Appendix 15-D

Scale-Integrated Grizzly Bear Habitat Modeling to Inform Environmental Assessment for NWP Coal's Crown Mountain Project

SCALE-INTEGRATED GRIZZLY BEAR HABITAT MODELING
TO INFORM ENVIRONMENTAL ASSESSMENT
FOR NWP COAL'S CROWN MOUNTAIN PROJECT

Prepared by:

Clayton Apps, PhD, RPBio
Aspen Wildlife Research Inc.
Clayton Lamb, PhD Candidate
University of Alberta

For:

NWP Coal Canada Ltd.
and
Keefer Ecological Services

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1 ACKNOWLEDGEMENTS

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The work and outputs described herein make use of empirical datasets of two independent, multi-year research programs led by Clayton Apps and Clayton Lamb. These programs benefited from multiple funders and contributors that are acknowledged in reports for these programs that are cited herein. This report is a subcomponent of a larger collaborative analytical effort and agreement between the authors to address specific research goals (see Introduction). This larger research project is entitled "*Spatio-Behavioural Responses by Grizzly Bears to Habitat & Human Influence Across Scales in the Southern Canadian Rocky Mountains*".

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2 SUMMARY

As part of a collaborative research program, we analyzed behavioural responses by grizzly bears against a suite of factors pertaining to habitat and human attributes. Our goal was to derive predictive models of relative habitat quality that consider changing relationships by season and across spatial scales. Our collective data were sampled from GPS collars deployed on 75 grizzly bears 99 times between 2003 and 2018, with a variable interval of location fixes. Inferred from these data, or directly observed, were 41 grizzly bear den sites. To explain and predict grizzly bear habitat selection, we derived habitat and human variables from existing and available land cover, terrain, and human-use data data, as well as vegetation indices derived from Landsat remotely-sensed imagery. We stratified our analyses by three seasons (pre-berry, berry, post-berry) as well as overwinter denning. We employed a multi-level analysis design that compared grizzly bear locations to paired-random locations at fixed distances across three nested spatial scales. The size of landscapes compared and the distance between use and random locations were successively smaller from broadest (level 1) to finest (level 3) scales. For each variable, we characterized associations with grizzly bear habitat use, comparing among seasons and across scales.

Grizzly bears showed landscape selectivity in association with most variables considered, with differences apparent among seasons and scales. Habitat use was generally related to open, herbaceous and shrub-dominated conditions, with an avoidance of landscapes of exposed rock or forest domination. Preference for shrub-dominated landscapes was notably greater during the post-berry season. Attributes associated with attributes of natural or human disturbance were selected by bears at finer scales and more so during pre-berry and berry seasons. Preferred landscapes were broadly associated with higher-elevation, steeper and more rugged terrain during pre-berry and berry seasons, but the opposite was apparent during the post-berry season. Terrain associations differed at the finer scale, with preferred habitats characterized by subdued and lower-slope conditions. Relationships with metrics of human use or influence were most obvious at the intermediate scale and were mostly negative especially with respect to roads, access, and high intensity human use. Grizzly bears avoided actively mined areas, especially at the intermediate scale, but response to abandoned and/or reclaimed mine areas was neutral or positive. Grizzly bear dens were associated with broader landscapes that are relatively high and rugged, of moderately steep slope, slightly above treeline but not within barren rock. In addition to predictable habitat and human factors, our data indicate that space-use by bears spatially and temporally exposed to known carcass disposal pits were influenced by such, especially during the post-berry season.

Based on scale- and season-dependent results for each variable, and considering ecological function, we selected independent variables that we expected to be most predictive of grizzly bear habitat selection within each season and at the most relevant scale. We employed a multi-variable analysis to derive resource selection function (RSF) models for each season, for which we

characterized fit and predictive efficacy. Models performed well and can be employed to support environmental assessment, mitigation and conservation planning.

3 BACKGROUND

3.1 Collaborative Research Program

Achieving population conservation objectives for wide-ranging species requires proactive planning approaches that are spatially nested (e.g., Erasmus et al. 1999, Lindenmayer 2000, Wiens et al. 2002). These different levels of conservation planning require supporting information with appropriate detail and confidence. Such a nested approach also accounts for distinct ecological scales, among which habitat and human influences and associated relationships with a given species can differ.

The factors limiting grizzly bear populations are appropriately evaluated by sampling animal occurrence (Apps et al. 2016), density (Lamb et al. 2018), and vital rates (McLellan 2015) over regional landscapes and at scales that can reflect factors and processes influencing persistence and abundance. By contrast, data of grizzly bear space-use and movements, as typically sampled using GPS collars, reflect behavioural responses within occupied landscapes but may not identify factors important for population persistence, density and connectivity. Detailed behavioural responses obtained with GPS monitoring, however, can be highly relevant to conservation planning and environmental assessment, particularly when recorded in a landscape with human activities that are thought to influence grizzly bear population status. Such finer-scale information is especially pertinent within areas with potential human-caused fractures, identified through population-level sampling and modeling, and is helpful in predicting the potential impacts of habitat conversion from resource extraction. Here it can be argued that the spatial pattern of foraging, movement and dispersal can underpin population connectivity, natural augmentation or recovery, and persistence. In the southern Canadian Rockies, human-dominated landscapes are common, especially those associated with the Highway 3 (Crowsnest) transportation and development corridor that bisects the region. Understanding and predicting the spatial pattern of grizzly bear habitat use and movement in such a landscape can inform assumptions about population connectivity as well as the effects of various human activities.

Through our collaborative research, we are analyzing spatial responses by grizzly bears to factors of habitat and human influence across multiple scales in the southern Canadian Rocky Mountains. For this work, we are pooling datasets of grizzly bear locations and movements sampled using GPS collars. This includes data collected from 2003 to 2011 in the lower Elk Valley and Crowsnest Pass area to inform decisions pertaining to population connectivity maintenance and enhancement (Apps et al. 2007). Also included are more recent data collected through a currently active study in the Elk Valley (2016-current) to address broader-scale questions relevant to human-wildlife conflict, unreported mortality, and population ecology (C. Lamb, pers. comm.). The collective dataset is derived from collared grizzly bears that were mostly resident in and around the Elk Valley of British Columbia and the Highway-3 transportation corridor that bisects the Rocky Mountains through Alberta and British Columbia. Across this combined region, the pooled data and predictive outputs that can be derived from them are relevant to assessing and mitigating potential impacts of human-use and resource development proposals. Therefore, in addition to characterizing the spatial responses of individual grizzly bears to landscape attributes of habitat and human activity, we describe the development of empirically-derived predictive models that can support environmental assessment and mitigation planning in a manner that is transparent and defensible. From modeling that integrates relationships across spatial scales, we expect that outputs will support inferences, within defined assessment area(s), of (1) seasonal habitat quality and security, (2) the spatial context and connectivity of important core-habitat (foraging) areas, and (3) patterns of grizzly bear movement and landscape permeability including the potential for restricted or otherwise habitually-used routes. With respect to predicting and mitigating impacts on the above, we expect the results of our collaborative analyses will provide empirical support in predicting grizzly bear responses to metrics of individual and cumulative human activity.

Our primary objective is spatial prediction with appropriate confidence to support localized conservation planning and environmental assessment. The habitat-related predictors we consider may influence or associate with bear plant foods and potentially reflect indirect relationships with sources of meat-protein; they are therefore relevant to spatial prediction. However, several variables do not reflect well-defined habitat factors that influence grizzly bear energetics in a way that is simple and understandable. Therefore, we do not directly address hypotheses pertaining to habitat selection. We do, however, create a predictive spatial model to evaluate the behavioural response of grizzly bears to measures of human influence and environmental variables.

3.2 Analysis & Modeling Parameters for NWP Coal's Crown Mountain Project

Within the context of the larger collaborative research program described above, a subcomponent was directly commissioned by NWP Coal (through Keefer Ecological Services) to support their environmental assessment requirements specific to their proposed Crown Mountain Project. For this endeavor, we were given specific directive and parameters to work within. First, a regional and local study area were pre-determined, the rationale for which are described elsewhere and follow recommendations provided by C. Apps. Second, the application of our modeling in assessing individual and cumulative impacts from the proposed project were not necessarily to be carried out by us but possibly by an outside party designated by NWP Coal.

3.3 Study Area

3.3.1 Research Study Area

The combined study area of the two aforementioned grizzly bear collaring efforts is mostly encompassed within the Border Ranges ecosection (Demarchi 1996). The physiography of this mountainous area is fairly subdued relative to elsewhere in the southern Canadian Rockies, though it is punctuated by steep, rugged ridges, and elevations that range from 1100-3200 m. The folded and faulted sedimentary rocks that compose this portion of the Rockies result in prominent bare limestone ridges and significant coal deposits. The local climate is cool, dry, continental as influenced by both Pacific and Arctic air flows. The most common sequence of biogeoclimatic zones (Meidinger & Pojar 1991) here consists of Montane Spruce (MS) at low elevations, Engelmann Spruce-Subalpine Fir (ESSF) at middle elevations, and Alpine Tundra (AT) at high elevations; the Interior Douglas-fir (IDF) zone occurs in the driest valley bottoms. In the MS and ESSF zones, the climax overstorey is primarily hybrid Engelmann/white spruce (*Picea engelmannii* x *glauca*) with a greater composition of subalpine fir (*Abies lasiocarpa*) at higher elevations, while Douglas-fir (*Pseudotsuga menziesii*) is the primary climax species in the IDF. On the eastern slopes of the Lizard Range, high levels of precipitation yield an Interior Cedar-Hemlock (ICH) zone, with climax stands of western red-cedar (*Thuja plicata*), western hemlock (*Tsuga heterophylla*) and hybrid spruce. Seral stands of lodgepole pine (*Pinus contorta*) occur at various elevations, in association either with western larch (*Larix occidentalis*), Douglas-fir and aspen (*Populus tremuloides*) at low elevations or with whitebark pine (*Pinus albicaulis*) at higher elevations. The AT is dominated by barren rock, with small patches of meadow and wind-swept alpine grasses. Land within the region is subject to various uses, including oil and gas wells/pipelines, open-pit coal mining, timber harvesting, agriculture and livestock grazing, human settlements (including the communities of Fernie and Sparwood), and both motorized and non-motorized recreation. The study area is also bisected by Highway 3 that carries approximately 7000 vehicles per day during summer, with 8-16 freight trains per day on the railroad that parallels the highway (BC Ministry of Transportation & Highways, unpubl. data).

3.3.2 Environmental Assessment Study Areas

In environmental assessment, it is necessary to define regional and local study areas for application of wildlife habitat ratings (RISC 1999). For NWP Coal's Crown Mountain Project, a larger regional study area (RSA) was defined, within which a smaller local study area (LSA) was nested (C. Apps, unpublished report). The RSA ensured that the larger regional grizzly bear population context was appropriately captured. At this scale, ecologically meaningful inferences relate to population distribution and variation in population density, core habitat areas and landscape-level population connectivity. The RSA also encompasses an area over which a quantitative analysis could be carried out for comparison against established standards and thresholds. This includes the Elk Valley Cumulative Effects Management Framework (CEMF; 3,314 km^2). The RSA also includes both the South Rockies (8,303 km^2) and Flathead (5,677 km^2) grizzly bear population units (GBPUs) with which the proposed LSA (see below) overlaps. While satisfying these criteria, wildlife management units (WMUs) were also identified within Alberta to encompass a regional area around WMU 4-23 in which the project falls. These include WMUs 404, 402, 303, 400, and Waterton Lakes National Park in Alberta. Based on these criteria, the RSA encompasses >15,805 km^2 that is not restricted by jurisdiction (Figure 3-1).

In addition to the RSA, a single LSA was established for application in modeling and quantitative assessment of individual and cumulative impacts for grizzly bears and possibly other large and wide-ranging terrestrial mammals. An appropriate localized scale of assessment was considered to equate to an occupied landscape area of 300 km^2, an area expected to encompass a female home range for grizzly bears. To objectively delineate the LSA, a 10 km radius was applied as a buffer to the project footprint area. As noted, the RSA and LSA and constituent units within them define the scale for predicting and understanding individual and cumulative impacts associated with the Project. This may involve both qualitative and quantitative assessment. However, outside the context of established management objectives or thresholds, or comparison among defined scenarios, absolute measures of change related to Project impacts cannot be interpreted directly with respect to determining significance.

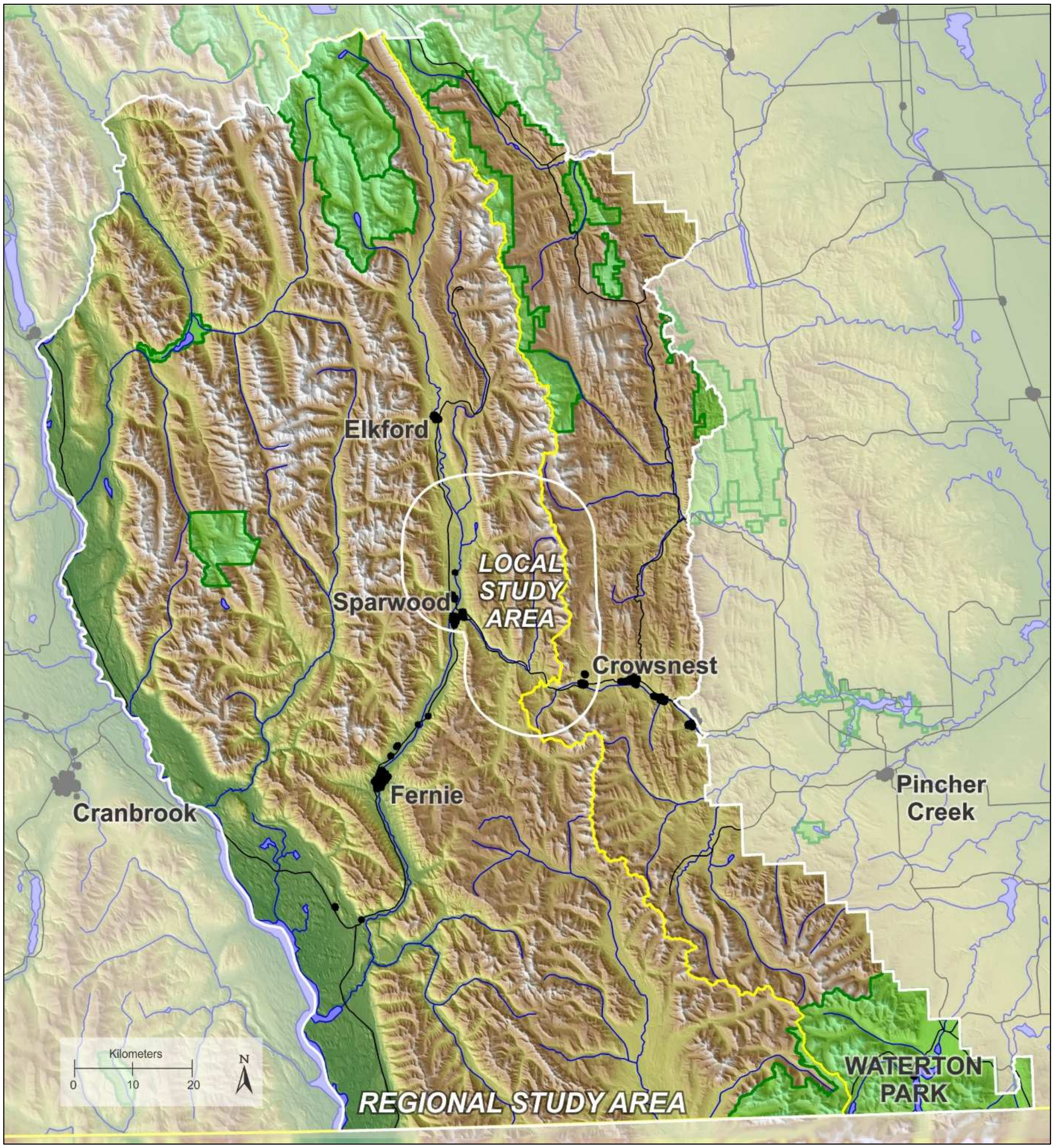

Figure 3-1. Location of regional and local study areas for grizzly bear habitat modeling to support environmental assessment for NWP Coal's Crown Mountain Project within the southern Canadian Rocky Mountains.

