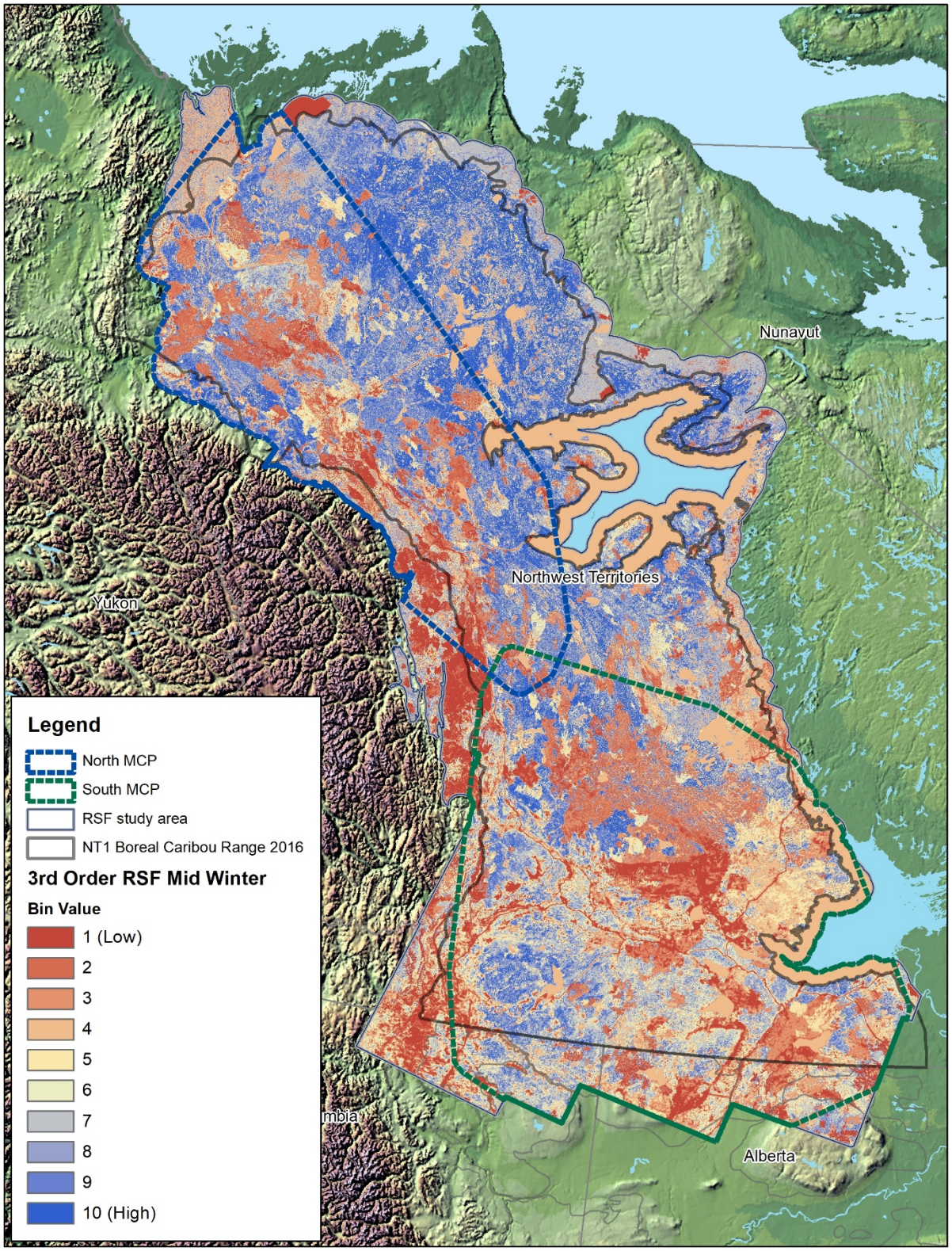


Figure I 14: Map of predicted RSF values at the 3rd order scale during the **Mid Winter** season partitioned into 10 equal area bins.

