Can. J. Remote Sensing, Vol. 34, No. 4, pp. 390–404, 2008

Effects of cutline density and land-cover heterogeneity on landscape metrics in western Alberta

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Abstract. Forest cutlines are narrow, linear features created in geophysical surveys. In many areas of Canada, forest cutlines are not consistently detected using relatively coarse spatial resolution land-cover maps, such as those produced by classification of Landsat Thematic Mapper (TM) imagery. However, such features may be important in certain wildlife management applications, including those which require an assessment of landscape structure, or forest fragmentation, at various scales. Higher spatial resolution satellite imagery obtained from sensors on platforms such as Satellite Pour l'Observation de la Terre (SPOT) and the Indian Remote Sensing (IRS) system may be used to map forest cutlines for these applications. In this study, a TM-based land-cover map of western Alberta is analyzed with forest cutlines mapped from a TM–IRS fusion image, and the effect of increasing cutline density is quantified on five commonly used landscape metrics used to characterize landscape structure in grizzly bear habitat assessment. The accuracy of the fusion image interpretation was determined to be 88%. Simulated landscapes were tested first, and the study area was divided into 104 hexagon-shaped sample landscapes of about 6 km diameter each. Across these sample landscapes, cutline density and initial landscape heterogeneity were significant parameters in explaining change in three metrics, namely edge density, mean patch size, and patch context (expressed as mean nearest-neighbour distance). Patch size variability (expressed as the coefficient of variation of mean patch size) and patch dispersion (expressed as the coefficient of variation of mean nearest-neighbour distance) required additional information on cutline positioning. Overall, the density of the introduced cutline network and the pre-cutline metric value reliably predicted and quantified the response of landscape metrics of interest to grizzly bear biologists. This study shows the importance of mapping forest cutlines regarding their role in changing landscape structure quantification and points out the necessity of using additional remotely sensed data when the feature responsible for the landscape transformation is of too small a size to appear reliably in common TM-based classified imagery.

Résumé. Les lignes coupées sont des étroites éclaircies linéaires créees par les enquêtes géophysiques. En général au Canada, les lignes coupées dans les forêts ne sont pas détectées de manière fiable sur les cartes de couverture du sol créees à part des images à basse résolution spatiale telles Landsat. Pourtant, ces lignes peuvent être importantes pour des fins d'aménagement de la faune, surtout si les décisions doivent tenir en compte la structure du paysage ou la fragmentation de la forêt, et ce à plusieurs échelles. Il est possible de cartographier les lignes coupées à ces fins à partir des images à résolutions plus fines, telles SPOT et IRS. Dans la présente recherche, on analyse une carte de couverture du sol de l'ouest de l'Alberta créée à partir d'une image Landsat fusionnée avec une image IRS. On quantifie l'effet d'une augmentation de densité des lignes coupées sur cinq des mesures du paysage (« landscape metrics ») utilisés pour caractériser la structure du paysage pour évaluer l'habitat des ours grizzli. L'exactitude pour les lignes coupées de l'image fusionnée est de 88 %. Au début, on examine des paysage simulés, en divisant la région d'étude en 104 paysages-échantillons d'un diamètre de 6 km chaque. Sur ces paysages-échantillons, la densité des lignes coupées et la hétérogénéité primordiale du paysage se sont révélés comme paramètres significatifs pour expliquer les changements dans trois des mesures : densité des bords, taille moyenne des îlots et contexte des îlots (moyenne des distances à l'îlot voisin le plus proche). Expliquer la variabilité des îlots (la coefficient de variation de la taille moyenne des îlots) et la dispersion des îlots (la coefficient de variation de la distance moyenne à l'îlot voisin le plus proche) demande plus d'information sur le positionnement des lignes coupées. Globalement, la densité du réseau des lignes coupées et la valeur avant la coupe du mesure du paysage prévoient fidèlement et quantifient la réponse des mesures du paysage d'intérêt aux biologistes qui étudient le grizzli. Cette recherche montre l'importance de la capacité de cartographier les lignes coupées, à cause de leur rôle important dans la quantification des changements de la structure du paysage. Aussi, elle souligne la nécessité d'ajouter des images supplémentaires lorsque les éléments responsables pour la transformation du paysage sont trop petits pour paraître fidèlement sur les images Landsat traditionnelles.

Received 12 December 2007. Accepted 2 June 2008. Published on the *Canadian Journal of Remote Sensing* Web site at http://pubs.nrc-cnrc.gc.ca/cjrs on 12 September 2008.

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Introduction

Remotely sensed land-cover maps have been used to quantify landscape structure and forest fragmentation in support of wildlife management at various scales (Diaz, 1996; Cushman and Wallin, 2000; McGarigal et al., 2001). Of the many possible examples, only a few are cited here because of their relevance to those interested in the role of remote sensing in species-at-risk habitat analysis.

Nesting behaviour and population dynamics for several bird species have been related to forest fragmentation and landscape structure; for example, Bayne et al. (2005) found a significant response by boreal forest ovenbirds to forest dissection caused by geophysical exploration and oil and gas development. In another study, Zharikov et al. (2006) related habitat selection and breeding success in a British Columbia population of marbled murrelet to forest fragmentation caused by forest harvesting (mapped by Landsat Thematic Mapper (TM) imagery). These two studies used remote sensing imagery primarily to update basic land-cover geographic information system (GIS) maps from which landscape metrics of interest were derived. Hamer et al. (2006) investigated the decline in Wyoming grassland bird richness associated with the transformation of native grassland landscape structure; they separated the impact of the "area of grassland" (i.e., landscape composition) from the "arrangement of grassland patches" (i.e., landscape configuration) as mapped using TM imagery. Hamer et al. (2006) found that species richness was positively associated with grassland area and increasing edge between grassland and nongrassland cover but negatively associated with decreasing patch context (measured by mean nearest-neighbour distance between grassland patches). Gorresen and Willig (2004) investigated eight bat species in tropical forested and deforested landscapes and found species-specific variations in abundance with forest patch configuration mapped using TM imagery. Another significant finding was that landscape composition (measured as forest area) was a significant predictor for most bat species examined. In other work, Knutson et al. (1999) related amphibian abundance and species richness to wetland fragmentation and landscape composition in Iowa and Wisconsin; their study used digitized GIS maps (scale 1 : 24 000) of locations and attributes of wetlands derived from the US Fish and Wildlife Service to represent fragmentation and landscape metrics.

Common to such studies is the suggestion that habitat use or selection by species must be understood first and that one of the basic steps in developing this understanding is to acquire or develop (*i*) a basic land-cover map at the appropriate scale for the species of interest, and (*ii*) a way to update the map for changes associated with management practices that occur on the landscape and may affect that species. Our own work (Franklin et al., 2001; McDermid, 2005) maps land cover and continuous biophysical variables, such as leaf area index, in Alberta for use in studies designed to provide insights into grizzly bear behaviour and population dynamics. It supports the notion that landscape structure and change are important in habitat and habitat selection (Popplewell et al., 2003; Nielsen et al., 2004; Linke et al., 2005). Human-caused forest disturbances of interest in grizzly bear management include clearcuts, roads, and forest cutlines (McLellan and Shackleton, 1989; Nielsen et al., 2004; Linke et al., 2005). Understanding how landscape structure changes, with changes associated with increased human-caused land-cover disturbance, is an important new element in applications of species-at-risk assessment and wildlife management (Gergel, 2007). Remotely sensed imagery of the appropriate spatial resolution is important in the development and updating of such maps.

Typically, landscape structure is quantified using landscape metrics derived from the available land-cover map. Patches are sets of connected pixels having the same land-cover class; patches combine with the background mosaic in which they are embedded to create landscape structure. The landscape metrics characterize landscape structure into two components: (*i*) composition (in terms of patch types or land-cover classes in the map legend), and (*ii*) configuration (the spatial arrangement of these patches or land-cover classes) at the scale of the mapped landscape (McGarigal and Marks, 1995).