4 DATA & PREDICTIVE COVARIATES

4.1 Grizzly Bear Location Data

The grizzly bear GPS location data applied in our analyses were collected across an extensive research study area (Figure 4-1). Grizzly bears were captured through localized ground trapping primarily using cable-snares, some use of culvert traps, and free-range darting. Across the entire study area, grizzly bears were also captured using helicopter searching and aerial darting. Primarily in association with the Crowsnest Highway (including lower Elk Valley and Crowsnest Pass), we placed GPS radiocollars (Lotek 4000/4400M) on 32 adult grizzly bears (15M, 17F) 37 times between 2003 and 2010. Location fixes were attempted at intervals of either 2 hr or 1 hr. More recently, in association with the Elk Valley, GPS radiocollars (Followit or Vectronic) were deployed on 43 (22M, 21F) grizzly bears (11 subadults) 62 times between 2015 and 2018. Location fixes from this collaring effort were attempted at intervals of mostly 6 hr, but with some at fix intervals of 2, 4, 13 hrs or daily.

The accuracy of successful location fixes from GPS collars without differential correction have been reported to average 10.6 m ±0.29 m SE (D'Eon et al. 2002). However, where possible, we inferred spatial error for each location using standard techniques (Rempel et al. 1997, Moen et al. 1997), and screened for positions with unacceptable spatial error. We also modified the dataset to account for inherent habitat-induced bias in GPS fix-success (Rempel et al. 1995, Dussault et al. 1999) using multiple imputation (Frair et al. 2003). As a result, 18% of our total GPS location dataset was based on inference between successful fixes.

4.2 Winter Den Sites

From GPS location data, we isolated den sites that had been used by grizzly bears during the overwinter period (~ November – April). Where den site locations were not known through direct observation, we inferred them based on clustering of GPS location data during the expected denning period. Across all years of data, our sample of grizzly bear den sites totaled 41.

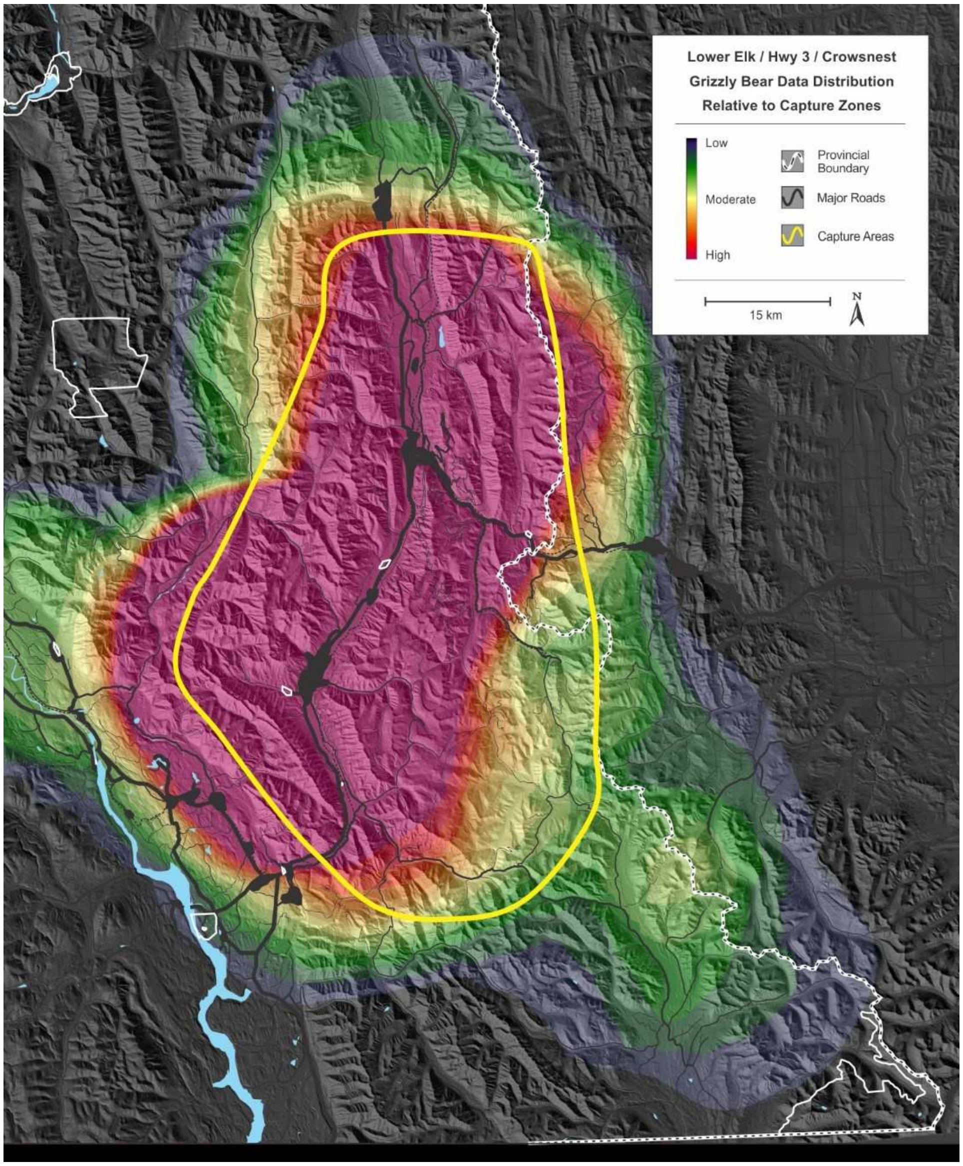

Figure 4-1. Lower-Elk/Crowsnest study areas in the southern Canadian Rocky Mountains and distribution of grizzly bear location data. Study area boundaries define grizzly bear capture zones, within which the distribution of location data from resulting study animals is considered representative.

4.3 Habitat and Human Use Predictors

Grizzly bear habitat selection and diet has been investigated in several smaller study areas within or near to our regional and local study area (Hamer & Hererro 1987, Waller & Mace 1997, McLellan & Hovey 2001, Neilson 2005). Features such as avalanche chutes, riparian habitat, and early seral conditions following wildfires have usually found to be preferred by grizzly bears. The fruits of huckleberry (*Vaccinium membranaceum*) and buffalo berry (*Shepherdia canadensis*) are the major high-energy foods (Hamer & Hererro 1987, Mace & Jonkel 1986, McLellan & Hovey 1995, Munro et al. 2008) consumed by bears in the summer and autumn when bears deposit fat needed for hibernation and reproduction (McLellan 2011) and their abundance influences reproductive rates and population density (McLellan 2015). We did not expect to that current inventory systems would allow us to directly account for the distribution of all resources relevant to grizzly bears across the study region. But we considered several indicator or surrogate variables in order to collectively account for the distribution of key resources in a multivariate context.

The factors we considered for analysis of spatial-behavioural responses by grizzly bears pertain to terrain conditions, land cover, human influence, and remotely-sensed vegetation indices (Table 4-1). From these we defined explanatory and predictive variables that may be differentially relevant across scales. Spatial data were rasterized for analysis at 100 m (1 ha). This resolution we considered appropriate given the scale and accuracy of the source data, and the finest analytical scale we planned to consider (see Multi-Scale Design, below).

<u>Physiography</u> – We did not directly consider climatic variables because the scale of such variation would not be relevant for evaluation and prediction of spatio-behavioural responses by individual grizzly bears. We did expect that localized variation in terrain conditions would be relevant to understanding and predicting grizzly bear habitat quality, and we assembled a 1:20,000 digital elevation model (DEM; BMGSB 2002, AltaLIS 2015) from which we derived several static variables. Candidate predictors included elevation (m; ELEV) and slope (%; SLOPE). A terrain curvature index (CURVA) reflected the maximum rate of change of a curve fit through each pixel in the context of its neighbors (profile curvature; Pellegrini 1995). Using known sun azimuths and a digital elevation model, mean daily maximum solar insolation (kJ; SOL-EN) and duration (h; SOL-DU) was calculated for each pixel in the study area based on 1-hour increments between 1 May and 30 October (Kumar et al. 1997, Meszaros et al. 2002). We also derived a terrain complexity index (COMPLX) that is independent of slope by measuring the standard deviation of terrain curvature values within a defined landscape radius.

<u>Land Cover & Vegetation</u> – Across the regional study area spanning both provinces, we acquired a Landsat-derived classification assembled for the earth observation for sustainable forest development (EOSD) forest monitoring program (Wulder et al. 2008). This coverage provides general land cover classes derived from coarse-filter remotely sensed imagery, which we defined eight variables relevant to our analysis: broad-leaf (EOSD_BL), coniferous (EOSD_CN), herbaceous (EOSD_HB), mixed wood

(EOSD_MW), rock and exposed (EOSD_RE), shrub (EOSD_SH), snow and ice (EOSD_SI), and wetland (EOSD_WT).

Across the regional study area, we assembled a merged coverage of orthorectified Landsat-5 Thematic Mapper Plus (TM) satellite imagery (30 m native resolution of multispectral bands). Coverage for the greater area required a mosaic of 12 cloud-free scenes with dates between 19 July and 26 August of the years 2009 and 2010. We expected that reflectance values in these mid-summer scenes would most accurately depict spatial variation in vegetation conditions across the regional study area with minimal influence of snow-cover. Each scene was initially corrected for atmospheric and geometric distortions. However, to correct for variation among scenes due to atmospheric conditions and time of day (sun angle), we adjusted reflectance values for each spectral band using an averaging algorithm that compares values at shared pixels between overlapping scenes (Schowengerdt 2007). Using a DEM at 25 m resolution, we modeled the spatial distribution of solar energy for the minute each image was taken (Kumar et al. 1997, Meszaros et al. 2002), and we used this to apply a correction for topographic redistribution of solar radiation for all spectral bands of Landsat imagery (Civco 1989).

In addition to the land-cover classification, we derived ratio-scale indices of vegetation characteristics. We calculated the normalized difference vegetation index (NDVI) using the standard formula (Band4 – Band3) / (Band4 + Band3). We also applied a Tassled-Cap transformation to the component spectral bands (Crist & Cicone 1984, Mather 1989) to obtain the green (GVI), wet (WVI) and bright (BVI) vegetation indices. The GVI is known to respond to net primary vegetation productivity or the amount of herbaceous phytomass within pixels (Schwartz & Reed 1999) and is expected to relate to the nutritional quality and abundance of many grizzly bear herbaceous plant foods (Mace et al. 1999, Stevens 2001). For each VI, we constrained extreme values within a range that reflects variation in habitat conditions we expect to be relevant to grizzly bears (e.g., variation of values within rock/ice or water was considered irrelevant)[1].

We expected that the above VIs would correlate similarly with functionally-different habitat conditions. However, discrete habitat conditions with similar site-specific VIs may differ according to the patterns of spectral variability within the surrounding landscape, and this may relate to grizzly bear habitat selection. Thus, for each of the VIs, we derived variables reflecting both its standard deviation (*VI-SD) in the landscape at a specific scale .

Across the regional study area, we obtained spatial outputs from models of berry productivity (kilocalories) for huckleberry (*Vaccinium membranaceum*; BERRY_VM) and buffaloberry (*Sheperdia canadensis*; BERRY_SC). These models are a predictive function of soil, climate, fire, canopy cover and topography (Proctor et al. 2015).

[1] Minimum index values: GVI = 0→60, NDVI = 0→100, WVI = -110→+15; BVI = 0→200

The land cover and vegetation data we employed in our analysis and modeling are specific to defined dates, which was appropriate given the average date of our grizzly bear location data. However, there is potential that the vegetation data do not reflect specific conditions to which some animals were exposed at certain times. We expect the implications of such mismatch to be only with respect to statistical power rather than potential bias. In isolation of human influence, grizzly bears respond positively to forest overstorey disturbance (Zager 1980, Waller 1992), and where there has been such disturbance not reflected in our data, model predictions of habitat suitability could be biased low. This issue could be rectified by using, in model application, recently updated land cover and vegetation data. If more recently acquired Landsat multi-spectral imagery are assembled for model application, I recommend that reflectance values be calibrated to the older data we applied in analysis using a subset of areas with no known recent disturbance.

Human Use – Depiction and prediction of human use and accessibility are fundamental to our analyses. As such, it is imperative that human-use data and assumptions be as accurate and defensible as possible. We are aware that source inventories of human linear transportation features are in some places erroneous (e.g., exclusion of new roads and inclusion of impassible road segments). We therefore compared multiple inventories of human-use point, linear and area features and used what we consider the best available data in building a human-use database that captures existing infrastructure known to facilitate and influence human use across the landscape.

Across the larger regional study area, the most recent inventory of road features of all classes was obtained from the British Columbia Digital Road Atlas (GeoBC 2019). The DRA is a data management system representing a complete and updated network of all the roads across the province. Responsible government agencies contribute feature inventories typically mapped at 1:20,000 or finer. For Alberta, comparable road data were obtained from the ABMI “wall-to-wall” human footprint inventory for year 2014 and at a scale of 1:15,000 (ABMI 2017). Other features of human settlement, transportation and administrative boundaries were obtained from a national CanVec inventory (CTI 2010). We derived a road-density variable (ROADS) by classifying linear human features following a standard weighting system reflecting expected traffic type and volume (Apps 1997), and then removing road networks to which we knew public motorized access was closed or restricted.

For the regional focal area and local study area, we assembled a cadastral database primarily from 1:50,000 NTS blocks of CanVec data (CTI 2010). From this, we extracted relevant point and polygon features of localized human use under the following themes: (1) buildings and structures, (2) energy, (3) industrial and commercial areas, and (4) places of interest. We classified features given our expectation for localized human use that is "high" (LHU-HI) or "low" (LHU-LO). Also from CanVec data, we defined areas specifically delineated as "residential" (RESDEN). Predominant human land uses were inferred from baseline thematic mapping (BTM; Geographic Data BC 2001) and from land-use zoning (AltaLIS 2019), from which we defined urban, settled, and agricultural lands (URB-AG). We considered mines separate from other human use variables, which we split into two variables reflecting mines we know to be presently active (MINE_A) and those we are aware to be presently abandoned and/or reclaimed (MINE_R).

Carcass Pits – We expected that landscape use by some animals would be influenced by availability of carrion within known carcass pits. We therefore identified the point locations of these pits as a variable in order to account for this influence in habitat selection by grizzly bears with respect to variables relevant to habitat prediction. In doing so, we accounted for the known timing with which the pits were used to dump carcasses, and we considered each a potential influence only to grizzly bear locations corresponding to the time period with which each was active.