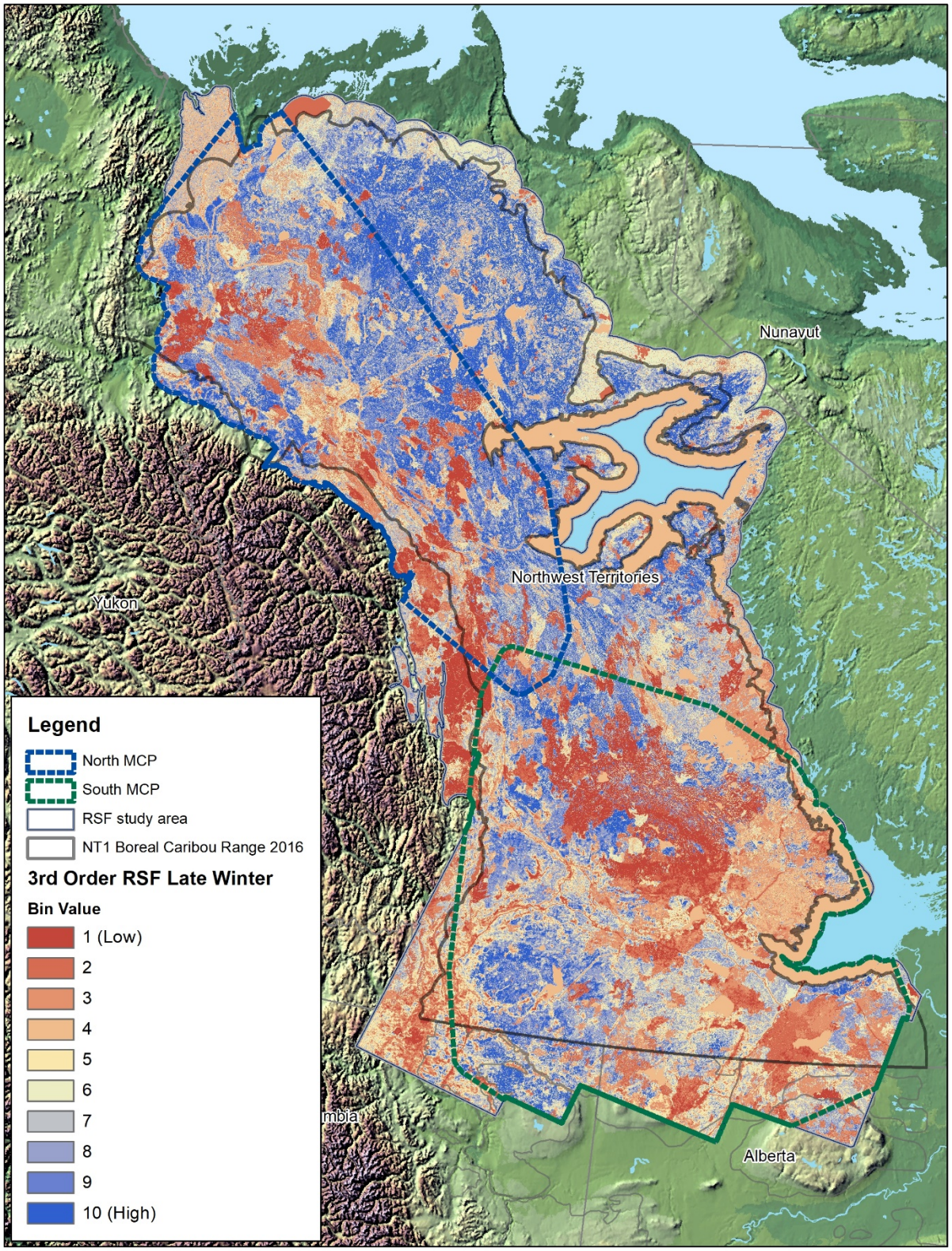


Figure I 15: Map of predicted RSF values at the 3rd order scale during the **Late Winter** season partitioned into 10 equal area bins.