One land-cover change that can have a large impact on landscape structure is the insertion of linear features on that landscape. The impact of adding road features to an existing landscape and the effects of road development on landscape structure have been relatively well described (Hawbaker et al., 2006). Roads generally constitute a significant change because they dissect large patches and convert interior habitat patches to edge habitat (Ripple et al., 1991; Reed et al., 1996; Hawbaker and Radeloff, 2004). Some other important impacts of roads in forest areas include reductions in largest patch size and mean patch size, increases in edge density, and a more regular, simplified patch shape. Several studies have found that road density alone is insufficient to quantify road landscape impacts, which also depend on the spatial distribution of the road network (Miller et al., 1996; Tinker et al., 1998; Saunders et al., 2002). For example, a high road density may yield smaller changes in certain metrics if roads are spatially clumped, as compared with a lower road density where roads are distributed more evenly (Reed et al., 1996). In addition, the specific configuration or heterogeneity of the original landscape results in different metric responses to road development (Miller et al., 1996). This effect has been observed mainly through interaction effects of metric changes within specific cover types (Saunders et al., 2002; Tinker et al., 1998).

Another linear disturbance feature, namely forest cutlines, is closely associated with geophysical surveys and oil and gas exploration. Recent work has suggested there may be a significant impact by forest cutlines on important wildlife–habitat relationships (Bayne et al., 2005; Linke et al., 2005). Insight gained from looking at the impact of roads cannot be automatically extrapolated to cutlines, as they differ in important ways. Typically, cutlines are more evenly distributed, straighter, narrower, and more constant in width than roads. Forest cutlines may create more edges per unit area than do roads. However, like roads, forest cutlines fragment the

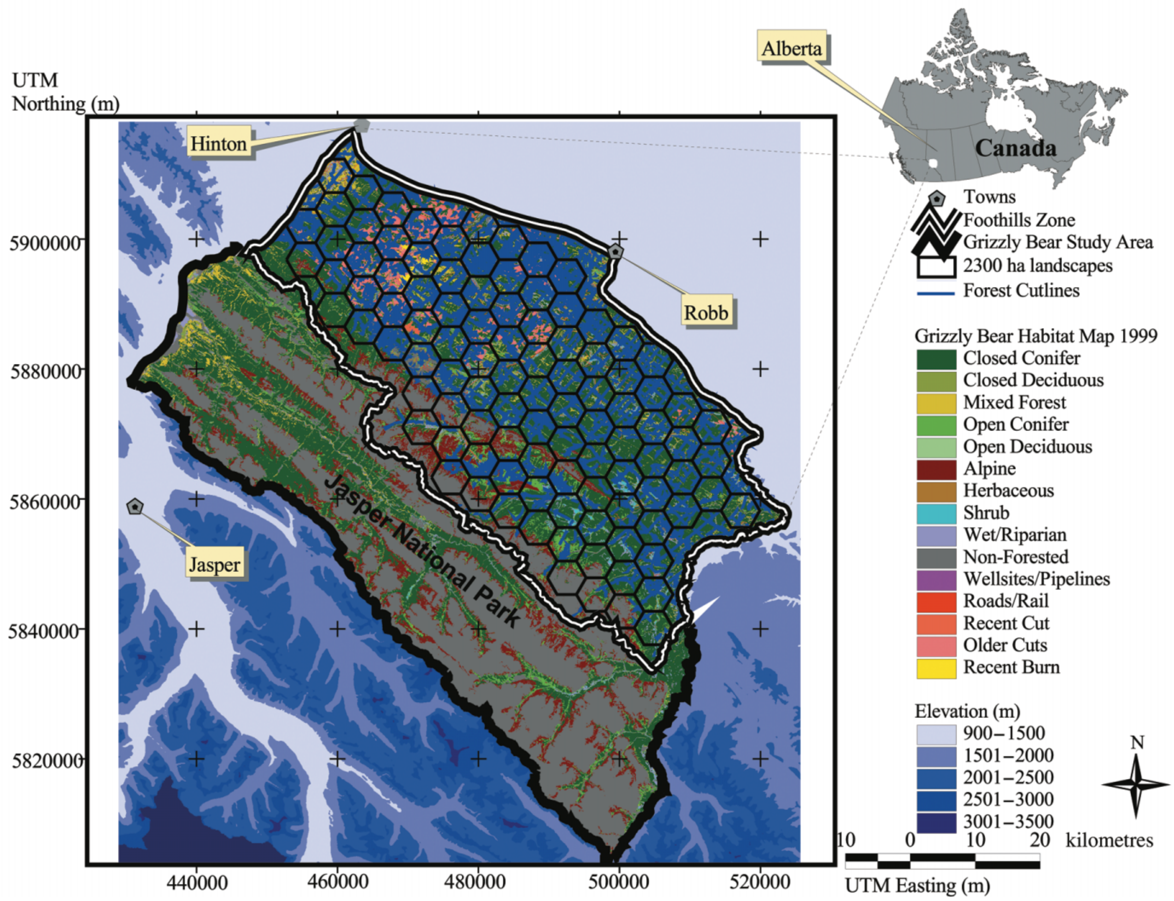

Figure 1. Foothills Model Forest Grizzly Bear Research Project (FMFGBRP) area showing grizzly bear land-cover map and forest cutlines in 1999 and the stratification of the Foothills Zone study area into 2300 ha hexagons in the context of surrounding topographic gradients (blue colour gradient outside FMFGBRP) and major towns (Universal Transverse Mercator (UTM) zone 11).

landscape by dissecting contiguous patches. In Alberta, numerous forest cutlines, typically 5–10 m wide, have been introduced in networks of variable density. Primary oil and gas exploration areas have a mean cutline density of approximately 15 m/ha (Lee and Boutin, 2006). Forest cutlines are rarely maintained, but they can persist on the landscape because they are often used as recreational pathways for off-road vehicles (Revel et al., 1984). Lee and Boutin (2006) estimated that complete recovery would take more than 100 years, even in the absence of any human activity after the geophysical survey. Because of both persistence and increased geophysical activity, forest cutline densities are expected to increase significantly in the future (Schneider et al., 2003). This prospect emphasizes the need to understand and predict the impacts of forest cutlines on landscape structure.

Two variables, namely cutline density and pre-cutline landscape heterogeneity, are analyzed in this paper. First, a simulation of cutline-induced changes to landscape structure is presented. Second, a sample of real landscapes is described, taken from a study area previously classified into TM-derived land-cover classes of interest in grizzly bear habitat assessment. The forest cutlines are interpreted using Indian Remote Sensing (IRS) satellite data fused with multispectral TM imagery to create an update feature to the TM-based land-cover classification map. A series of tests are interpreted that explain landscape metric behaviour based on changes in cutline density and landscape heterogeneity.

Methods

Research design

This study was undertaken as part of the Foothills Model Forest Grizzly Bear Research Project in west-central Alberta (**Figure 1**) (Stenhouse and Graham, 2005). Incorporation of landscape structure constitutes an improved explanation of habitat selection. Models that use measures of configuration have a greater explanatory power in grizzly bear selection than does information relying on landscape composition alone (e.g., amount and type of specific land cover or habitat types) (Popplewell et al., 2003; Nielsen et al., 2002; Linke et al., 2005). For example, higher grizzly bear densities and increased grizzly bear landscape use have been associated with landscapes with lower edge density, higher mean patch size,

Table 1. Description (McGarigal et al., 2002) of landscape-level metrics investigated in this study.