Table 4-1. Independent landscape variables addressed to explain and predict grizzly bear space-use and habitat selection across the Elk/Crowsnest study area of the southern Canadian Rocky Mountains, 2003 - 2018.

Land Cover		Terrain	
EOSD_BL	broad-leaf	ELEV	Elevation (m)
EOSD_CN	coniferous	SLOPE	Slope (%)
EOSD_HB	herbaceous	CURVA	Terrain curvature and soil wetness/seepage index
EOSD_RE	rock & exposed	COMPLX	Terrain complexity index
EOSD_SH	shrub	SOL_DURA	Mean daily max solar duration (min), May - Oct
EOSD_SI	snow & ice	SOL_ENER	Mean daily max solar insolation (KJ), May - Oct
EOSD_WT	wetland		
		Human Influence	
Landsat VI		ROADS	Weighted density of linear transportation features
BVI	Mean of the bright vegetation index	URB-AG	Urban, settled, & agricultural lands
BVI-SD	Standard deviation of the BVI at specified scale	LHU-HI	Localized human-use - "high" intensity
GVI	Mean of the green vegetation index	LHU-LO	Localized human-use - "low" intensity
GVI-SD	Standard deviation of the GVI at specified scale	RESDEN	Residential polygons
WVI	Mean of the wet vegetation index	ACCESS	Index of human accessibility/remoteness
WVI-SD	Standard deviation of the WVI at specified scale		
NDVI	Mean of the normalized difference vegetation index	Mines	
NDVI-SD	Standard deviation of the NDVI at specified scale	MINE_A	Mines Active
		MINE_R	Mines Abandoned and/or Reclaimed
Berry			
BERRY_VM	Predicted berry kcal - *Vaccinium membranaceum*		
BERRY_SC	Predicted berry kcal - *Sheperdia canadensis*		

5 ANALYTICAL METHODS

5.1 Analysis Stratification

The two collaring efforts from which our grizzly bear GPS location data are derived were temporally distinct but did not correspond to different ecological zones. We therefore chose to pool data between them for analyses and modeling across the combined study area within the southern Canadian Rockies. We designed our analysis in accordance with Thomas and Taylor's (1990) Study Design 2 with inferences relevant at the population level. We did not otherwise constrain our analyses within any specific habitat condition. However, for predictive modeling, we did account for individual variation among animals in evaluating grizzly bear relationships with habitat human use predictors as described below.

Grizzly bears typically exhibit distinct seasonal patterns of food habits and associated habitat preferences. We therefore stratified our analyses into three seasons based on changes in grizzly bear diet (McLellan & Hovey 1995). The "pre-berry" season spanned the period from den emergence (April) to 31 July. The "berry" season occurred from 1 August to 20 September, and the "post-berry" season spanned 21 September to denning (November). We also considered an overwinter "Denning" period (generally November – April), analyses for which was based on 41 known or inferred den sites. We pooled data between sex as there is no expectation that foraging strategy differs markedly (McLellan & Hovey 1995).

5.2 Multi-scale Design

Space-use and movements of animals are determined by perceptions at different spatial scales (Turchin 1998). We employed an analysis design that accounted for the scale-dependent nature of wildlife-habitat associations (*sensu* Apps et al. 2001). Spatial scale in ecology is characterized by the geographic extent of analysis and the spatial resolution of data. We analyzed grizzly bear-habitat associations at three nested spatial scales, corresponding to successively smaller landscapes of used and available habitat (Figure 5-1). At each scale (level) we sampled landscape composition at grizzly bear locations and at paired locations at fixed distance but random azimuth from grizzly bear locations (Figure 5-2). At level 1, the broadest scale of analysis, grizzly bear and paired-random locations were separated by 16.9 km, a radius that defines the largest area (i.e., 897 km^2) we consider consistently *available* to bears in moving between sequential locations within an 8-day sampling interval, which is the period beyond which grizzly bear movements asymptote. Over this time period, 5% of net movements were ≥16.9 km (Figure 5-3), and we therefore weighted points with an 8-day sampling interval to be independent within this radius. By applying a 0.207 multiplier (rational below) to the 16.9 km distance, we defined a 3.50 km radius within which we defined the *used* landscape at level 1. At levels 2 and 3, the *available* landscape radius was defined by the *used* landscape radius at the previous broader scale, and the used landscape radius was again calculated using the 0.207 factor. This multiplier ensured that the ratio of used to available landscape radii remained constant across scales, and that the radius used to scale habitat composition at level 3 (the finest scale of analysis), encompassed the assumed spatial error of grizzly bear GPS locations within the pooled dataset. We also note that the radius of available area at level 3 was greater than the minimum mappable unit of the smallest-scale data (1:20,000) from which spatial covariates were derived.

Based on the movement rate analysis discussed above, we weighted GPS locations to avoid autocorrelation at each analysis scale. The effect was reduced sample size at broader scales where locations of short time interval could not be considered independent. Specifically, we weighted locations using independence intervals of ≥1 hr (level 3; available area = 0.70 km radius), ≥6 hrs (level 2; available area = 3.5 km radius), and 8-days (level 1; available area = 16.9 km radius). Hence, the size of the independent-location sample varied among scales (Table 5-1). The weighting factor applied was dependent on the fix attempt interval of the collar- and time-specific data.

At each analysis level, we adjusted the resolution of habitat variables to the used and available landscape radius by aggregating data (Bian 1997) using a GIS moving window routine. Pixels thus reflected each variable's mean value or proportional composition within a surrounding circular landscape. Lands for which any of the habitat or human-use data sources were not available, and water bodies, were not considered part of the landscape when aggregating data using the moving window routine.

Den sites – We also applied the above design in analyzing den site selection, with each den site representing an independent observation at each scale. However, the den site location sample size (n = 41) was very low as compared to GPS locations used for analyzing habitat selection. Therefore, to ensure that "available" landscape conditions were adequately represented, we generated 10 random points matched with each den site at each scale. We weighted these points as a single location in comparing to matched den site locations.

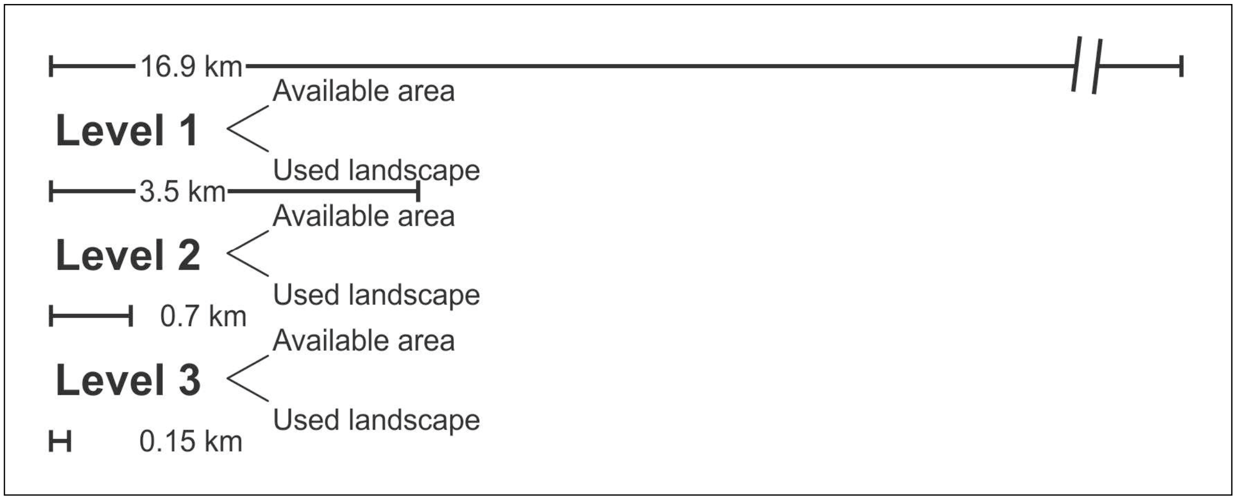

Figure 5-1. Hierarchical scales considered in analyzing grizzly bear habitat selection in the southern Canadian Rocky Mountains, British Columbia and Alberta. Scales were defined by radii of used and available landscapes.

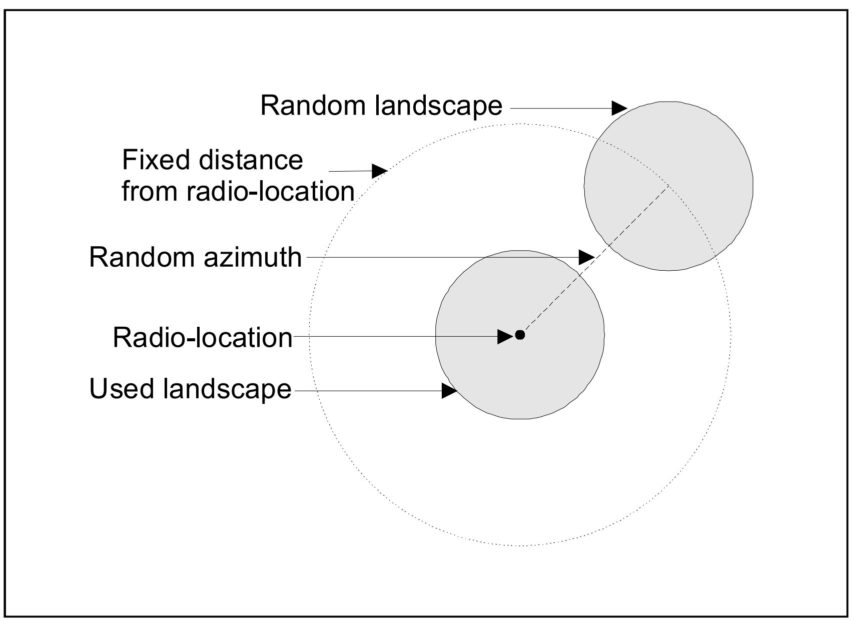

Figure 5-2. Scale-dependent design for analyzing grizzly bear habitat selection in the southern Canadian Rocky Mountains, British Columbia and Alberta (from Apps et al. 2001).

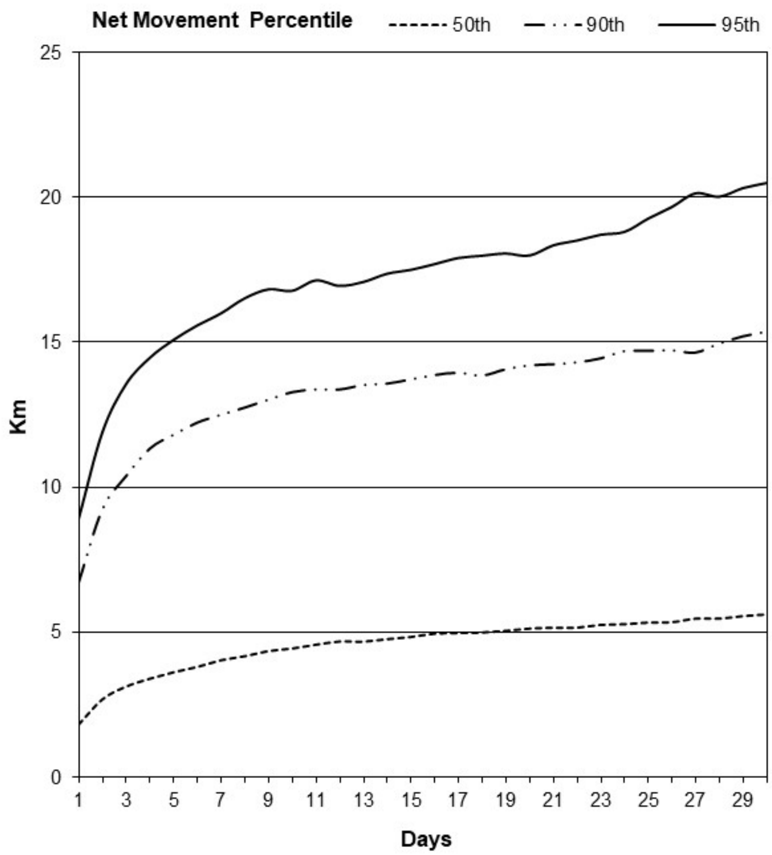

Figure 5-3. Net movements of GPS-collared grizzly bears over successive days in the southern Canadian Rocky Mountains, British Columbia and Alberta, 2003 – 2018.

Table 5-1. Effective sample size of grizzly bear observations considered to be independent at scales ranging from broadest (level 1) to finest (level 3).

Analysis Scale	Pre-Berry	Berry	Post-Berry	Denning	Total
Level 1	511	301	291	41	1,144
Level 2	4,089	2,411	2,331	41	8,872
Level 3	58,763	35,726	24,745	41	119,275

5.3 Statistical Methods

5.3.1 Univariate Analyses

For each variable and at each analysis level (scale), we extracted attributes for grizzly bear and paired-random locations. We assessed univariate associations with grizzly bear habitat selection by evaluating differences between grizzly bear used and random landscapes using paired-sample *t*-statistics. Univariate analyses were applied primarily in exploring descriptive associations and in variable screening, and the Dunn-Šidák adjustment (Sokal & Rohlf 1981:242) should be applied in any direct interpretation of significance. We described and compared season-specific associations among variables within scales, and among scales for individual variables, based on the sign and magnitude of *t* statistics.

5.3.2 Multivariable Modeling

Recognizing the multivariate nature of grizzly bear preference for landscape composition, we analyzed habitat associations in the context of multiple predictors. We initially selected variables based on ecological function and discriminatory power among scales. In doing so, we considered bivariate relationships to avoid multicollinearity ($R < 0.7$). We also included CARCASS at the most relevant scale to account for covariation of habitat selection with the attractive influence of carcass pits. We carried out this process independently for each defined grizzly bear season (pre-berry, berry, post-berry) plus denning. Across scales, we then evaluated the deviation between grizzly bear used and paired-random locations using logistic regression (Hosmer et al. 2013). Our intent was to derive predictive functions that reflected relative habitat value across the study area and not dependent on changing conditions within locally "available" landscapes. For each season plus denning, we derived independent models for each unique combination of study animals minus 1 (k-1), and we averaged predictive coefficients among the k models. Because the covariate CARCASS represented an ephemeral attractant that is not relevant to habitat suitability, it was excluded from final predictive functions. We standardized predictive coefficients for description and comparison of relative influence among variables (Menard 2012), and we assessed coefficient variability among models that differed by animal. We then applied the parameter coefficients within a resource selection probability equation (Manly et al. 2002; section 5.4) using spatial algebraic modeling to obtain grizzly bear habitat-selection probability surfaces across the study area for each season and that integrate predictive relationships across scales.

Our independent variables included two competing approaches to account for conditions of land cover and vegetation: (1) EOSD land cover classes, or (2) Landsat-derived vegetation indices. Intermixing variables from both groups in the same model would involve redundancy and unnecessary complexity in a given model. Therefore, we carried out the above modeling while independently considering each type of land cover representation. Considering the two approaches to be competing models (hypotheses), we applied information-theoretic methods.to compare them (Burnham & Anderson 2002). Accordingly, final, predictive output was based on weighed model averaging, given support by the data based on Akaike's information criterion (Akaike 1973).