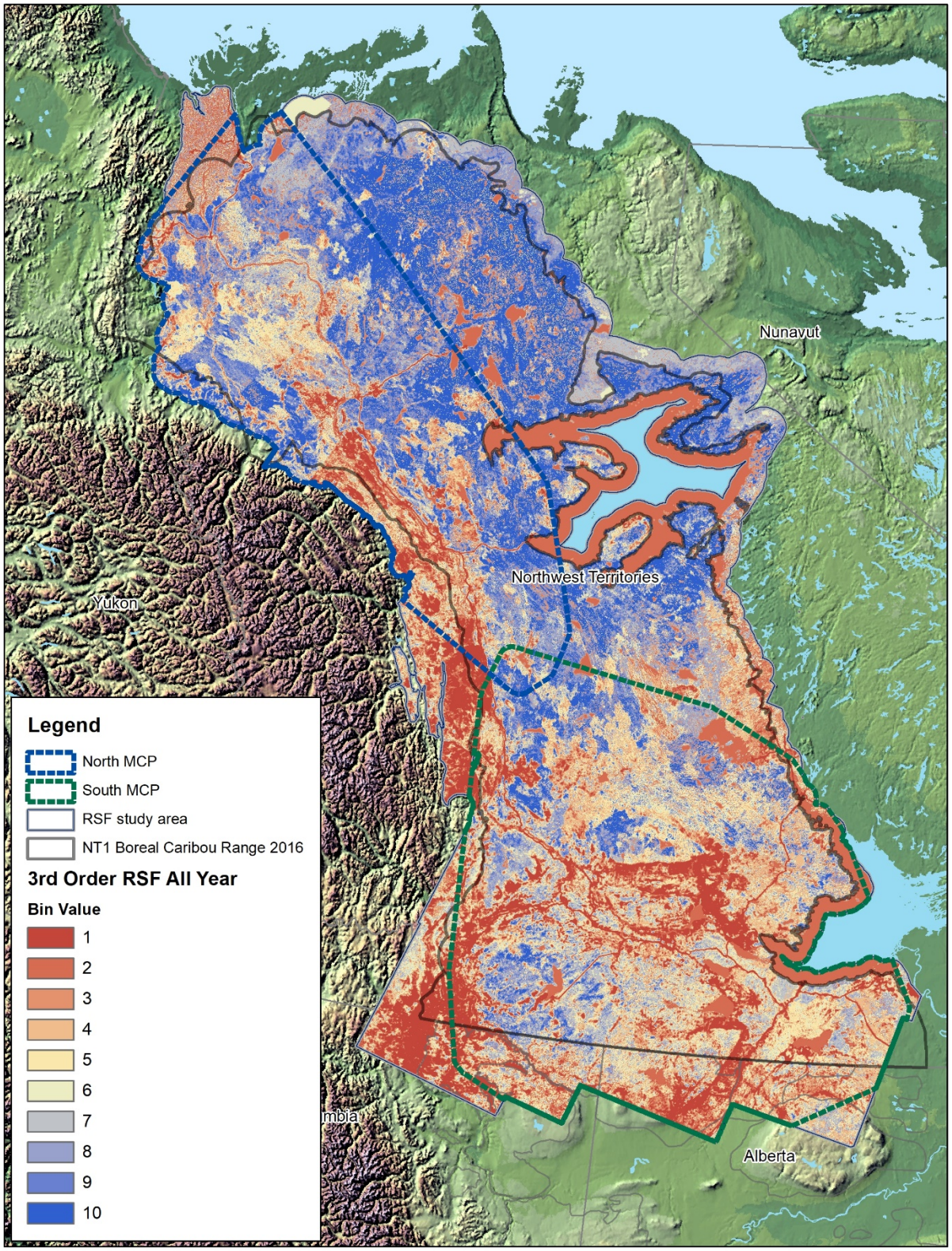


Figure I 16: Map of predicted RSF values at the 3rd order scale from the **All Year** model partitioned into 10 equal area bins.