Name	Full name	Description
Edge density (m/ha)	Edge density (ED)	Amount of edge per unit area as a spatially implicit measure of landscape configuration; landscapes with higher values may be considered more fragmented
Mean patch size (ha)	Mean patch size (Area_MN)	Distribution of patch area summarized by its mean across all patches of all types; landscapes with lower means may be considered to be more fragmented
Patch size variability (%)	Coefficient of variation of mean patch size (Area_CV)	Distribution of patch area summarized by its coefficient of variation of the mean across all patches of all types; greater variation indicates less uniformity in pattern
Patch context (m)	Mean nearest-neighbour distance (ENN_MN)	Measure of patch context, summarized by the mean of all shortest straight-line distances between each patch and its nearest neighbour of the same class; landscapes with higher means may generally indicate higher isolation and fragmentation of patches
Patch dispersion (%)	Coefficient of variation of mean nearest-neighbour distance (ENN_CV)	Measure of patch dispersion as summarized by the coefficient of variation of the mean nearest-neighbour distance; greater variation generally indicates more irregular and uneven distribution of patches

greater patch size variability, nearer patch context, and lower patch dispersion. Appropriate metrics selection can be guided by parsimonious approaches based on common multivariate statistics techniques (e.g., Riitters et al., 1995; Linke and Franklin, 2006; Cushman et al., 2008). The landscape metrics selected for the current research (see **Table 1**) were those suggested as relevant to grizzly bear landscape use and density classes in the studies cited in this paragraph and were representative excerpts of three of the six universal and consistent parsimonious metric groups (Linke and Franklin, 2006; Cushman et al., 2008): (*i*) edge density (ED); (*ii*) mean patch size (Area_MN); (*iii*) patch size variability, as expressed by the coefficient of variation of patch size (Area_CV); (*iv*) patch context, as expressed by the mean nearest-neighbour distance (ENN_MN); and (*v*) patch dispersion, as expressed by the coefficient of variation of mean nearest-neighbour distance (ENN_CV).

In this study, for each of the five metrics listed previously, the percent change is estimated as a function of cutline density and the pre-cutline value of that metric. Cutline density is calculated as the total length of cutlines divided by the landscape area (m/ha). The pre-cutline metric value corresponds to the landscape configuration prior to the introduction of cutlines and is used as an indicator of initial landscape heterogeneity as measured by that metric. Percent change in a specific metric is the cutline-induced percent change relative to the pre-cutline value of that metric. First, a controlled experiment was set up by creating a series of simulated binary landscapes of differing initial spatial heterogeneity. Simulated forest cutlines were then imposed on the binary landscapes in several different densities and patterns. Regression equations were developed using cutline density and the pre-cutline metric value for predicting change in each metric chosen, and the shape of the regression was determined. The conclusions from the simulated landscapes were then tested on and the equations applied to real landscape samples. These landscape samples were selected from a TM-based land-cover map and a TM–IRS fused image, from which cutlines were visually digitized. This application yielded estimates and level of significance of variable coefficients and a measure of regression equation goodness-of-fit.

Sample landscape description

The response of the five landscape metrics (**Table 1**) to increasing forest cutline density was tested in sample landscapes of different landscape heterogeneity, and hence differing compositions and configurations. Each sample landscape is 2300 ha with a minimum mapping unit of 5 m (resampled from the 30 m spatial resolution of the original TM-based land-cover map to allow the addition of 5 m resolution forest cutlines). Hexagonal landscape boundary outlines were imposed (rather than square boundaries) because their shape, being closer to that of a circle, reduces corner effects. The diameter of the hexagons, 5.9 km, was selected to match the mean clustering distance of grizzly bear occurrence locations. This was acquired from global positioning system (GPS) data of seven collared grizzly bears tracked in the region (Linke et al. 2005).

Two types of landscape samples were analyzed, namely simulated and real. Seven simple, simulated landscapes of binary land cover (forest versus nonforest) were created (**Figure 2**). The first six simulated landscapes have increasing levels of initial landscape heterogeneity. The first landscape has just one contiguous patch; subsequent simulated landscapes were created by arbitrarily dividing this patch into an increasing number of patches. Progressing numerically from landscapes 1 to 6, the mosaics contain more patches, more edge, and more variation in nearest-neighbour distances. Landscape heterogeneity as measured by the coefficient of variation in mean patch size increases in the sequence of landscapes 1, 2, 5, 3, 6, and 4 (**Figure 2**; **Table 2**). Simulated landscape 7 was created by reclassifying a randomly selected

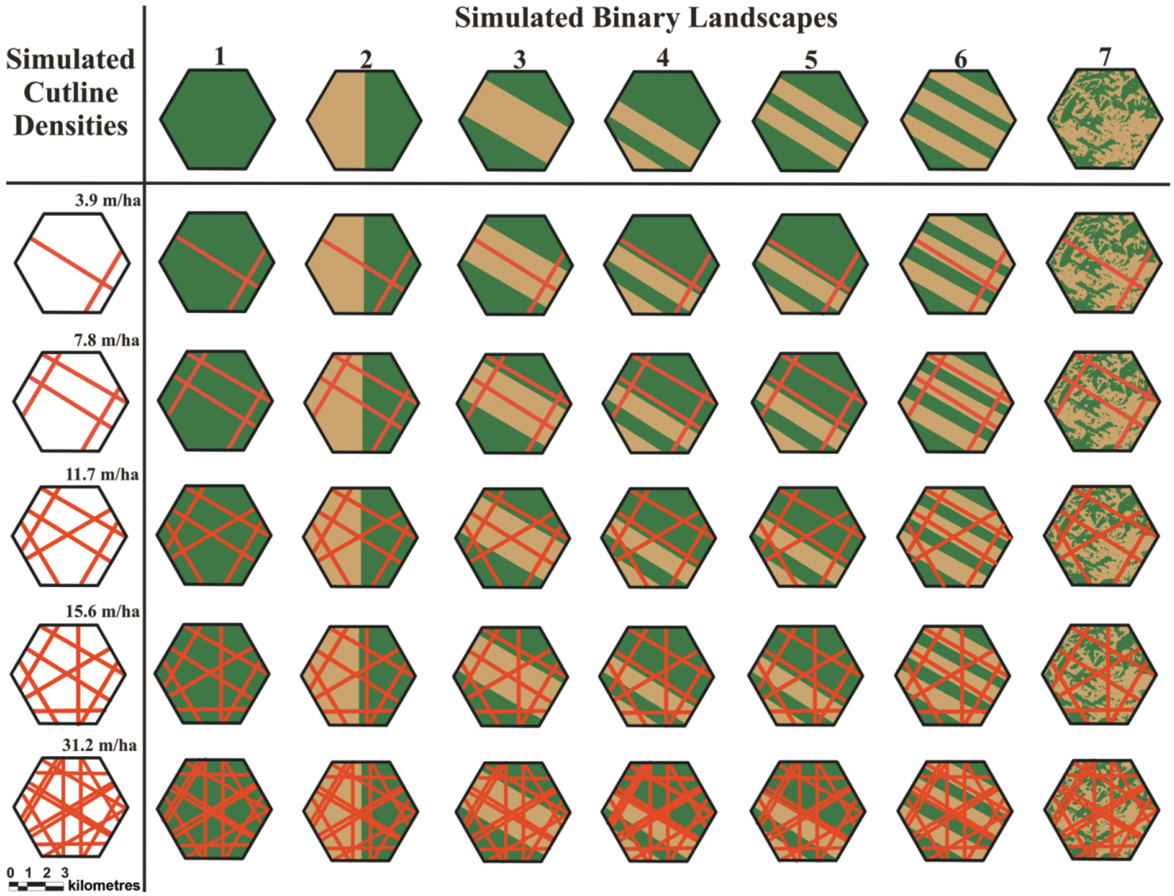

Figure 2. Simulations of seven hypothetical, binary landscapes with increasing initial landscape heterogeneity and increasing cutline densities.

Table 2. Initial landscape heterogeneity of simulated binary landscapes as indicated by the pre-cutline values of five selected landscape-level landscape metrics, namely edge density, mean patch size, patch size variability, patch context, and patch dispersion.

	Simulated binary landscapes with increasing fragmentation from left to right						
Landscape metric	1	2	3	4	5	6	7
Edge density (m/ha)	0	2	6	8	12	16	78
Mean patch size (ha)	2230	1150	766	575	460	328	13
Patch size variability (%)	0	0	32	75	18	36	749
Patch context (m)	0	0	2160	857	752	731	67
Patch dispersion (%)	0	0	0	10	21	22	72

real landscape into a binary landscape; it represents the most heterogeneous landscape among the simulated landscapes and was included as a control to determine whether the trends in metric responses of the simple landscapes are consistent with those of a more realistic landscape (**Figure 2**; **Table 2**).