5.3.3 Model Evaluation & Validation

To evaluate model performance and predictive efficacy, we carried out a k-fold cross validation (Hastie et al. 2009). For each animal k – 1 season-specific model, we calculated habitat selection probability for the animal subset data that were withheld from model derivation. We then repeated this process k times with each k subsample used once in testing model prediction based on the other animals. We evaluated model fit of the combined validation sample by tabulating the proportion of animal locations within 16 equal-interval classes of predicted habitat probability. We divided each value by the area of its respective probability class to account for the difference in area among classes (*sensu* Boyce et al. 2002). We then evaluated the relationship between area-adjusted frequency values and the ordinal classification of habitat-selection probability using Spearman rank correlation coefficients (r_s). The assessment of model fit and predictive efficacy informed confidence in application of predictive outputs.

6 RESULTS

6.1 Univariate Relationships

Grizzly bears showed notable landscape selectivity in relation to many if not most variables considered. However, differences were apparent among seasons (Figure 6-1) and scales (Figure 6-2).

Land Cover - Bears were associated with open, herbaceous and shrub-dominated conditions, avoiding landscapes of exposed rock and forest, with scale- and season-dependent differences. Shrub-dominated landscapes were more preferred during the berry season. Grizzly bear habitat use was generally not associated with forest-dominated landscapes, and the mild association with deciduous conditions may relate to human and/or natural disturbance.

Vegetation Indices - With the exception of WVI, the association of grizzly bear habitat selection and vegetation indices were strongly positive across seasons, and especially at intermediate and finer scales. Spatial variability in these indices was particularly relevant for the GVI at the intermediate scale but much less so at the finer scale. Den site selection showed broad-scale association with the BVI but that relationship reversed at finer scales, and the WVI was also positive at finer scales. At broader scales, grizzly bear den sites were also strongly associated with relatively high landscape variability among all vegetation indices.

Berry Models – Relationships of grizzly bear habitat selection with models of Sheperdia and Vaccinium berry potential varied by both season and scale. During the pre-berry and berry seasons, relationships with Vaccinium models were positive especially at intermediate and broader scales, and slightly stronger during the berry season. For Sheperdia, relationships were negative at broader scales during the pre-berry season and slightly positive at finer scales during the berry season. During the post-berry seasons, the Sheperdia and Vaccinium relationships of the earlier seasons reversed at broader scales, but they turned positive for Vaccinium and negative for Sheperdia at the finer scale.

Den sites were weakly associated with Vaccinium potential at the intermediate scale but were negatively related to Sheperdia across scales.

Terrain - Considering terrain conditions, preferred landscapes were broadly associated with higher-elevation, steeper and more rugged terrain during pre-berry and berry seasons, but the opposite was apparent during the post-berry season. Terrain associations differed notably at the finer scale, with preferred habitats characterized by subdued and lower-slope conditions. Grizzly bear dens were associated with broader landscapes that are relatively high and rugged, of moderately steep slope, slightly above treeline but not within barren rock.

Human Influence - Relationships with human influence factors were most obvious at level 2 and were clearly negative during both pre-berry and berry seasons especially with respect to roads and access. During the post-berry season, associations with human influence factors were largely positive at broader scales, more so for roads and urban/agricultural areas. Little relationship was apparent at the finer scale, although the association with roads changed sharply to negative between intermediate and finer scales. Den site associations with human influence was generally negative at broader to intermediate scales.

Carcass Pits - For those bears spatially and temporally exposed to known carcass disposal pits, the data suggest positive associations at intermediate to broader scales during the three seasons, but the relationship was notably strongest during the post-berry season (Figure 6-3).

6.2 Model Performance & Testing

Integrated across scales, models reflecting environmental variation derived from the suite of variables considered were effective predictors for each season, explaining much variation in grizzly bear space-use and related habitat selection (Table 6-1). Models with land cover represented by either Landsat vegetation indices or EOSD classes performed similarly well. Selected predictors varied in relative contribution to models specific to each of the three defined seasons and denning (Figure 6-4). These models are applied to input variables described herein using unstandardized coefficients (Table 6-2). In testing against independent data, seasonal models fit well and are predictive when considered across habitat selection probability levels, with discriminatory power that is reasonable and consistent (Figure 6-5). While the sample used for the denning model is understandably low, this model does also predict reasonably well within the study area (Figure 6-5). Interpretation of model performance should consider that random locations closely followed the distribution of grizzly bear use locations (depending on scale), with many undoubtedly falling within suitable habitat. Thus, the AUC values, that all well exceed 0.50 for each of the four models, and the high r_s values indicate that the models perform well and are predictive. Within the context of spatial structure and distribution of the regional grizzly bear population, spatial outputs for season-specific habitat models are relevant to localized conservation, impact assessment, and mitigation planning (Figures 6-6 – 6-9).

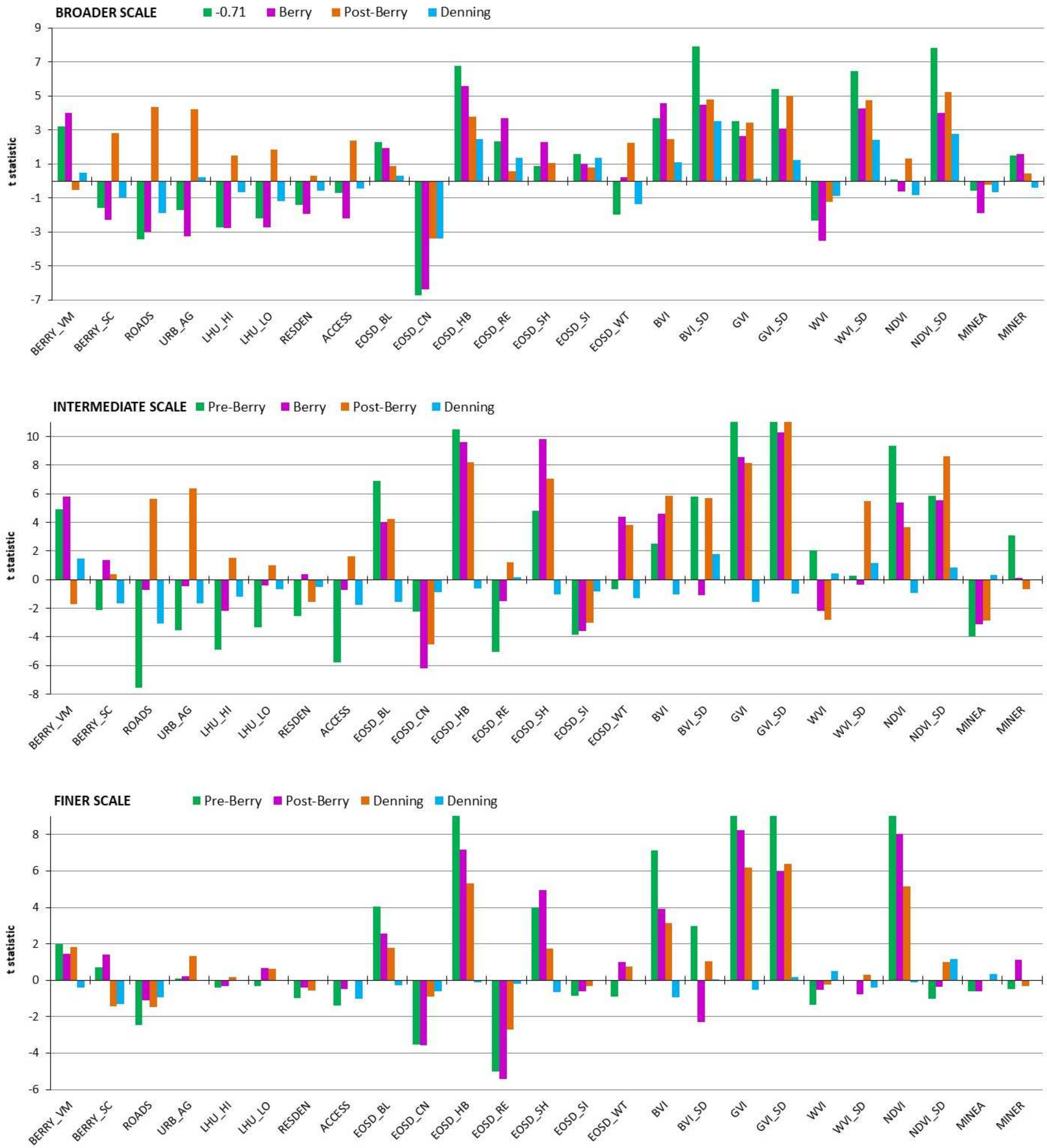

Figure 6-1. Univariate associations of grizzly bear habitat selection with defined predictor variables in the lower-Elk/Crowsnest/Highway-3 study area of the southern Canadian Rocky Mountains, 2003 – 2018. Sign and magnitude of t-statistics are based on comparison of grizzly bear used relative to paired random landscapes. The size and fixed-distance between paired (use/random) landscapes are defined by scale from broadest (level-1) to finest (level 3).

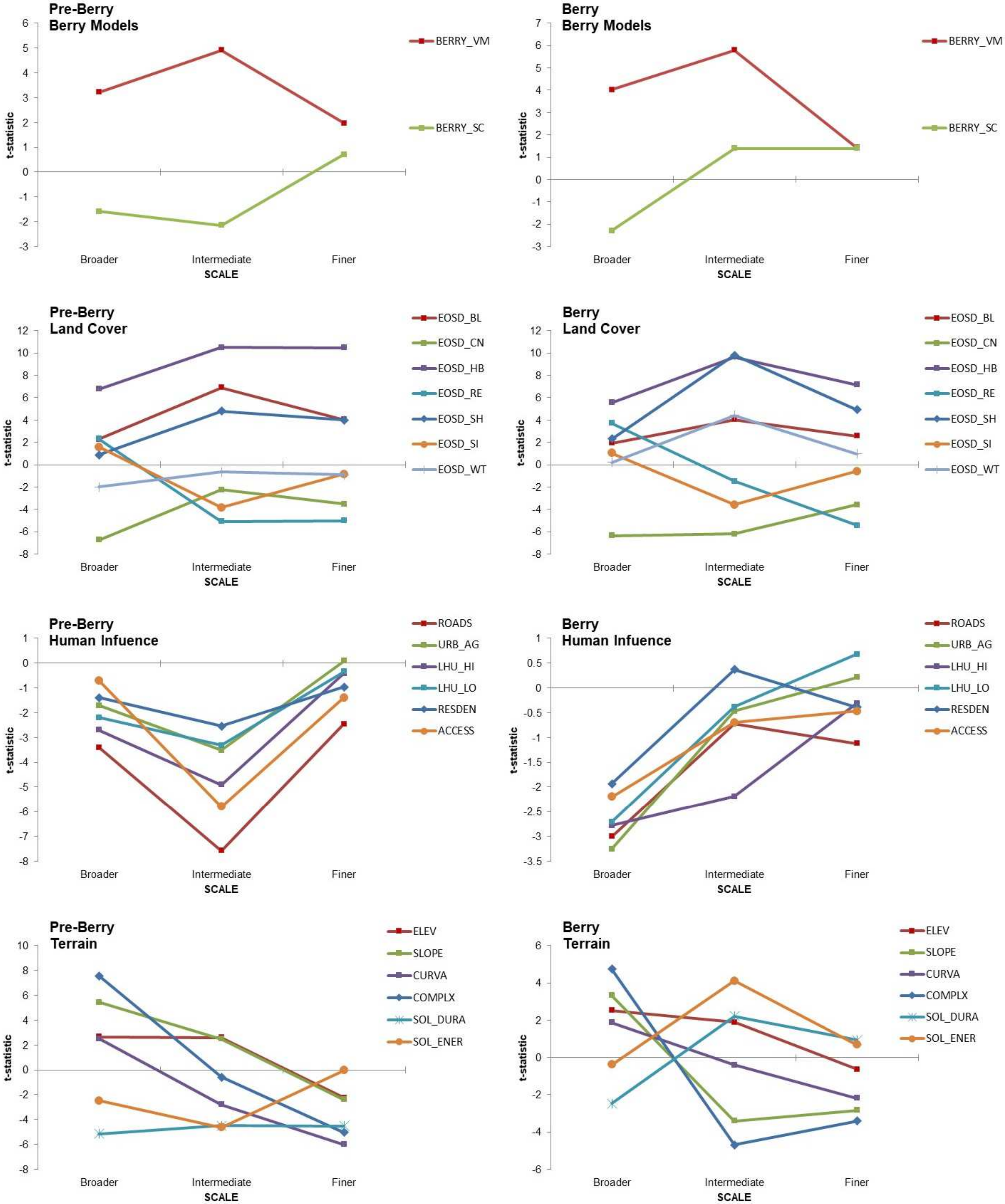

Figure 6-2. Univariate associations of select variable groups with grizzly bear habitat selection across scales from broadest (level 1) to finest (level 3) in the southern Canadian Rocky Mountains, 2003 – 2018. Strength and sign of t-statistics are based on comparison of grizzly bear used relative to paired random landscapes, with landscape size and distance between pairs defined by scale. ***Figure continues next page.***