The 104 real landscapes used in this study were obtained by clipping the TM-based land-cover map produced using methods described by Franklin et al. (2001) and McDermid (2005), using as clip the 5.9 km hexagonal grid shown in **Figure 1**. All 104 real sample landscapes fell completely within the area of significant oil and gas exploration and development (including roads, pipelines, and well sites), mining, human settlements, and forest harvesting. Forest cutlines in this area are typically narrower than the 30 m spatial resolution of TM imagery and so rarely influence the original land-cover classification. Therefore, this land-cover map is a surrogate of the pre-cutline configuration. When the interpreted cutlines are imposed on this map, the metrics are computed to represent the landscape structure with those changes incorporated into the final metric values (**Figure 3**).

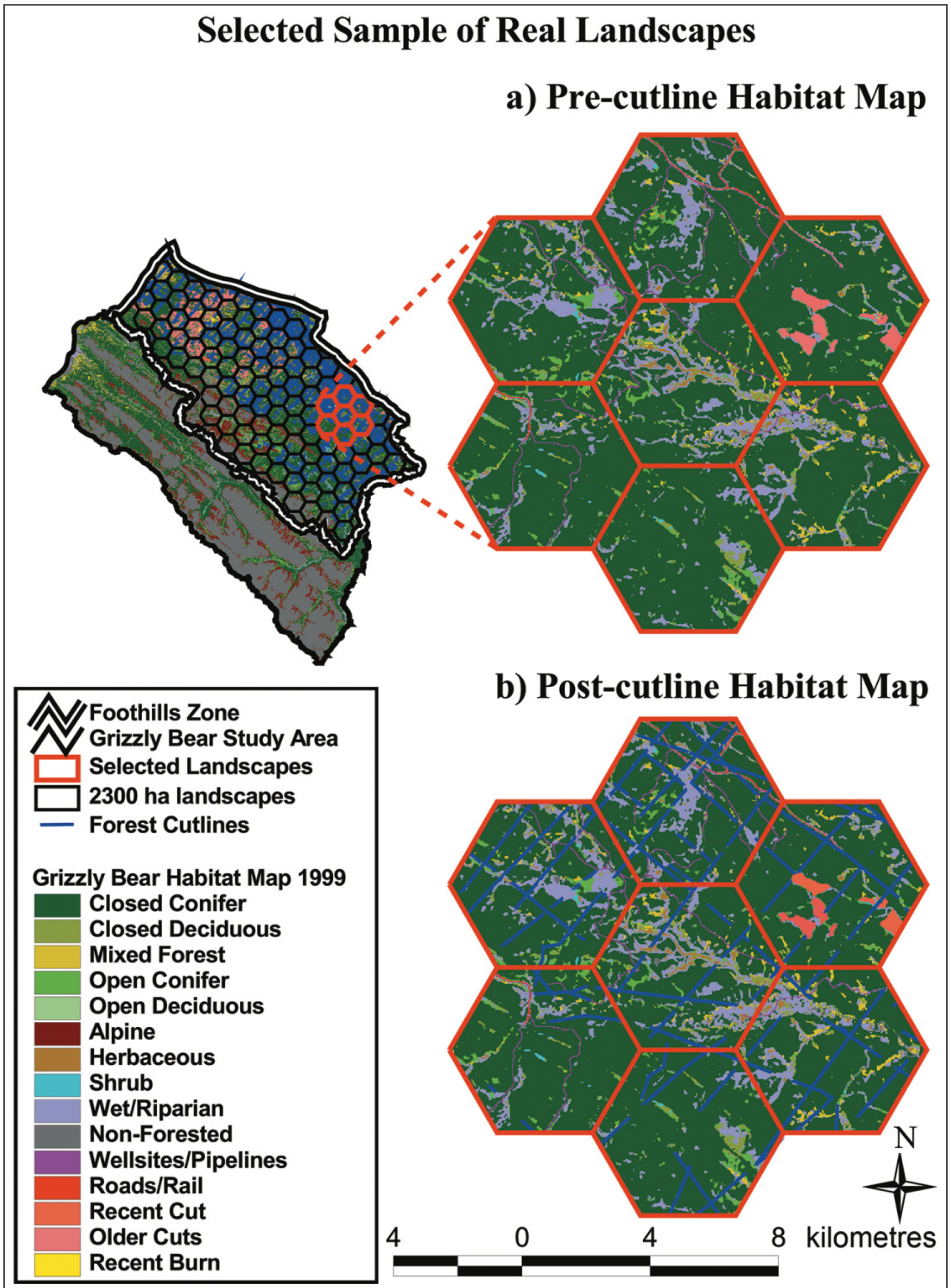

Figure 3. Selected sample of real landscapes showing (a) pre-cutline and (b) post-cutline representations of the grizzly bear land-cover map.

Image acquisition and forest cutline interpretation

Two satellite sensor data sources were used in this study: (*i*) five geometrically and atmospherically corrected IRS panchromatic images (six-bit data at 5.6 m resolution) acquired between April and September 1998 as part of the ACCESS program of Alberta Environment; and (*ii*) one 30 m resolution, multispectral Landsat TM scene acquired 29 August 1998. This TM image was atmospherically and geometrically corrected using the ATCOR operations in Xpace and the GCPWorks tool of the remote sensing processing software PCI Works 7.0 (PCI Geomatics, 2000). The TM image was subsequently resampled to 5 m for the purpose of merging spectral information to the high-resolution IRS panchromatic imagery and also was employed as the main data source for the land-cover classification (Franklin et al., 2001; McDermid 2005). The IRS images were mosaicked together to cover the area of the TM scene.

To assess the effects of forest cutlines on landscape structure, cutlines were visually interpreted based on a TM–IRS fusion product (**Figure 4**) and imposed on all 104 real landscapes. First, to create the fusion image, the IRS mosaic was

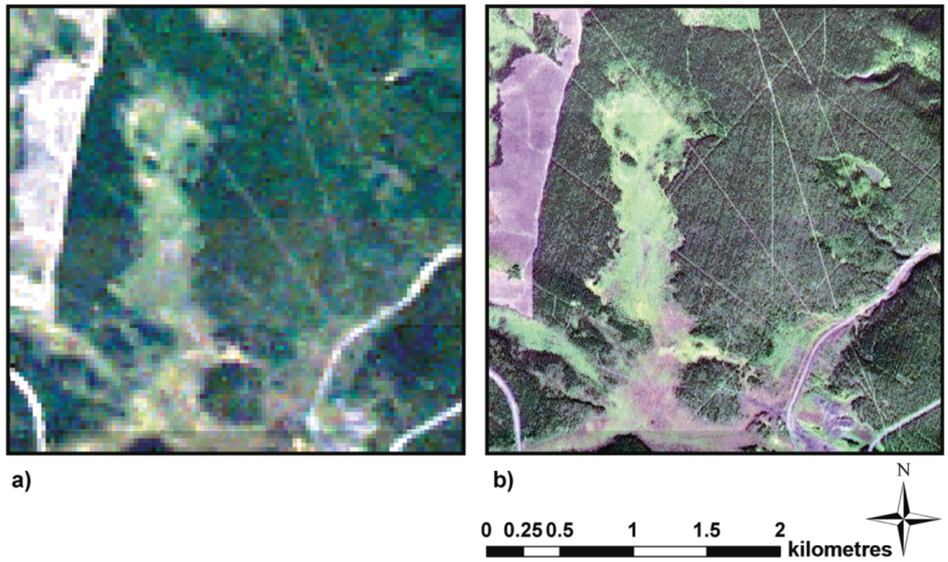

Figure 4. Sample comparison between (a) the original 30 m resolution Landsat TM 1998 image and (b) the fused TM image with 5.6 m resolution panchromatic IRS 1998 image.

coregistered to the TM scene using 52 ground-control points yielding a root mean square (RMS) error of 0.7 pixels. Three infrared bands (4, 5, and 7) of the TM image were merged with the panchromatic IRS intensity image using the intensity–hue–saturation transformation; the subsequent fused image was resampled using the nearest-neighbour method. To facilitate forest cutline visual detection, an edge enhancement filter, averaging the absolute differences for each pixel surrounding the centre of the kernel window, was applied to the three fused bands at three filter sizes (3 × 3, 5 × 5, 11 × 11). Visual inspection revealed that the 11 × 11 filter size provided the most effective enhancement of the cutline features. The centrelines of cutlines were digitized on screen from the enhanced fused image. The resulting polylines were converted to polygons using a buffer distance of 5 m, the polygons were rasterized using a 5 m cell size, and the detected cutlines were then inserted in the 5 m resampled, TM-based land-cover map.