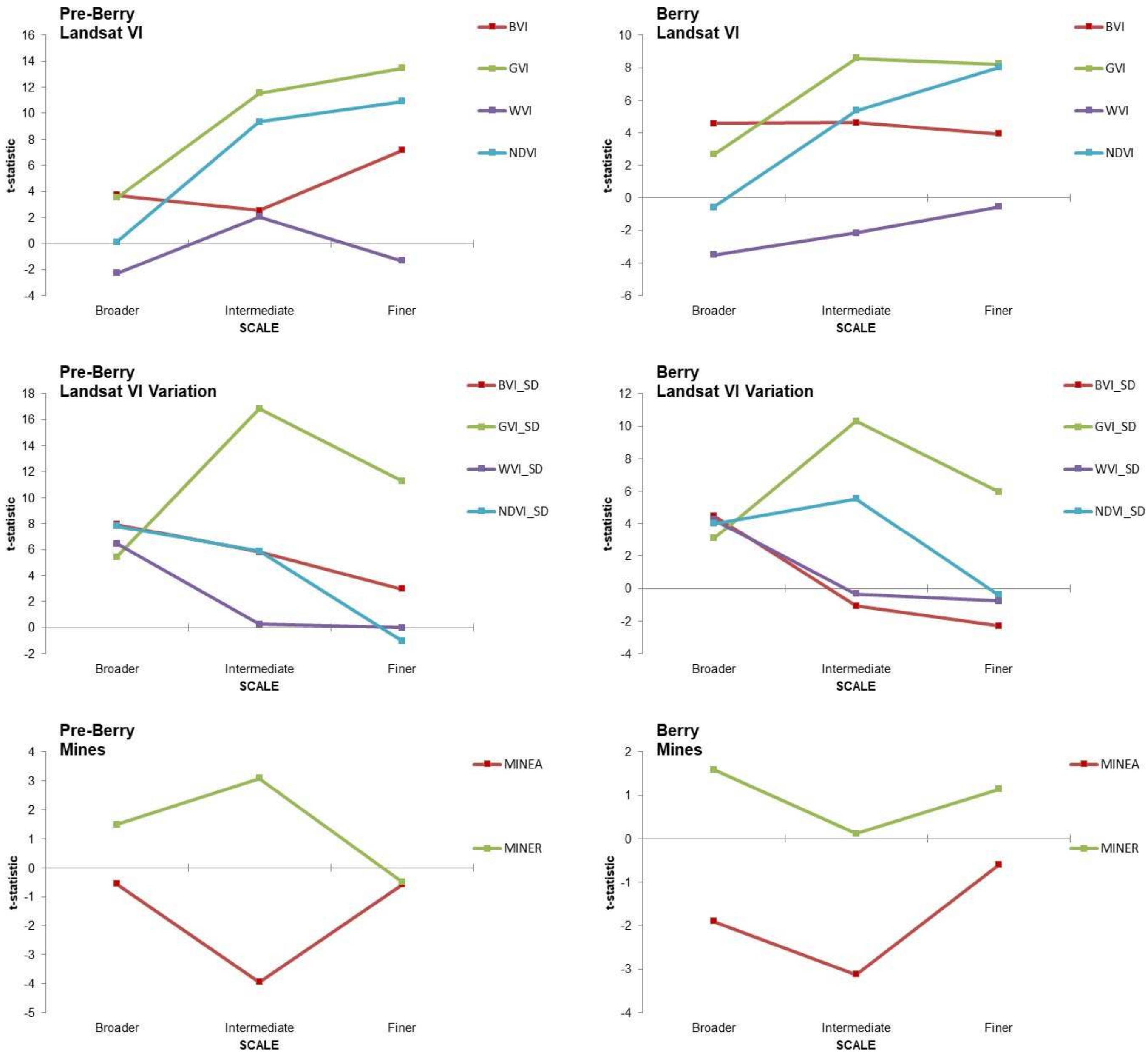

Figure 6-2. ***Continued*.**

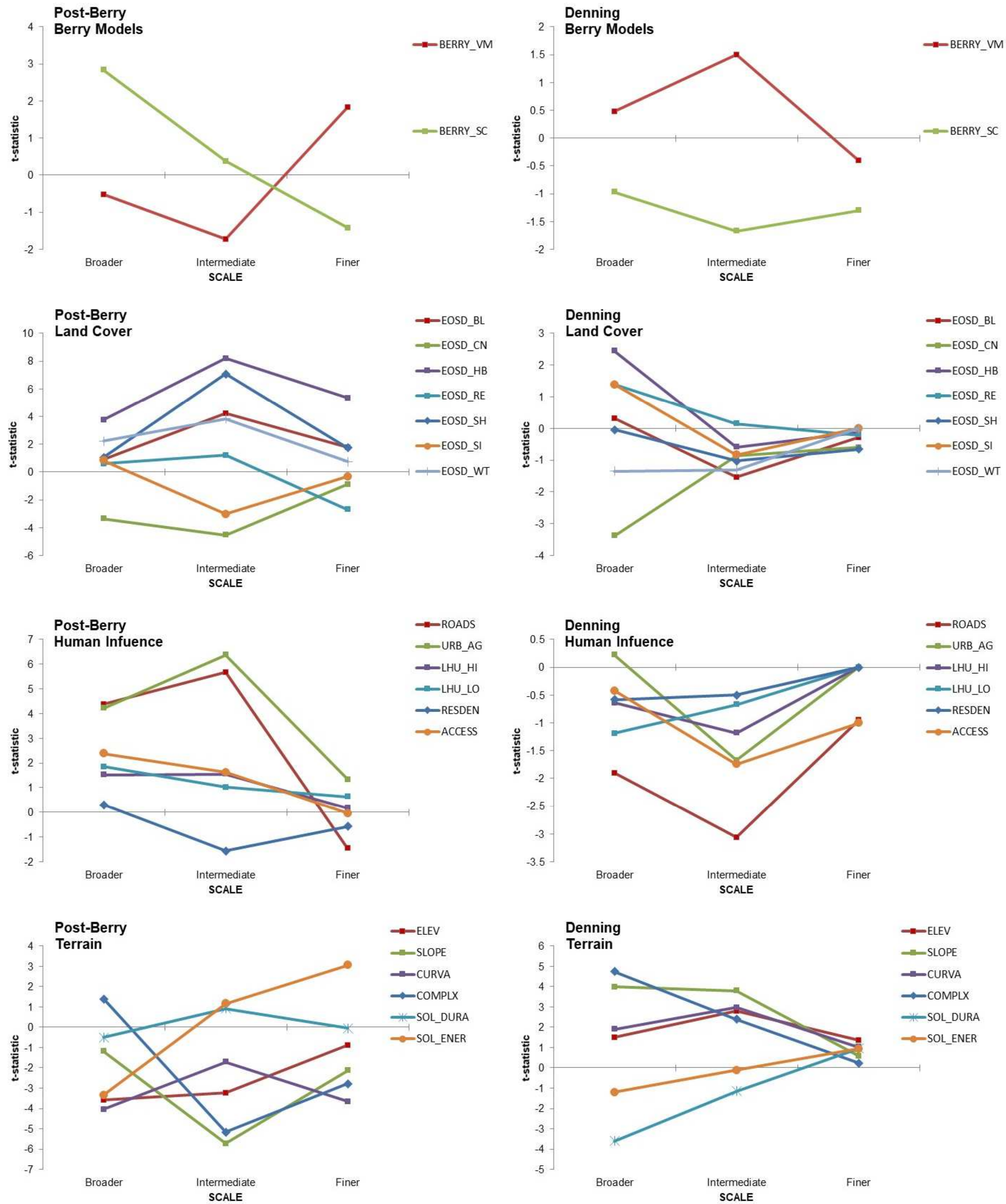

Figure 6-2. *Continued.*

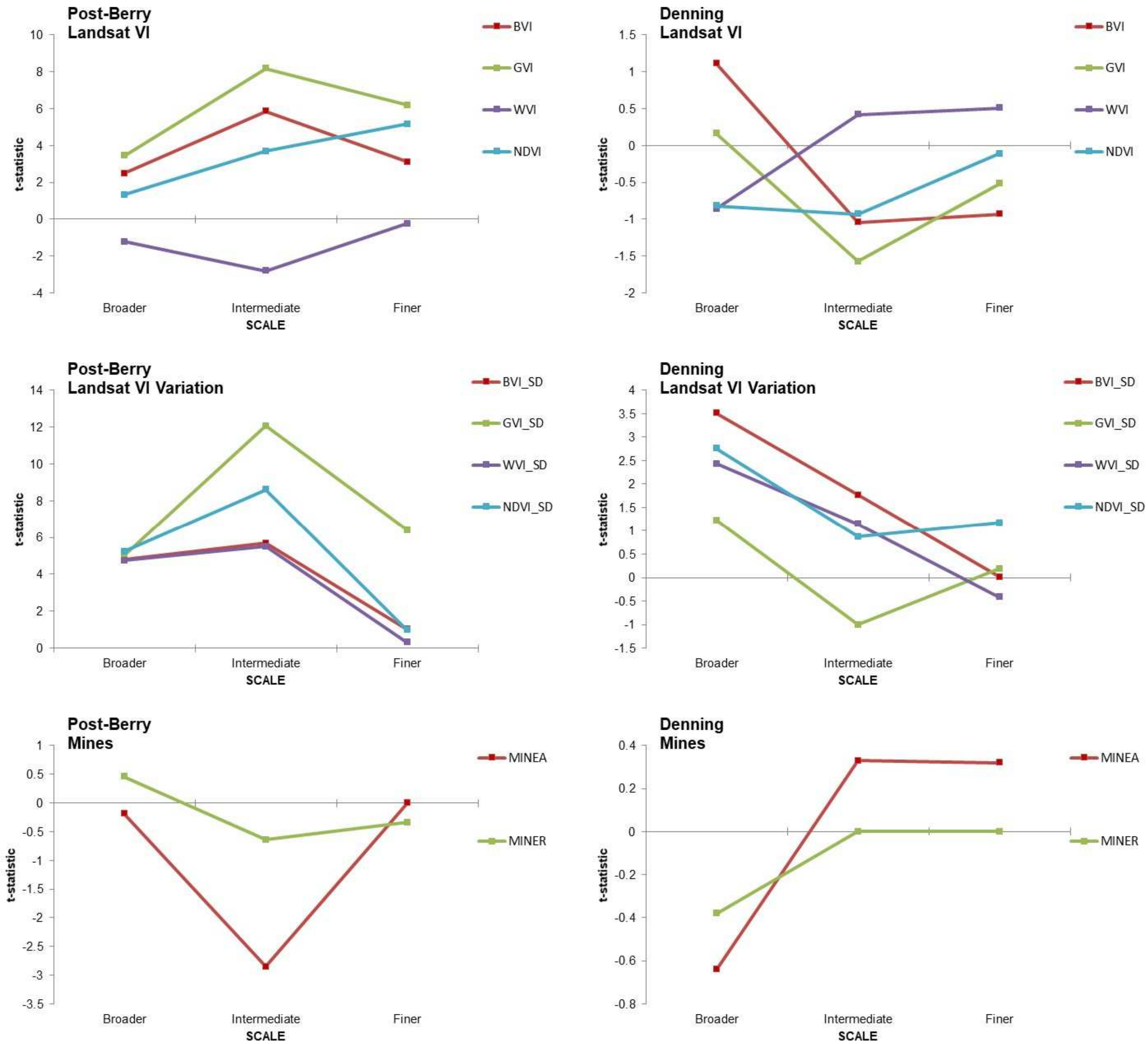

Figure 6-2. ***Continued*.**

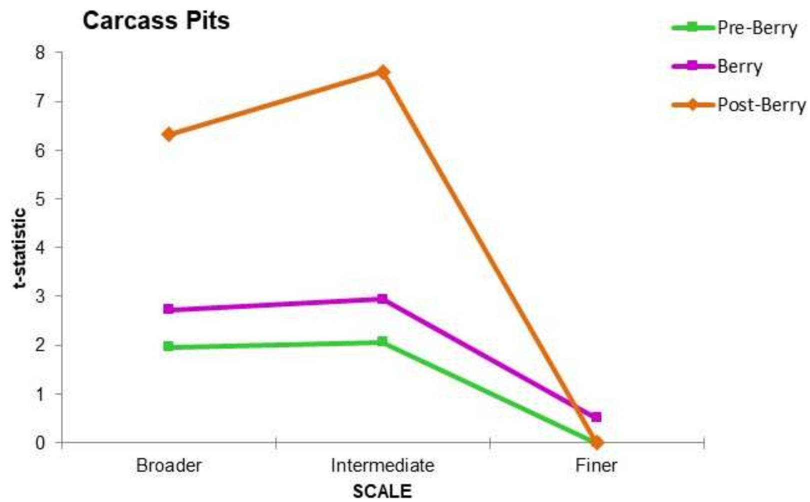

Figure 6-3. Season- and scale-specific univariate relationship between grizzly bear space use and known carcass disposal pits within the Elk Valley, southeastern British Columbia, 2015 – 2018.

Table 6-1. Predictive efficiency among models of grizzly bear habitat selection derived for pre-berry, berry, post-berry, and denning seasons across the lower-Elk/Crowsnest/Hwy3 study area of the southern Canadian Rocky Mountains, 2003 - 2018. Statistics given are the area under the receiver operating characteristic curve (AUC), Spearman-rank correlation (r_s), and model classification success (CS) at cutpoint *P* = 0.5. Statistics are shown for competing models where land cover (LC) variables are derived from either Landsat vegetation indices (Landsat VI) or EOSD data. The AIC weight (*W*) indicates the relative degree to which either option is supported by data as being a "better" model.

	LC = Landsat VI					LC = EOSD				
Model	AUC	SE	r_s	CS	*W*	AUC	SE	r_s	CS	*W*
Pre-Berry	0.60	0.002	0.98	59.0	0.502	0.61	0.002	0.99	60.0	0.498
Berry	0.61	0.002	0.94	60.0	0.495	0.64	0.002	0.92	63.0	0.505
Post-Berry	0.55	0.003	0.97	56.5	0.498	0.60	0.003	0.90	58.5	0.502
Denning	0.77	0.056	0.95	67.6	0.475	0.79	0.053	0.95	69.1	0.525

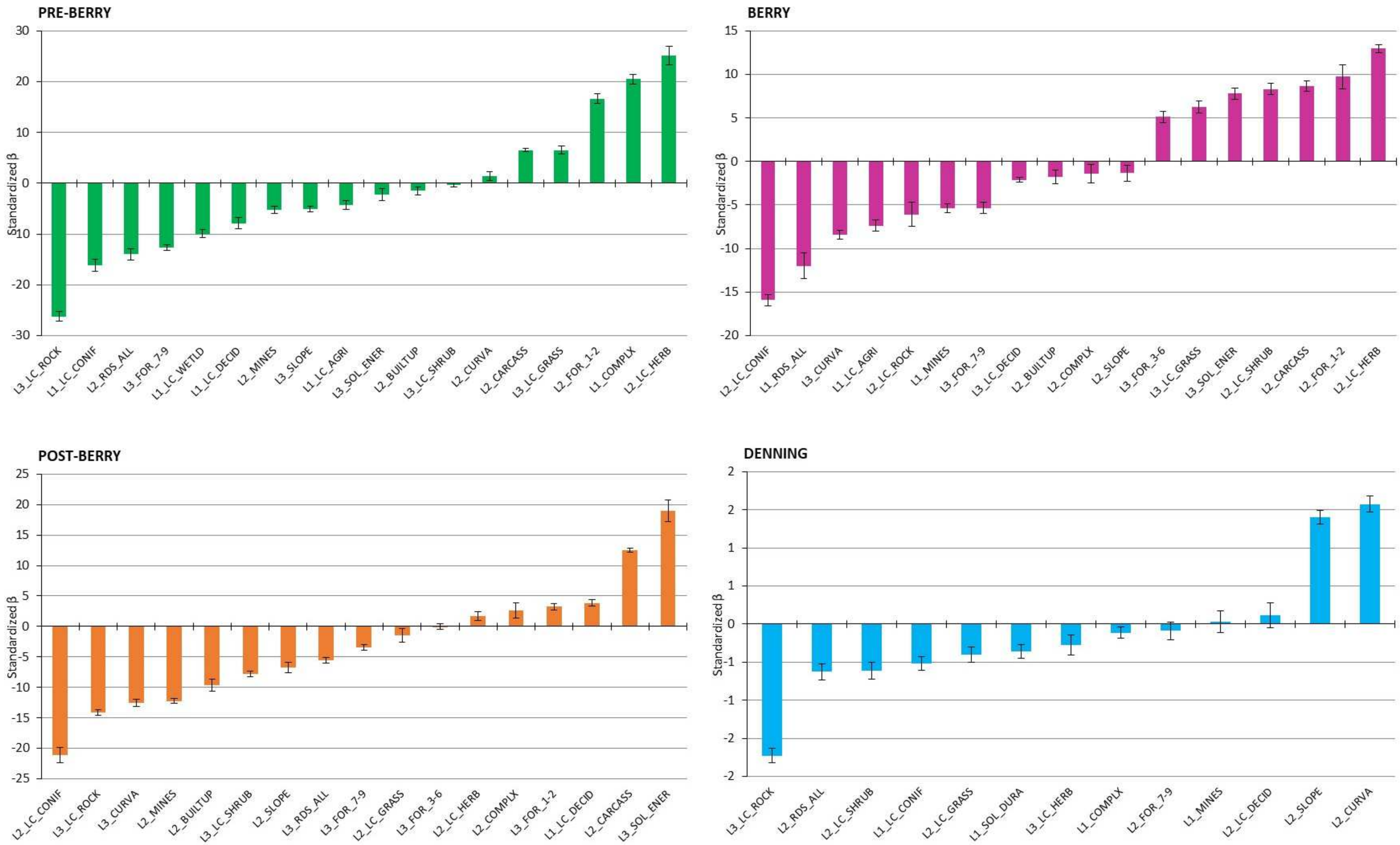

Figure 6-4a. Standardized coefficients predicting grizzly bear habitat selection among seasons plus denning, and integrated across spatial scales, in the southern Canadian Rocky Mountains, 2003 – 2018 (Land cover = Landsat VI). The prefix on variable names denote the scale at which it is represented, from broadest (level 1) to finest (level 3). Coefficients are averaged (±1 SD) among models derived from all combinations of *n*-1 animals.

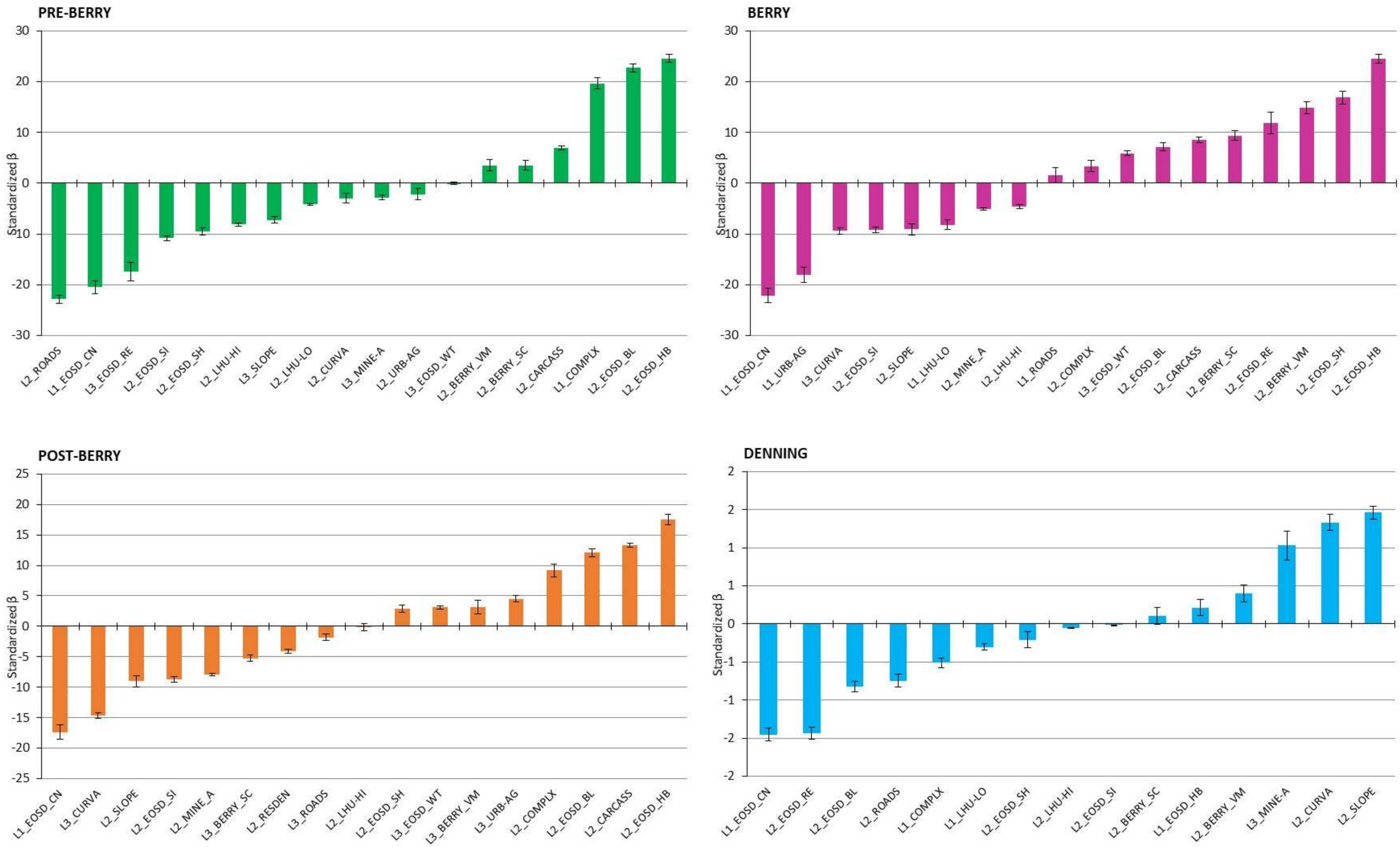

Figure 6-4b. Standardized coefficients predicting grizzly bear habitat selection among seasons plus denning, and integrated across spatial scales, in the southern Canadian Rocky Mountains, 2003 – 2018 (Land cover = EOSD). The prefix on variable names denote the scale at which it is represented, from broadest (level 1) to finest (level 3). Coefficients are averaged (±1 SD) among models derived from all combinations of *n*-1 study animals.

Table 6-2a. Coefficients[1] predicting grizzly bear habitat selection for pre-berry (1 May - 31 July), berry (1 August – 20 September), and post-berry (21 September - November 1) grizzly bear seasons within the southern Canadian Rocky Mountains, 2003 – 2018 (Land cover = Landsat VI). Relative habitat selection probability is predicted as $P = 1/(1 + exp(-1(\beta_1 X_1 + \cdots \beta_p X_p))$, where *P* is habitat selection probability (interpreted as relative quality), and β is the coefficient and *X* is the parameter of respective predictive variables. Coefficients for CARCASS are excluded. Among models, the most effective scaling of raw *P* values for 0→1 indices of grizzly bear habitat quality uses saturation levels of 0.25 and 0.75.

Pre-Berry		Berry		Post-Berry		Denning	
Variable	β	Variable	β	Variable	β	Variable	β
L1_COMPLX	0.000522	L1_ROADS	-0.000233	L2_LHU-HI	-0.000030	L1_LHU-LO	-0.008687
L2_BERRY_VM	-0.000074	L1_URB-AG	-0.000112	L2_RESDEN	-0.000475	L1_COMPLX	-0.001740
L2_BERRY_SC	-0.000116	L1_LHU-LO	-0.006640	L2_SLOPE	-0.008120	L1_BVI	-0.013507
L2_ROADS	-0.000227	L1_WVI	-0.029590	L2_COMPLX	0.000779	L1_GVI	-0.028706
L2_URB-AG	-0.000003	L2_BERRY_VM	0.000150	L2_BVI	-0.007381	L2_BERRY_VM	0.000535
L2_LHU-HI	-0.000618	L2_BERRY_SC	0.000072	L2_GVI	0.043233	L2_BERRY_SC	0.000116
L2_LHU-LO	-0.001166	L2_LHU-HI	-0.000043	L2_WVI	-0.022412	L2_ROADS	-0.000722
L2_CURVA	-0.000572	L2_SLOPE	-0.011456	L2_MINE_A	-0.000158	L2_LHU-HI	-0.106122
L2_WVI	-0.007095	L2_COMPLX	0.000434	L3_BERRY_VM	0.000046	L2_SLOPE	0.038212
L2_MINE_A	-0.000004	L2_BVI	-0.003591	L3_BERRY_SC	-0.000128	L2_CURVA	0.008308
L3_SLOPE	-0.001596	L2_GVI	0.038307	L3_ROADS	-0.000013	L3_WVI	0.022722
L3_BVI	-0.005315	L2_MINE_A	-0.000089	L3_URB-AG	0.000015		
L3_GVI	0.039624	L3_CURVA	-0.006658	L3_CURVA	-0.014809		

[1] Average from models derived among all-possible unique combinations of *n* - 1 study animals

Table 6-2b. Coefficients[1] predicting grizzly bear habitat selection for pre-berry (1 May - 31 July), berry (1 August – 20 September), and post-berry (21 September - November 1) grizzly bear seasons within the southern Canadian Rocky Mountains, 2003 – 2018 (Land cover = EOSD). Relative habitat selection probability is predicted as $P = 1/(1 + exp(-1(\beta_1 X_1 + \cdots \beta_p X_p))$, where P is habitat selection probability (interpreted as relative quality), and β is the coefficient and X is the parameter of respective predictive variables. Coefficients for CARCASS are excluded. Among models, the most effective scaling of raw P values for 0→1 indices of grizzly bear habitat quality uses saturation levels of 0.25 and 0.75.

Pre-Berry		Berry		Post-Berry		Denning	
Variable	β	Variable	β	Variable	β	Variable	β
L1_COMPLX	0.001139	L1_ROADS	0.000032	L1_EOSD_CN	-0.000069	L1_LHU-LO	-0.017414
L1_EOSD_CN	-0.000082	L1_URB-AG	-0.000165	L2_LHU-HI	-0.000007	L1_COMPLX	-0.002376
L2_BERRY_VM	0.000042	L1_LHU-LO	-0.006183	L2_RESDEN	-0.000592	L1_EOSD_CN	-0.000252
L2_BERRY_SC	0.000067	L1_EOSD_CN	-0.000112	L2_SLOPE	-0.009896	L1_EOSD_HB	0.000110
L2_ROADS	-0.000183	L2_BERRY_VM	0.000183	L2_COMPLX	0.001209	L2_BERRY_VM	0.000247
L2_URB-AG	-0.000007	L2_BERRY_SC	0.000235	L2_EOSD_BL	0.000279	L2_BERRY_SC	0.000092
L2_LHU-HI	-0.000586	L2_LHU-HI	-0.000307	L2_EOSD_HB	0.000141	L2_ROADS	-0.000446
L2_LHU-LO	-0.000981	L2_SLOPE	-0.009187	L2_EOSD_SH	0.000046	L2_LHU-HI	-0.108383
L2_CURVA	-0.000695	L2_COMPLX	0.000403	L2_EOSD_SI	-0.013989	L2_SLOPE	0.048037
L2_EOSD_BL	0.000411	L2_EOSD_BL	0.000145	L2_MINE_A	-0.000176	L2_CURVA	0.011910
L2_EOSD_HB	0.000147	L2_EOSD_HB	0.000172	L3_BERRY_VM	0.000038	L2_EOSD_BL	-0.001800
L2_EOSD_SH	-0.000114	L2_EOSD_RE	0.000059	L3_BERRY_SC	-0.000085	L2_EOSD_RE	-0.000288
L2_EOSD_SI	-0.008013	L2_EOSD_SH	0.000211	L3_ROADS	-0.000007	L2_EOSD_SH	-0.000135
L3_SLOPE	-0.002058	L2_EOSD_SI	-0.011047	L3_URB-AG	0.000018	L2_EOSD_SI	-3.302504
L3_EOSD_RE	-0.000052	L2_MINE_A	-0.000144	L3_CURVA	-0.014181		
L3_EOSD_WT	0.000000	L3_CURVA	-0.007196	L3_EOSD_WT	0.000081		
L3_MINE_A	-0.000028	L3_EOSD_WT	0.000148				

[2.] Average from models derived among all-possible unique combinations of *n* - 1 study animals

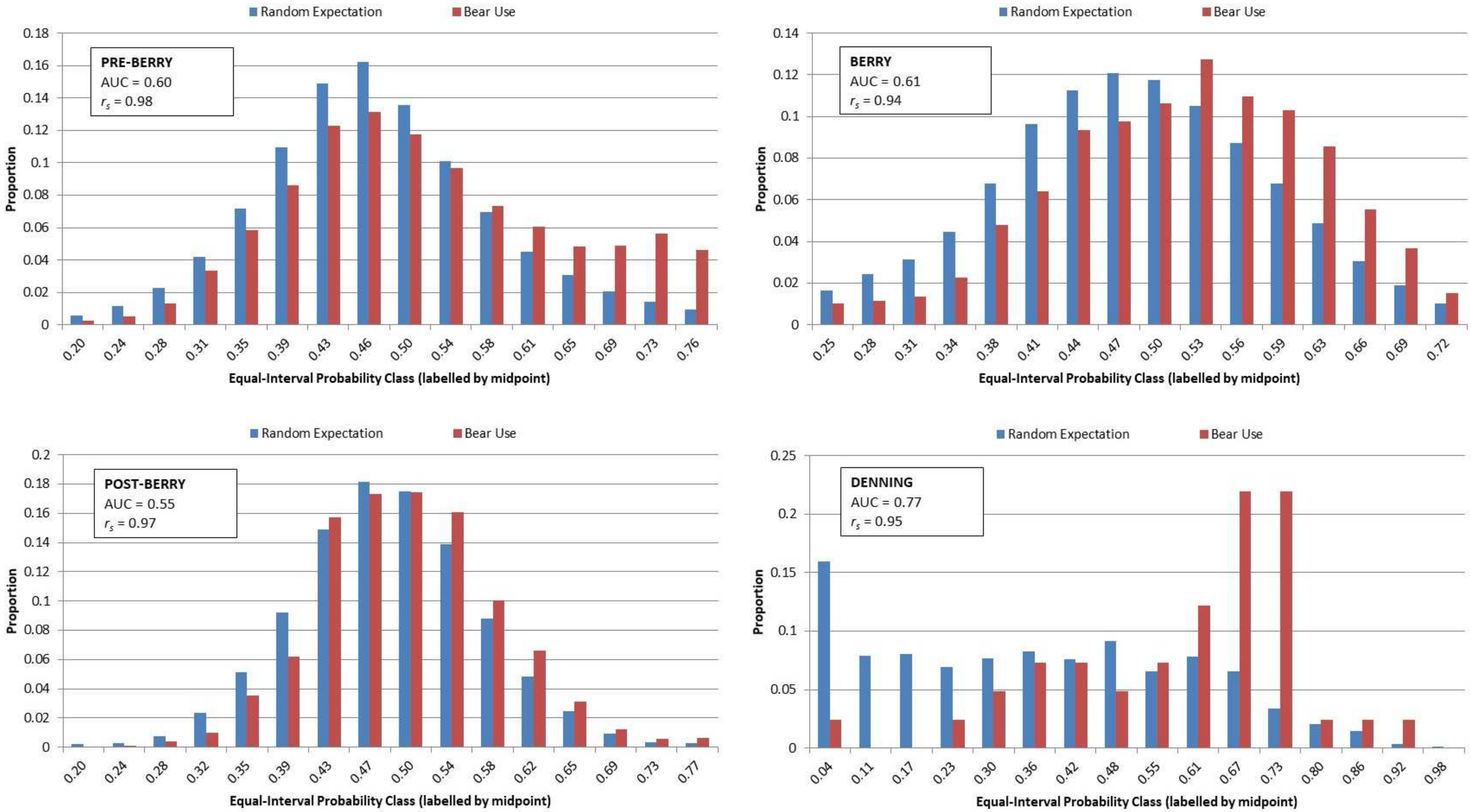

Figure 6-5a. Fit and predictive efficacy in cross-validation of spatially-explicit models of multi-scale habitat selection by grizzly bears in the southern Canadian Rocky Mountains (Land cover = Landsat VI). Shown is the proportional use by grizzly bears (data withheld from model derivation) relative to sampling representation (availability) among equal-interval probability classes. Statistics are the area under the ROC curve (AUC) measuring predictive efficacy, and the Spearman Rank correlation assessing the consistency with which relative use by bears increase with increasing habitat probability.