For the seven simulated landscapes, five cutline networks of arbitrary pattern and increasing density were manually created (cutline densities of 3.9, 7.8, 11.7, 15.6, and 31.2 m/ha were used as shown in **Figure 2**). These cutline networks were imposed on the simulated landscapes to enable a model of structure to be developed for specific metric values pre-cutline and post-cutline disturbance.

Cutline accuracy assessment

To collect data on the accuracy of these two maps, a field sampling program was carried out in June and July 2001 in two test sampling areas selected because of known geophysical activity in the recent past. (Note that more detailed assessment of cutline accuracy was presented by Linke (2003); for example, Linke conducted an assessment of cutline detection accuracy in areas of higher or lower quality imagery because some of the IRS imagery exhibited significant atmospheric haze.) Several cutline sections clearly visible in the IRS mosaic, each approximately 5 km long, were randomly selected while stratifying by the two dominant seismic cutline directions, northeast and southeast, and by image tile. The presence and absence of intersecting seismic cutlines were recorded in the field. The intersection point was recorded with a hand-held Garmin GPS. The total of 70 km of sampling lines constituted on average about 4% of IRS mapped seismic lines per image tile. Errors of omission and commission and overall accuracy for the update layers and spatial extents were computed based on the number of cutlines found in the field compared with the number of cutlines mapped from the TM–IRS fusion imagery. The overall accuracy of the cutline interpretation, compared with the field-based identification of cutline presence, was determined to be 88%. Forest cutline density across the 104 real landscapes ranged from 0.25 to 37.58 m/ha, with a mean density of 11.45 and a standard deviation of 7.00 (**Figure 1**).

Landscape structure assessment

The five metrics, namely edge density, mean patch size, patch size variability, patch context, and patch dispersion, together quantitatively capture aspects of the aggregate properties of the entire landscape mosaic when calculated at the landscape level. Each metric was computed at the landscape level twice on each sample landscape using Fragstats 3.1 software build 3 (McGarigal et al., 2002). The first computation was performed on the landscapes without forest cutlines yielding metric values for the pre-cutline landscape condition (**Figure 3a**); the second computation was performed on the landscapes with forest cutlines superimposed (using the five arbitrary networks of cutlines for simulated landscapes and the IRS-digitized forest cutline layer for the real landscapes), yielding metric values for post-cutline landscape condition.

Table 3. Mean, standard deviation, minimum, and maximum values of pre-cutline landscape metrics and cutline-induced percent changes in metrics across 104 real landscape samples, measured by edge density, mean patch size, patch size variability, patch context, and patch dispersion.

	Pre-cutline metric values (units as given with each metric)				Cutline-induced changes in metric values (% change relative to pre-cutline values)			
Landscape metric	Mean, X	SD, σ	Min.	Max.	Mean, X	SD, σ	Min.	Max.
Edge density (m/ha)	107.59	35.38	35.93	186.38	27.62	18.11	0.91	112.61
Mean patch size (ha)	4.01	1.84	1.61	10.36	–24.99	11.01	–51.20	–0.28
Patch size variability (%)	1010.65	371.23	389.85	1815.25	–13.97	20.01	–65.17	24.60
Patch context (m)	107.30	23.71	74.95	174.70	–20.78	11.72	–48.11	–0.28
Patch dispersion (%)	165.05	30.27	98.29	264.39	20.58	10.80	0.17	51.75

The eight-neighbourhood option was selected for all metric computations, meaning that patches are formed from pixels connected on the diagonal and from those with full connection on the pixel sides. The hexagonal frame bounding each landscape was excluded from edge calculations, since it represents an artificial boundary rather than a patch edge. Lastly, the cutline-induced change in each metric was expressed as a percent of its pre-cutline value.

Visual and statistical analysis

For each metric, a graph was created to show the percent change in each simulated landscape plotted against cutline density. There are seven curves per graph, one for each simulated landscape. Visual assessment was used to determine whether the relationship was linear or nonlinear and how the slope of the curve varied with initial landscape heterogeneity. This guided the choice of the type of regression equation required to predict cutline-induced change in the real landscapes.

Using the cutline-induced metric change values obtained from the 104 real landscapes, we derived for each selected metric one regression equation predicting the percent change as a function of both cutline density and the pre-cutline value of the metric, the latter of which is assumed to indicate the initial landscape heterogeneity. All the equations were forced through the origin, since no cutline-induced change could occur in the complete absence of cutlines. The regression coefficients were estimated via the ordinary least squares method. The goodness-of-fit was indicated by the standard r^2 for linear regressions and by pseudo-r^2 (Anselin, 1993) for nonlinear regressions. Pseudo-r^2 is computed as the squared correlation between the fitted and observed values. For nonlinear regressions, 95% confidence intervals were computed to indicate whether the parameter estimates for the two independent variables, namely the pre-cutline metric value and cutline density, were stable and not overlapping zero values. All models were also applied to obtain graph points over sequential interval data within the range of sampled data to provide a visual representation of the regression equations. Regression residuals were computed as the difference between predicted and observed values of the percent change in metric based on the 104 real landscapes. These residuals were then plotted as spline surfaces using linear extrapolation within the range of sampled data to demonstrate under what landscape and cutline conditions the models overpredict and underpredict. All computations were performed using S-Plus 2000 (MathSoft, Inc., 1999) loading the MASS library (Venables and Ripley, 2002).

Results and analysis

Two independent variables (cutline density and the pre-cutline metric value) could explain the percent metric change in four of the metrics (edge density, mean patch size, patch context, and patch dispersion) with varying degrees of goodness-of-fit (**Table 4**). Change in the remaining metric (patch size variability) could not be explained by these two variables alone, and visual examination of the graphs suggested that this explanation may require spatial pattern information (e.g., cutline positioning) (**Figure 5**).

Evaluation of metric responses on simulated landscapes

The introduction of networks of forest cutlines of increasing density in the seven simulated landscapes illustrated the general direction and type of change that can be expected in the five investigated landscape-level metrics (**Figure 5**). Observations included the following:

(1) Clear relationships between increasing cutline densities and percent changes were apparent in four of the investigated metrics, namely edge density, mean patch size, patch context, and dispersion. The second variable, pre-cutline metric value, appeared to be inversely related to rates of change (**Figures 5a**, **5b**, **5d**, **5e**).

(2) Percent change in edge density was positively and linearly related to cutline densities across all simulated landscapes, with the slope of this relation consistently decreasing from landscape 1 to landscape 7 (**Figure 5a**). This landscape sequence is in order of increasing initial mosaic heterogeneity as quantified by the pre-cutline edge density values (**Table 2**).

(3) Percent change in mean patch size and patch context had a negative exponential relation with increasing cutline densities. The curves asymptotically approach the

Table 4. Explanatory model parameters, showing regression equations, degrees of freedom (DF), significance (Pr), coefficients, standard error (SE), 95% upper (UCL) and lower (LCL) confidence limits, and pseudo-r^2 of cutline-induced percent changes in landscape metrics such as edge density, mean patch size, patch context, and patch dispersion over 104 real sample landscapes.

	Change in edge density	Change in mean patch size	Change in patch context	Change in patch dispersion
Model type	Positive linear	Negative exponential	Negative exponential	Positive exponential
Equation	(1) $y = \alpha x_1 + \beta x_1 x_2$	(2) $y^*(-100) = 1 - \exp(-\alpha x_1 - \beta x_1 x_2)$	(3) $y^*(-100) = 1 - \exp(-\alpha x_1 - \beta x_1 x_2)$	(4) $y = \alpha x_1 x_2 + \beta x_1^{\gamma}$
α coefficient	4.837	0.014	0.002	–0.005
SE	0.091	0.001	0.002	0.002
LCL	na	0.0110	–0.0030	–0.0090
UCL	na	0.0170	0.0080	–0.0015
t	53.082	na	na	na
Pr(>|*t*|)	<0.000	na	na	na
β coefficient	–0.021	0.003	0.0002	5.817
SE	0.00100	0.00100	0.00002	0.76700
LCL	na	0.0020	0.0001	4.4250
UCL	na	0.0040	0.0002	7.8080
t	–28.530	na	na	na
Pr(>|*t*|)	<0.000	na	na	na
γ coefficient	na	na	na	0.706
SE	na	na	na	0.072
LCL	na	na	na	0.514
UCL	na	na	na	0.839
t	na	na	na	9.70
DF	102	102	102	101
Goodness-of-fit: (adjusted pseudo-r^2)	0.98	0.83	0.88	0.41

Note: x_1 refers to the cutline density (m/ha), and x_2 refers to the pre-cutline metric value.

theoretical and practical lower limit of these metrics, i.e., –100% percent change (**Figures 5b**, **5d**). The rate at which the asymptote was approached decreased with an increase in initial heterogeneity (**Table 2**).