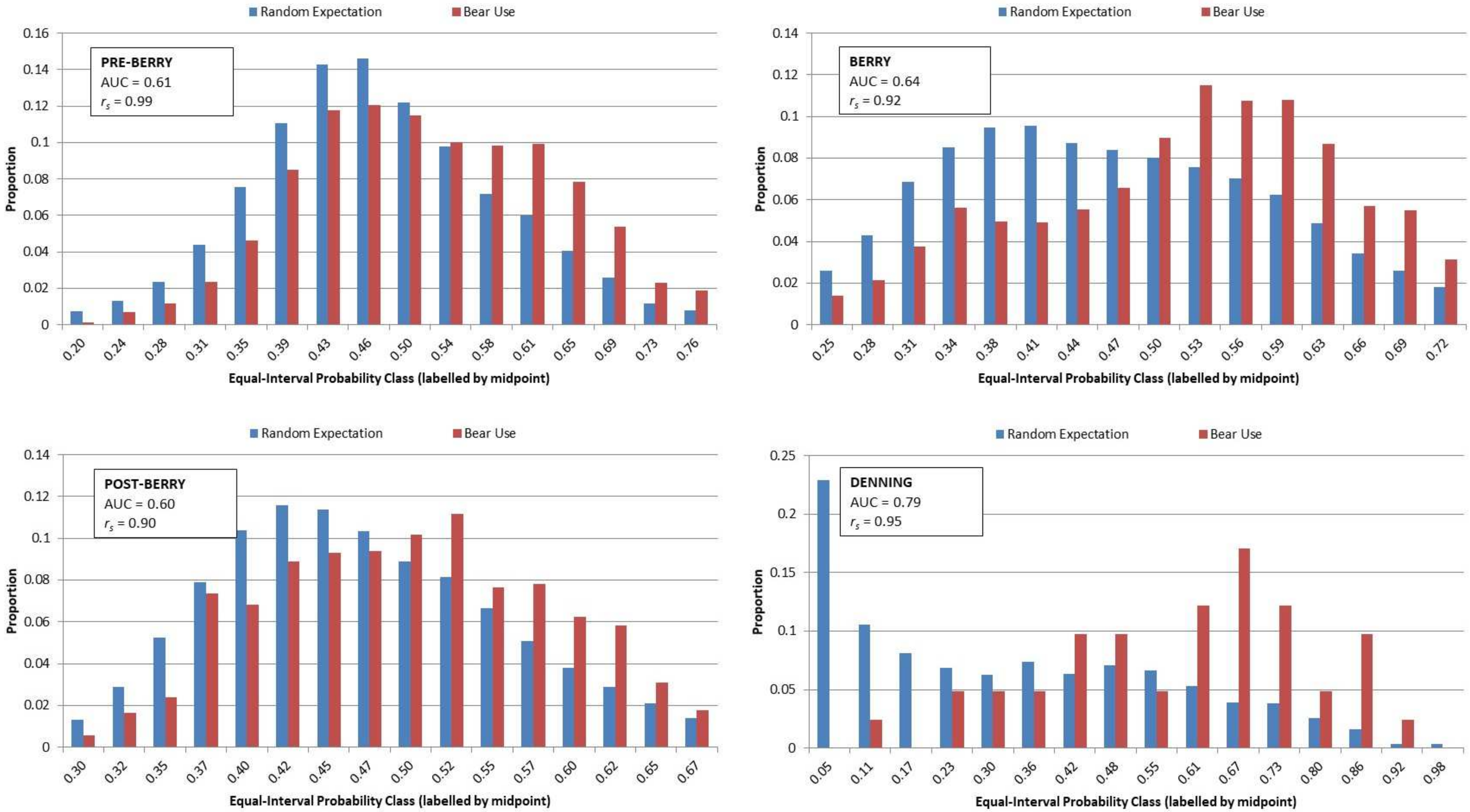

Figure 6-5b. Fit and predictive efficacy in cross-validation of spatially-explicit models of multi-scale habitat selection by grizzly bears in the southern Canadian Rocky Mountains (<u>Land cover = EOSD</u>). Shown is the proportional use by grizzly bears (data withheld from model derivation) relative to sampling representation (availability) among equal-interval probability classes. Statistics are the area under the ROC curve (AUC) measuring predictive efficacy, and the Spearman Rank correlation assessing the consistency with which relative use by bears increase with increasing habitat probability.

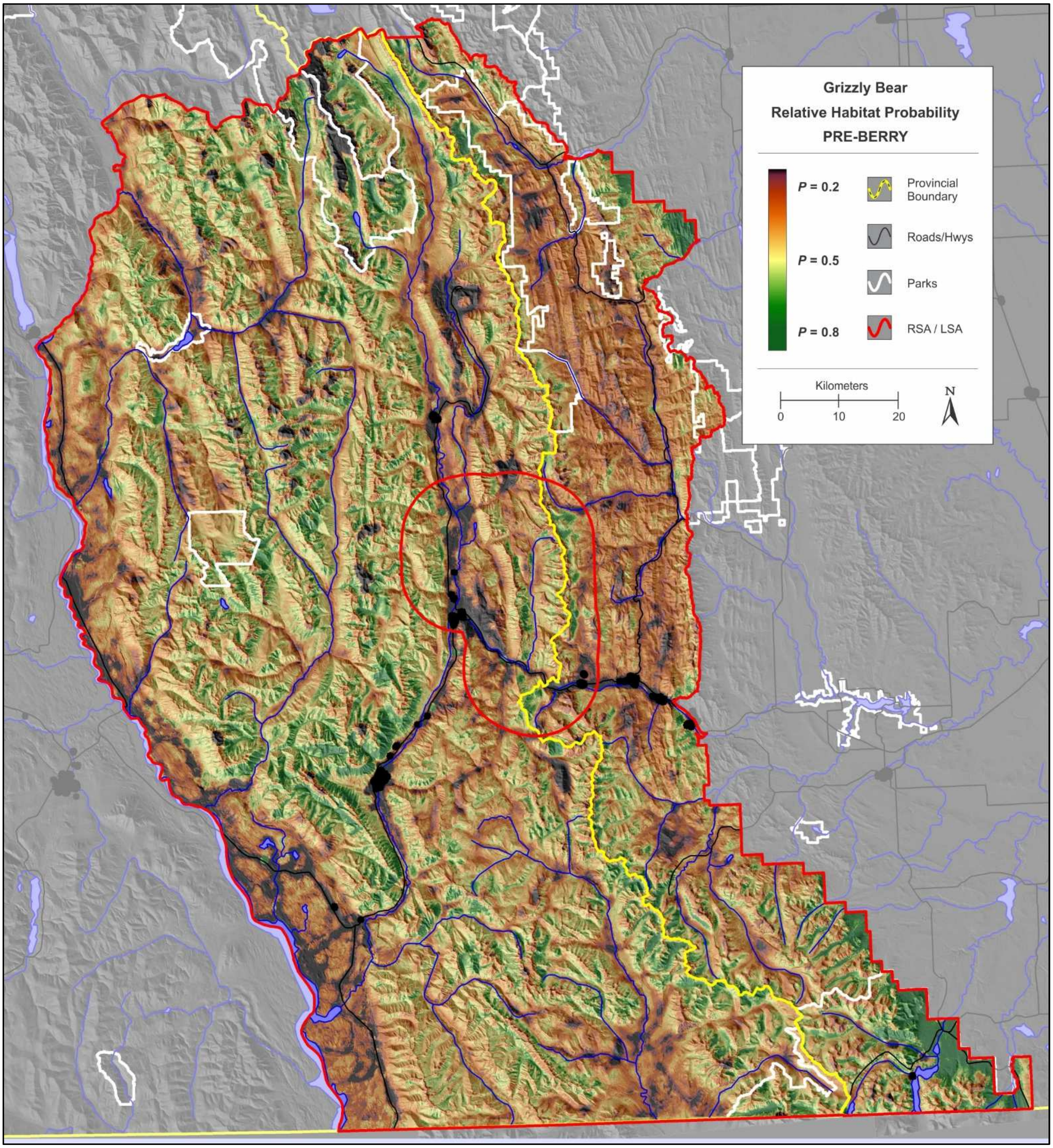

Figure 6-6. Spatial output of PRE-BERRY relative habitat probability for grizzly bears across the regional and local study areas to inform environmental assessment for NWP Coal's Crown Mountain Project within the southern Canadian Rocky Mountains.

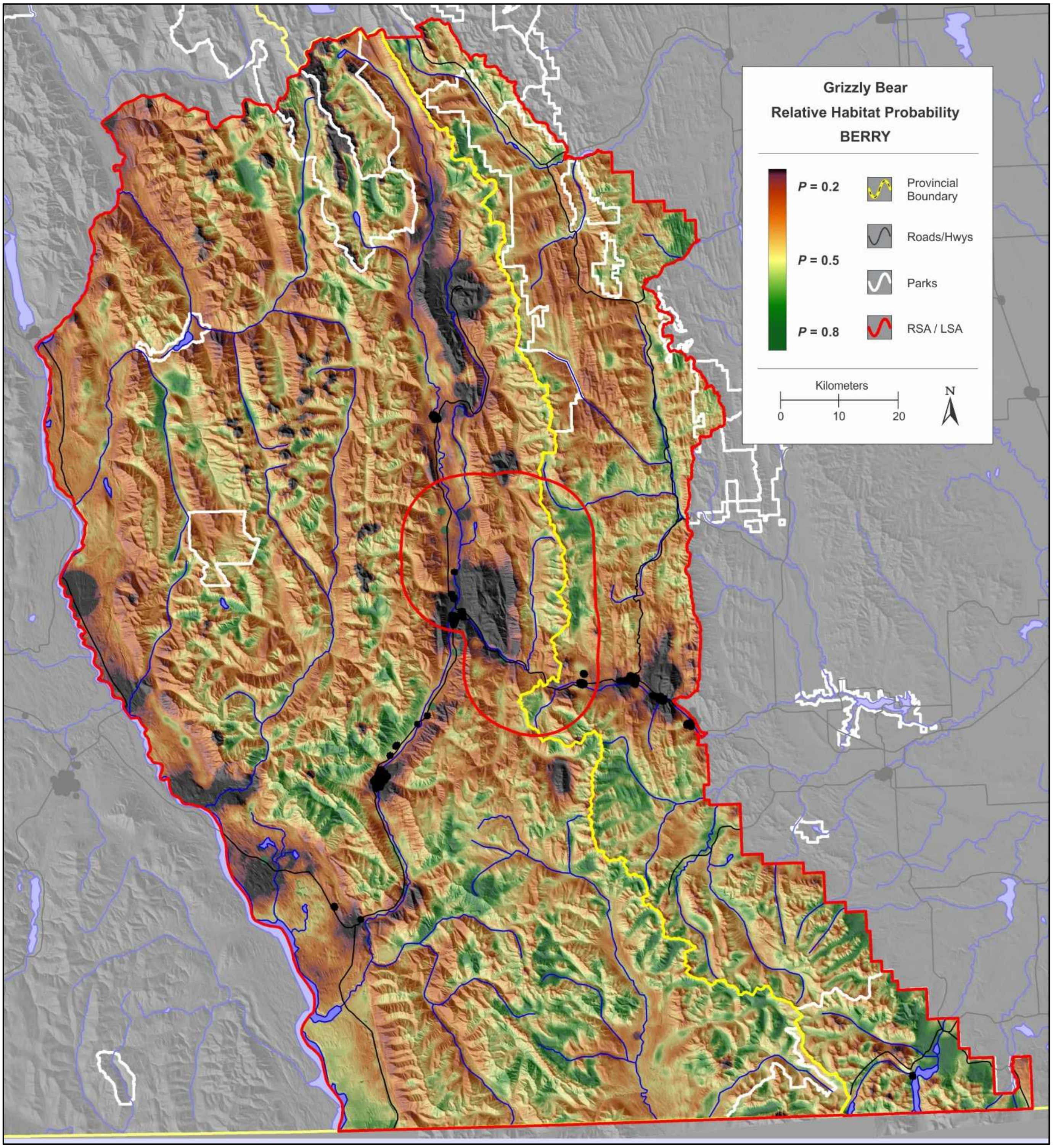

Figure 6-7. Spatial output of BERRY relative habitat probability for grizzly bears across the regional and local study areas to inform environmental assessment for NWP Coal's Crown Mountain Project within the southern Canadian Rocky Mountains.

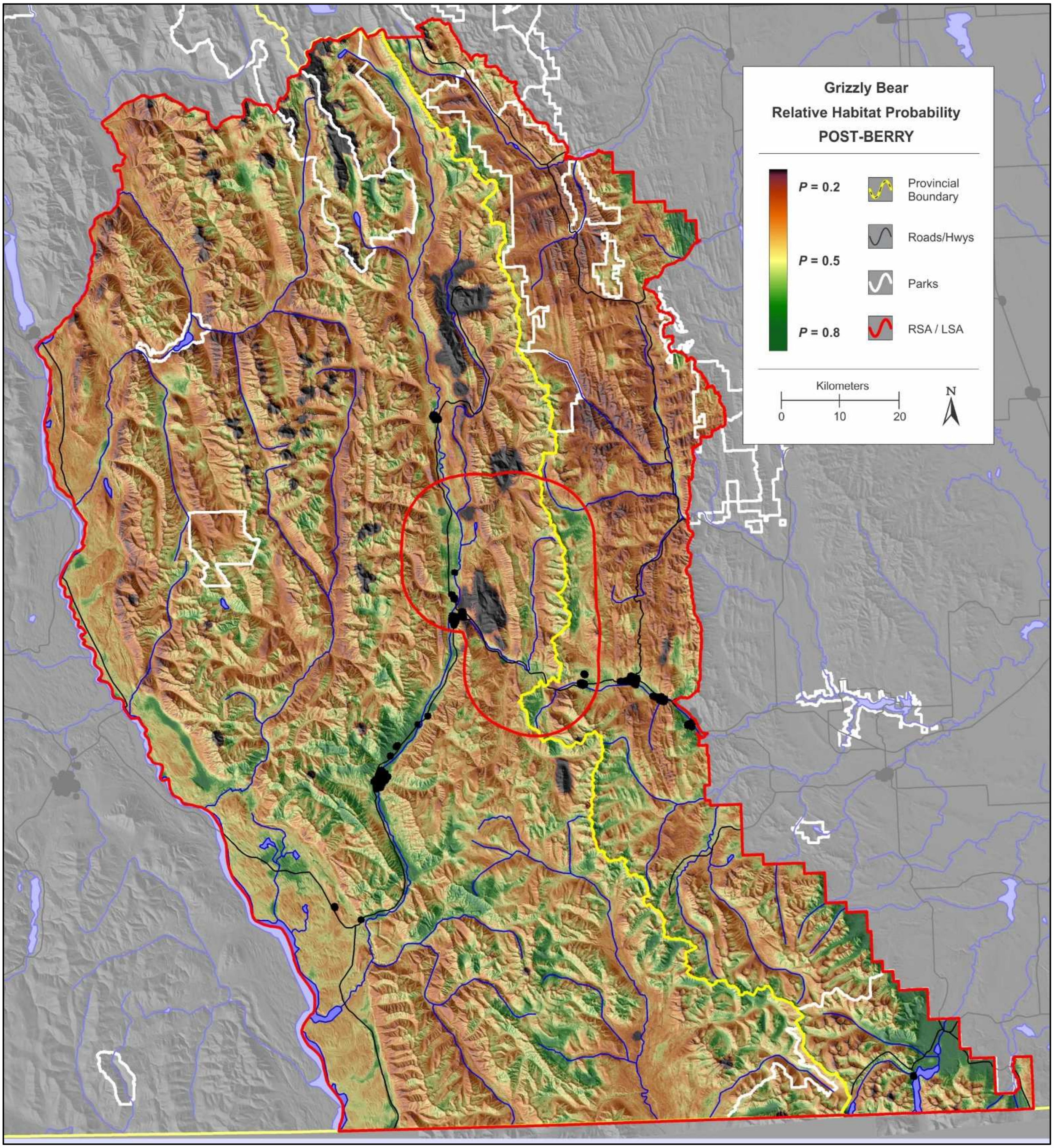

Figure 6-8. Spatial output of POST-BERRY relative habitat probability for grizzly bears across the regional and local study areas to inform environmental assessment for NWP Coal's Crown Mountain Project within the southern Canadian Rocky Mountains.