(4) The response of percent change in patch dispersion to increasing cutline density was observed using three of the simulated landscapes (4, 6, and 7; **Figure 5e**). Landscapes 1, 2, and 3 contained no initial variation of this metric (**Table 2**). For landscape 5, the first cutline density simulation dissected all unique patches with the constant cutline width, therefore separating all new nearest-neighbouring patches by that distance (landscape 5; **Figure 2**). The effect was to create a zero coefficient of variation in mean nearest-neighbour distances (**Figure 5e**). The remaining useful landscapes 4, 6, and 7 demonstrated a steep initial increase in percent change in patch dispersion at the first introduction of cutlines; increasing cutline density induced a lesser rate of change. The slopes of these relationships appeared to be an inverse function of initial level of patch dispersion.

(5) Responses of percent change in patch size variability to cutline density varied across the different cutline densities and among landscapes. Across landscapes 1–6, patch size variability responded positively to increasing cutline densities; the rate of change decreased across the gradient provided by increasing pre-cutline values of uniformity (**Figure 5c**; **Table 2**). The shape of the response curves was not quantifiable based on cutline density and appeared by visual inspection to be mainly driven by the positioning of the cutlines. Increases coincide with less evenly positioned cutlines (3.9, 7.8, and 31.2 m/ha cutline simulations), and decreases coincide with more evenly positioned cutlines (11.7 and 15.6 m/ha cutline simulations) (**Figure 2**). The seventh and more realistically configured landscape displayed a considerably larger pre-cutline variation in patch size (**Table 2**; **Figure 2**) and showed a negative exponential relation of percent change in patch size variability with increasing cutline density The curve slowly approaches the lower theoretical limit of –100% (**Figure 5c**). Cutlines split the largest patches into smaller units, decreasing the strong variability in patch sizes. This reiterates the importance of cutline positioning, here in relation to the underlying mosaic structure rather than in relation to other cutlines. If cutlines run through larger initial patches, the patch size variability decreases more than if the cutlines run through smaller initial patches.

Three model types were used to quantify percent change in metric value as a function of cutline density: (*i*) positive linear

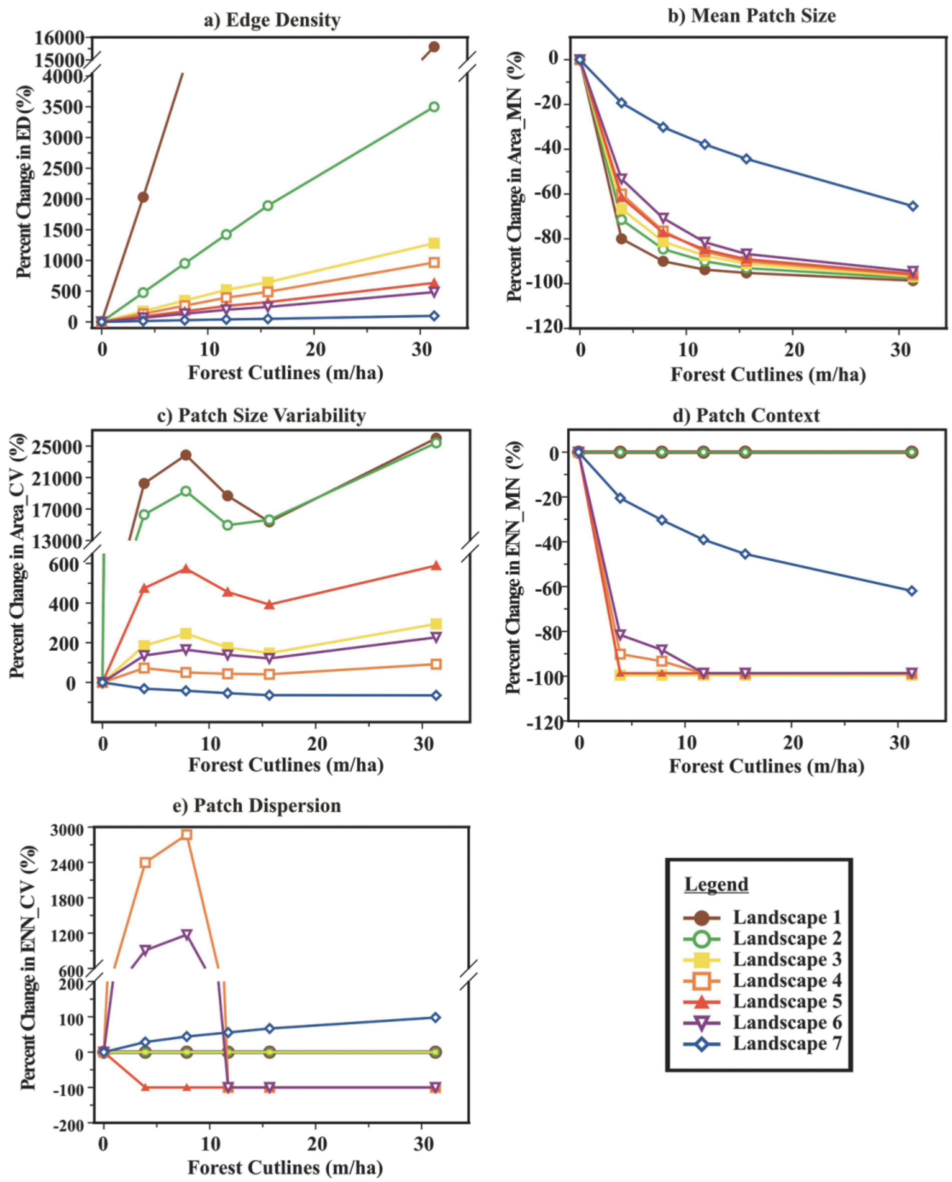

Figure 5. Effects of simulated cutline densities on selected landscape metrics across seven simulated binary landscapes of increasing initial landscape heterogeneity (see **Table 2**): (a) edge density (ED), (b) mean patch size (Area_MN), (c) patch size variability (Area_CV), (d) patch context (ENN_MN), and (e) patch dispersion (ENN_CV).

model for edge density, (*ii*) negative exponential model for mean patch size and patch context, and (*iii*) positive exponential model for patch dispersion (**Table 4**).

Note that there is an additional interaction term to account for the pre-cutline heterogeneity, as measured by the initial value of the given metric. For patch size variability, no acceptable model could be formulated using cutline density and pre-cutline heterogeneity alone.

Cutline density impacts on real landscape samples

To corroborate and parameterize the regression equations corresponding to the four metrics that showed a clear response in the simulated landscape responses, we applied the equations to the 104 real landscape samples (**Table 4**; model type and model parameters). These landscape samples exhibited a wide range of pre-cutline mosaic configurations and cutline-induced percent changes in the investigated metrics (**Table 3**; **Figure 1**). Cutline density and pre-cutline metric values were strong explanatory variables and had narrow 95% confidence intervals for percent changes in the metrics, with high goodness-of-fit pseudo-r^2 measures between 0.83 and 0.98 (Equations (1)–(3) in **Table 4**) and low residuals over the sampled data range (**Figures 6a–6c**; **Table 3**) for three of the four metrics: edge density, mean patch size, and patch context. Prominent overpredictions occurred near the lower and upper

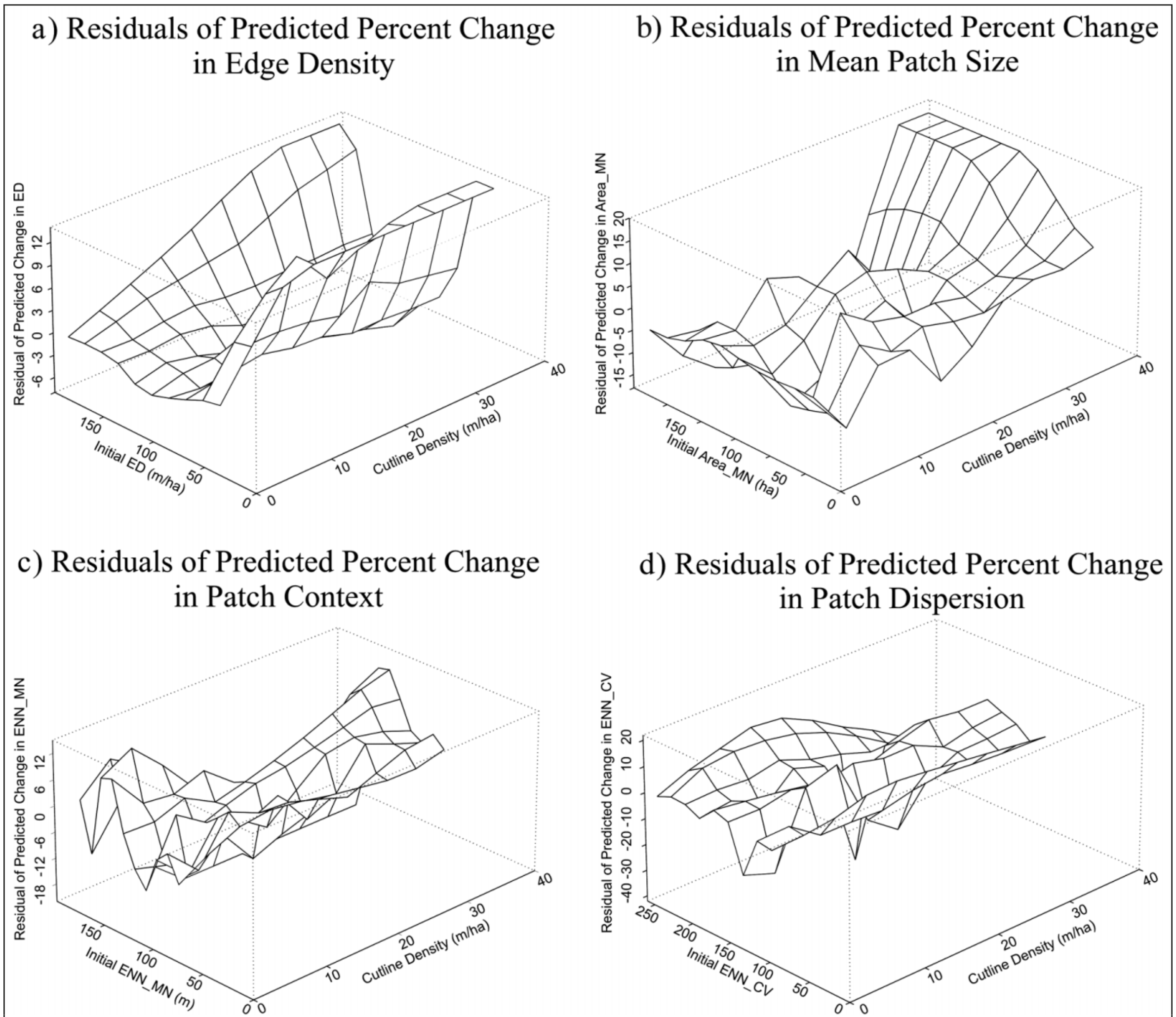

Figure 6. Residual surfaces (interpolated from 104 observations) of predicted percent changes in (a) edge density (ED), (b) mean patch size (Area_MN), (c) patch context (ENN_MN), and (d) patch dispersion (ENN_CV) in response to forest cutline densities and initial, pre-cutline metric values.

extremes of observed initial metric values for edge density where fewer samples were available to fit the linear model (**Figure 6a**). The two other nonlinear metric models demonstrated less prominent prediction errors near the intercept but more near the upper extremes of cutline density and initial metric value, where overpredictions occurred for mean patch size and underpredictions occurred for patch context (**Figures 6b**, **6c**).

The remaining metric, namely patch dispersion, exhibited a lower fit to the regression model, with a pseudo-r^2 of 0.41 (Equation (4) in **Table 4**) and higher residuals over the sampled data range (**Figure 6d**), although the coefficient estimates for cutline density and pre-cutline metric value were significant. Visual inspection of the prediction surfaces generated by the regression equations (**Figure 7**) showed that all four models were consistent with the metric behaviour in the simulated landscapes. The 104 real landscapes were comparable to the simulated landscapes in that percent changes in patch size variability varied inconsistently in relation to cutline density and pre-cutline values of patch size variability, thus preventing model formulation using these variables alone (**Figure 7**; **Table 4**).

Cutline density, cutline positioning, and differing initial landscape heterogeneity

The response of edge density to the introduction of forest cutlines was consistent with the general behaviour observed in relation to road development. Any new landscape feature introduces new edges regardless of its position in the landscape (McGarigal et al., 2002), but the actual percent change in edge density also depends on the shape of the introduced feature. Less change is introduced by more compact features, and more change is introduced by features of more irregular shape. Because forest cutlines have a consistent shape, increasing cutlines by any amount yields predictable edge density changes and hence generates very strong models. In the case of mean patch size, any new cutline dissects at least one patch into at