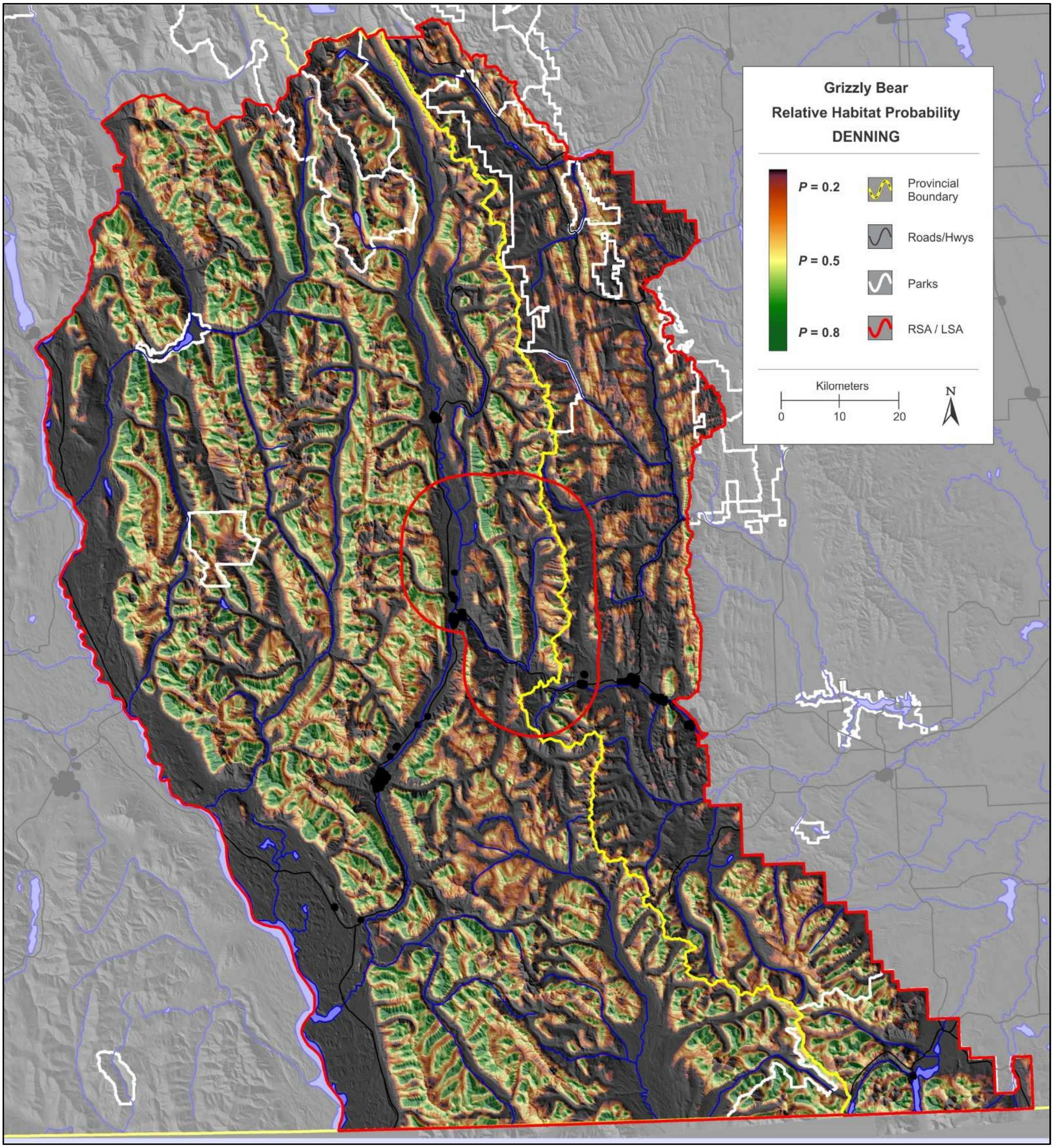

Figure 6-9. Spatial output of DENNING relative habitat probability for grizzly bears across the regional and local study areas to inform environmental assessment for NWP Coal's Crown Mountain Project within the southern Canadian Rocky Mountains.

7 DISCUSSION

7.1 Grizzly Bear Habitat and Human-Use Relationships

Grizzly bear habitat relationships have been extensively researched in Rocky Mountain ecosystems (e.g., Mace et al. 1996, Waller & Mace 1997, Mace et al. 1999, McLellan & Hovey 2001, Apps et al. 2004, Nielsen 2005, Herrero 2005). However, only a few studies have used high resolution GPS location data and have explicitly considered the influence of spatial scale in understanding probable requirements or in predicting habitat use. Our results suggest that during pre-berry and berry seasons, grizzly bears select for and/or are persisting in landscapes with conditions that tend to inhibit human access and habitation. These conditions involve relatively steep and rugged terrain, with low road densities and relatively low accessibility by, or remoteness from, human population centres. However, terrain conditions are also likely related to certain functionally important habitat features such as avalanche chutes. Measures of human influence, in particular, appear to function more powerfully and consistently at broader rather than finer scales. These findings are consistent with factors documented to influence grizzly bear population distribution (Apps et al. 2016).

With respect to land cover, habitat selection was most positively influenced by the proportion of landscapes classified as herbaceous and shrub, though shrub habitats were more important during the berry season. While grizzly bear diet varies by season, open habitats support concentrations of many plant foods preferred by grizzly bears across different seasons in our area and encompass habitats that are important but functionally quite different, such as avalanche chutes and shrub fields (McLellan & Hovey 1995, Waller & Mace 1995, Ramcharita 2000, McLellan & Hovey 2001). Such food distributions that are concentrated rather than dispersed may allow grizzly bears to successfully compete and exclude or persist with black bears (*U. americanus*) (Apps et al. 2006). While preferred landscapes are strongly associated with open conditions, some spring foods such as horsetails (*Equisetum arvense*) often occur within forested riparian habitats. This condition was difficult to account for directly in our analyses since water courses are likely a poor surrogate for true riparian conditions. Moreover, our defined pre-berry season does encompass a broad time frame across which grizzly bears are known to use a diversity of foods and habitats. Any net positive response to riparian-like conditions is most likely to be shared across several variables we considered but may be best captured by terrain at finer scales. Specifically, the strong association with concave landscapes at finer scales (levels 2 and 3) is consistent with selection for seepage sites, slope toes, and avalanche run-outs that are more likely to have soil and moisture conditions that promote preferred plant foods.

Vegetation indices derived from remotely sensed imagery have often been used in the evaluation and modeling of grizzly bear habitat, with most such studies documenting a positive predictive relationship between the green vegetation index (GVI) and grizzly bear habitat preference (Mace et al. 1999, Stevens 2001, Nielsen 2005). Our results revealed, however, that the relationship between grizzly bear habitat and vegetation productivity and related indices is scale-dependent. Most indices were of little relevance at broader scales consistent with Apps et al. (2004) who found a similar univariate relationship between GVI and grizzly bear population distribution. But our analyses of "within-home-range" behavioural responses found vegetation indices to be highly selected at intermediate to finer scales, consistent with other studies. The GVI and the related normalized-difference vegetation index (NDVI) are particularly powerful and reflect the importance of herbaceous phytomass concentrations in the context of broader-scale landscape selection. But high landscape variation in GVI and NDVI does also appear to be important likely because the habitat features that grizzly bears are selecting, such as avalanche chutes and possibly riparian stringers, are often interspersed with forested habitats that reflect low values of these indices. We have observed that higher values of the bright vegetation index (BVI) are associated with xeric, barren or rocky habitats. Despite the association of grizzly bear distribution with relatively rugged, rocky terrain (Apps et al. 2004), barren habitats rarely support grizzly bear foods. We expect the moderate positive univariate relationships with BVI reflects broader association of grizzly bear habitats landscapes of barren and rocky areas, as well as the finer-scale importance of certain habitats that are reasonably xeric such as high elevation huckleberry fields. Such patches tend not to be interspersed with forest at finer scales, which is consistent with the apparent irrelevance of landscape variation in BVI as opposed to our findings for GVI and NDVI. The wet vegetation index (WVI) reflects variation in site moisture as a result of macro- and micro-climatic variation. While a moist macro-climate is likely to enhance grizzly bear plant food productivity, optimal conditions are likely mesic rather than hygric at the scale of our analyses which may explain the moderately negative associations of grizzly bear habitat with this variable at finer scales. Finally, with respect to den sites, the relationships we measured are consistent with a broad-scale association with dry, barren, rocky areas, and a reversal of this at finer scales whereby dens are in relatively moist semi-vegetated pockets.

We addressed forest overstorey structure and composition only indirectly through EOSD and vegetation indices. However, considered in context of their relationships with human-use, terrain, and seasonally important plant foods, habitats preferred by grizzly bears are generally not associated with forest overstorey of mid- to late-succession with the exception of riparian and/or seepage sites as noted above. In additional to naturally open or non-forested conditions, we expect the distribution of recently harvested or regenerating stands to carry some positive relationship with grizzly bear habitat selection across scales. This expectation reflects the value of natural or human-caused forest disturbance in promoting the growth of fruiting shrubs (Zager 1980, Waller 1992) and/or in influencing ungulate densities (Geist 1998).

The negative influence of human-use variables on grizzly bear habitat selection tends to manifest at broader to intermediate rather than finer scales, and this is reflected in our results with respect to human influence variables we considered. We found that relationships were generally negative at the intermediate scale during the pre-berry season and at the broader scale during the berry season.

Relationships with roads were generally negative at broader scales during pre-berry and berry seasons, consistent with other studies (Proctor et al. 2018). However, this relationship did not hold during the post-berry season. After berries are no longer available, grizzly bears are likely to expand movements and be vulnerable to attractants within human-dominated landscapes such as fruit trees (Lamb et al. 2017), hunter gut piles and carcass pits. In fact, we found that the distribution of carcass pits strongly influenced landscape use by grizzly bears during the post-berry season. Across seasons, the much weakened relationship of bears with roads is likely to reflect a positive behavioural influence from roads with minimal traffic due to preferred plant foods within road easements (Roever et al. 2008) and the use of such features for travel particularly at night when there is little or no traffic (McLellan & Shackleton 1988). While the relationships we describe reflect broad-scale displacement effects, at least during pre-berry and berry seasons, inferences should be couched in the fact that our location data reflect behavioural responses and not mortality risk.

Like ACCESS, urban, settled and agricultural lands (URB-AG) is a relatively generalized measure of human activity. Hence, there is little response at the finer scale but relatively consistent, negative responses at broader scales. In contrast, localized human-use with high (LHU-HI) and low (LHU-LO) intensity as well as residential polygon density (RESDEN) are all conditions that vary at relatively fine scales. The slightly positive response to urban/agricultural areas and to low-intensity human use at the finer scale during berry and post-berry seasons, coupled with the stronger positive response to roads and urban/agricultural areas at the intermediate scale during the post-berry season, is consistent with some use of urban fringes by some animals on occasion despite an obvious broader avoidance of such landscapes. Bear associations with agricultural lands may be complex as livestock, orchards, or crops can attract bears but greatly increase their mortality risk (Wilson et al. 2006, Northrup et al. 2012, Lamb et al. 2017). Aside from the confounding effect of attractants, our collective results with respect to human-use metrics confirm that the intensity and concentration of human activity is relevant to the grizzly bear displacement effect observed.

7.2 Response to Mines

It was not within our scope to carry out detailed investigation of grizzly bear responses to coal mines or related activity. However, we considered mines as a specific variable, doing our best to differentiate active from abandoned and/or reclaimed mines. With respect to active mines, the spatio-behavioural response we measured was generally negative across seasons at intermediate scales, consistent with expectations given the lack of bear foods and associated human disturbance associated with such areas (Cristescu et al. 2016). The lack of apparent avoidance of mines at the finer scale may be related to (1) variable habitat conditions near the edge of what is mapped as active mining, (2) the possibility that the representation of mine disturbance is not mapped with high accuracy, and (3) the dynamic nature of actual mining activity that occurred across the 15 year period of our grizzly bear location data. With respect to abandoned and/or reclaimed mines, grizzly bear response generally was slightly positive to neutral depending on the season and scale. This difference from active mining areas is likely is due to preferred plant foods and low human use (Cristescu et al. 2015). Given these results, modeling and assessment that considers mining impacts should differentiate active versus those that have been abandoned or reclaimed for decades.

With regard to grizzly bear den site selection, our inferences are limited by low sample size and analytical power. Our results do suggest a negative response was apparent at the broader scale, but we have little confidence in making finer-scale inferences given analytical power and the considerations of data accuracy noted above.

7.3 Grizzly Bear Den Site Relationships

Among the 41 den site locations, we found study animals to be reasonably consistent in landscape attributes selected. Dens tended to be at relatively high elevations, in rugged and relatively unvegetated terrain, broadly near maximum elevation range available. A preference for moderately steep slopes is consistent with other studies (see LeFranc et al. 1987, Ciarniello et al. 2005, Apps et al. 2017). Sloped sites are likely to facilitate easier digging, with soil generally stabilized by boulders or root systems of shrubs and trees. We found that sites were consistently very near treeline in upper subalpine or alpine, and in slightly moister sites than the surrounding terrain. These locations may provide both thermal benefits and an availability of features appropriate for denning. Such features reported include natural rock caves and cavities related to large, old trees and root balls (Aune 1994, Ciarniello et al. 2005). With respect to human influences, the data are limited, but den sites were generally removed from landscapes associated with higher human access and road density.

7.4 Model Application in Decision-Support

Our underlying goal herein has been the empirically-based prediction of seasonal habitat quality for grizzly bears through analysis of spatio-behavioural responses by study animals to relevant environmental variation across nested spatial scales. Within landscapes occupied by grizzly bears, the multi-variable and scale-integrated seasonal models we describe can efficiently discriminate between habitats preferred by grizzly bears and those of a larger area available to study animals from broad to fine scales. Our analyses were based on an extensive and representative sample of grizzly bear GPS location data within the local and regional area, collected over a 15-year period. The methods employed measures to minimize the potential that our models reflect variation unique to our dataset. The derived seasonal models fit our data well but do not appear to be overfit, and we are confident in their application in localized environmental assessment and planning for mitigation and conservation especially within the area for which our data are representative. Here, we expect the models to be useful in characterizing potential impacts of proposed development, and in illuminating best mitigation options to minimize and/or offset expected impacts. Extrapolations well outside the area for which data are representative should be treated as provisional, especially for the denning habitat model that is derived from a limited number of den sites and restricted range of conditions to which these bears were exposed. For all models, particular caution should be exercised in extrapolating to landscapes where grizzly bear occupancy is uncertain. For such decision-support, we recommend that model predictions be considered in light of the broader context of regional grizzly bear population status and trend, including distribution, core occupied habitats, connectivity and the underlying natural and human influences.

The predictor variables we applied in this analysis were based on the best data presently available to us across the defined analysis areas. However, potential limitations of representations are noted herein. We recommend that any opportunities to improve modeling with respect to input predictor variables be pursued and that improvements to explanatory and predictive efficacy be evaluated. Despite potential for improvement, the models we describe do perform well and are appropriate for application as described above.

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