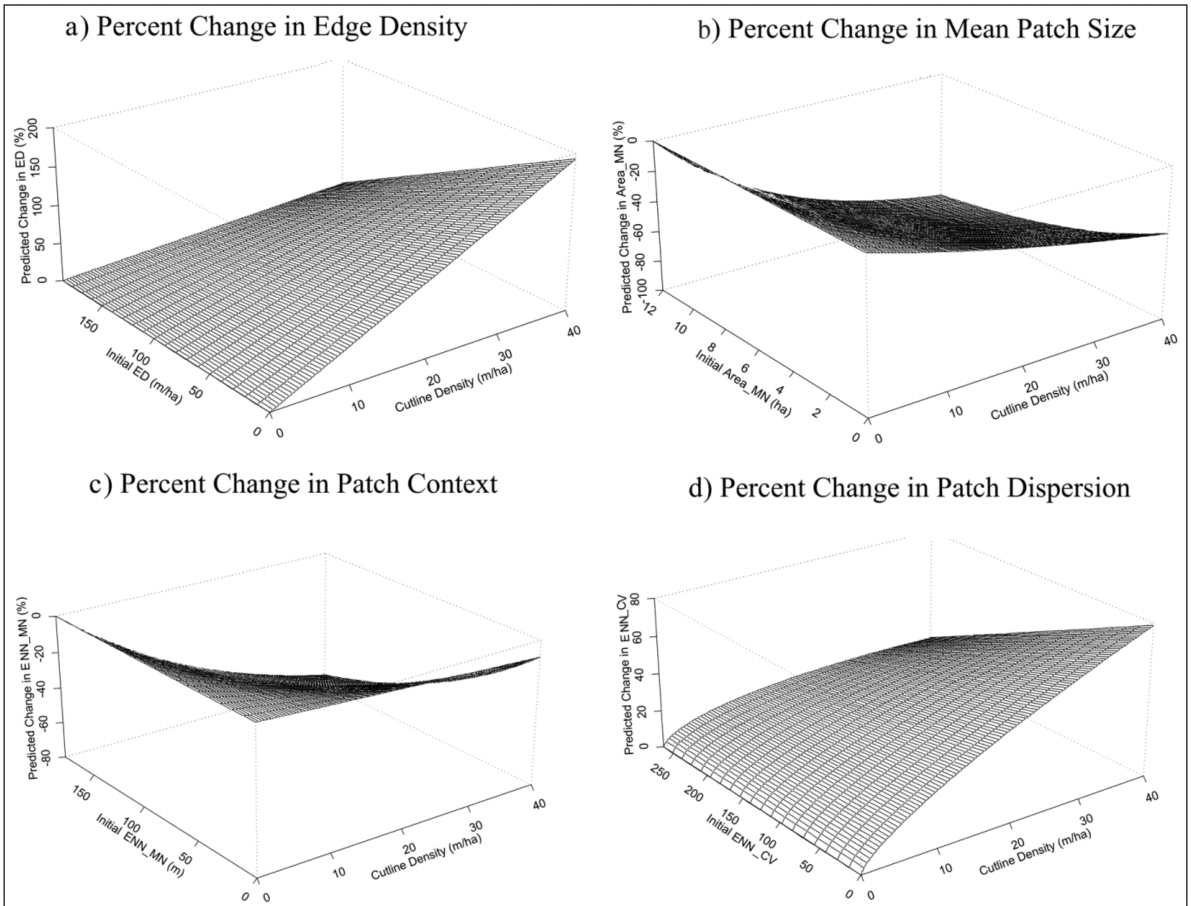

Figure 7. Prediction surfaces of percent changes in (a) edge density (ED), (b) mean patch size (Area_MN), (c) patch context (ENN_MN), and (d) patch dispersion (ENN_CV) in response to forest cutline densities and initial, pre-cutline metric values (for model details, see **Table 3**).

least two new patches, naturally leading to a decreasing trend in mean patch size. The more patches the landscape already contains, the more patches the cutline is likely to dissect, as demonstrated by the strong negative exponential model for change in this metric (**Figure 7**).

The regression for percent change in patch context also displayed a strong correlation. Greater patch context values, in other words higher patch isolation, might be expected to occur as the level of fragmentation in a landscape increases (**Table 1**) (McGarigal et al., 2002). In the particular context of forest cutlines, however, the land transformation process at hand is dissection. In this case, patch context values actually decrease, indicating a reduction in overall patch isolation, since each newly created neighbouring patch is separated from its neighbour of the same class only by the width of the cutline. Therefore, counter to intuition, a quantitative reduction in patch context values, and hence a reduction in overall patch isolation, cannot be equated to a landscape with lower fragmentation and fewer isolated patches. Instead, change in patch context needs to be interpreted in the context of the land transformation at hand. A landscape experiencing changes of similar intensity, but of a different shape or distribution of the imposed change polygons, could cause the inverse trend in patch context. For example, higher values of patch context might occur, in other words patches becoming more isolated in areas experiencing clearcutting, compared with an area with lower values of patch context responding to the introduction of a network of cutlines.

Theoretically, while patch context decreases, patch dispersion increases in response to increasing cutline density. This is because new patches are created separated by only the cutline. The proportional change is lower in landscapes where the pre-cutline value of dispersion is larger. However, the correlation obtained in the percent change of dispersion was low in the real landscape samples. Two landscapes with similar pre-cutline landscape mosaics and similar cutline density may yield very different changes in patch dispersion, such as 16% and 45%. In the first landscape, the cutlines are positioned to dissect fewer contiguous patches, creating a 30% increase in the number of patches; in the second landscape, however, the same cutline density dissects more patches, increasing their number by 95%, hence creating more new nearest neighbours and a relatively greater change in patch dispersion. Quantification of percent change in patch dispersion might then be improved with a third independent variable accounting for the number of new patches created due to cutline positioning.

Cutline positioning was even more important for change in patch size variability than for change in patch dispersion. As observed in the simulation graphics, a general positive change in patch size variability was caused by the cutline-induced creation of new patches, smaller than those initially present. Cutline proximity and clumping influenced the magnitude of this increase independently of cutline density (**Figures 2**, **3**). In contrast, in the landscape where cutlines were positioned to dissect mainly the largest patches, the initially existing smallest patches remained unaffected and the largest patches were reduced in size, lowering the patch size variability as reflected by the negative change (landscape 7; **Figures 2**, **3**). This conclusion was similar to that observed in the real landscapes.

Linking simulated and real landscapes to understand landscape metric behaviour

The direct linking between simulated and real landscapes, as applied in the quantification of metric responses to cutline density and initial heterogeneity, constitutes an important conceptual extension of existing work on the understanding of metric behaviour. Similar metric values with differing landscape structures have been observed in several simulated and real studies (e.g., Hargis et al., 1998; Trani and Giles, 1999; Tischendorf, 2001), rendering landscape change interpretation ambiguous. Neel et al. (2004) addressed this difficulty using replications of simulated binary landscapes across a wide range of gradients of landscape structure. They modeled 50 metrics as bivariate responses to composition (modeled by landscape proportion *P*) and configuration (modeled by landscape aggregation *H*) to assess how each metric quantifies differences in landscape structure. Their general trends of metric behaviour were consistent with the responses of the four metrics quantified in this study. For example, edge density and mean patch size, respectively, exhibited increases and decreases in response to increasing fragmentation (lower aggregation levels) for a given landscape composition (Neel et al., 2004).

The aggregation parameter *H* used by Neel et al. (2004) cannot be quantified in real landscapes, however, and therefore interpretations can only indirectly be linked with real landscapes. By coupling a controlled landscape experiment, quantified through real-world variables (such as cutline density and pre-cutline metric value), with an empirical analysis of real landscapes, this paper expanded the approach of Neel et al. The strategy advocated in this paper is to select metric response models based on simulated landscapes and then apply these to real landscapes to evaluate if the "theoretical patterns" observed in the simulations match the empirical patterns of real landscapes. This approach may also allow establishing relationships with real-world ecological systems and wildlife conservation issues. For example, in the context of Alberta's forest landscape, Linke et al. (2005) reported that grizzly bear landscape use declined with increasing patch dispersion (ENN_CV) and with decreasing mean patch size (Area_MN). Knowing how human activities, such as the development of forest cutlines in this case, change the value of those metrics may then provide a management tool for predicting impacts in wildlife habitat selection.

Conclusion

Recent work has shown that models predicting species richness, abundance, or habitat selection by some species, including bats, birds, and bears, can be improved when spatial landscape structure information is included as a predictor. However, this type of landscape structure work is relatively new in species-at-risk assessment and general wildlife management. In this study, the impact of forest cutlines associated with oil and gas development was quantified using five metrics of interest in grizzly bear management in Alberta. Cutline density and landscape heterogeneity were significant variables associated with high goodness-of-fit regression values for explaining cutline-induced change in three metrics, namely edge density, mean patch size, and patch context (expressed as the mean nearest-neighbour distance). Patch size variability (expressed as the coefficient of variation of mean patch size) and patch dispersion (expressed as the coefficient of variation of mean nearest-neighbour distance) required additional information on cutline positioning. Overall, however, the density of the introduced cutline network and the pre-cutline metric value sufficed to reliably quantify the response of landscape metrics of interest to grizzly bear biologists.

The approach presented in this study constitutes a step forward from contemporary landscape structure descriptions by allowing a direct connection between simulated and real landscapes through regression modeling. The approach also facilitates the understanding of the nature and causes of changes in landscape structure as a function of cutline density. Importantly, this provides a strong means to evaluate the expected effects of proposed human development without the need for undertaking time-consuming spatial simulations. Moreover, this study suggests the importance of mapping forest cutlines regarding their role in changing landscape structure quantification and points out the necessity of using additional remotely sensed data when the feature responsible for the landscape dissection is too small to appear reliably in common TM-based classified imagery. In conclusion, land-cover maps based on TM imagery updated with IRS imagery or similar higher spatial resolution imagery can be used to determine the effects of forest cutline disturbance on landscape structure.

Acknowledgements

This research was funded by a Natural Sciences and Engineering Research Council of Canada (NSERC) Collaborative Research and Development Grant and is part of the Foothills Model Forest Grizzly Bear Research Project. J. Linke was supported by an NSERC PGS A/B scholarship and an Alberta Ingenuity Award. The following are thanked for their contributions: K. McGarigal, R. Rempel, P. Ehlers, S. Bertazzon, F. Huettmann, M. Lavigne, G. Castilla, T. Spies,

D. Nuell, G. McDermid, A. Hudak, three anonymous reviewers, S.A. Linke, E. Linke-Welte, K. and S. Welte, J. Friars, the Presse family, and the Huettmann family.

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