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Measuring boreal forest fragmentation after fire: Which configuration metrics are best?

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ABSTRACT

Studying changes to the shape, size, and arrangement of patches of forest habitat remains a challenge in the field of landscape ecology. A major issue is that most landscape pattern metrics measure both the amount of habitat as well as habitat configuration. To obtain independent measures of habitat configuration, the established approach is a detrending analysis using regression residuals between configuration metrics and habitat abundance. We compared this detrending approach with a new set of three normalized configuration metrics and evaluated their suitability to detect changes to forest fragmentation in the Canadian boreal forest as a result of fire disturbance. We found that the combination of two of the three normalized configuration metrics responds well to habitat configuration dynamics after fire, whereas the classical approach provides an inferior measure of changes to habitat configuration. Our second objective was to examine whether spatial configuration metrics can be directly predicted from non-spatial surrogates that describe the initial habitat structure and the disturbance regime. This has practical value, because many models that guide forest management and conservation are non-spatial. We found that normalized configuration metrics were predicted with moderate accuracy (average adjusted $r^2 = 0.53$), while detrended metrics could not be predicted ($r^2 = 0.16$).

1. Introduction

Studying changes in landscape configuration – or the shape, size, and arrangement of patches of habitat – is an important challenge in the field of landscape ecology and forest management (e.g. Euler et al., 2000; With, 2002). Change of landscape configuration after disturbance has important implications for biodiversity, conservation, and ecosystem management (e.g. Davis et al., 2001). However, the validity of comparisons among different landscapes, or the representation of landscape fragmentation depends largely on whether the configuration measurements are appropriate. Habitat fragmentation is a process that reduces habitat abundance (p), increases the number of habitat patches, decreases habitat patch sizes, and increases patch isolations (Fahrig, 2003). Habitat fragmentation, therefore, includes two components: habitat loss and habitat configuration changes. We wanted to focus on the latter component and therefore define habitat fragmentation as configuration changes only, following Andren (1994), Fahrig (1997) and Schmiegelow and Monkkonen (2002).

The shape, size, and arrangement of patches of habitat are measured using means of configuration metrics. These metrics can be classified into two major categories that will be compared in this paper: stand table metrics and landscape pattern metrics. Stand table metrics, such as patch number, mean and standard deviation of patch sizes, are the non-spatial measurements that can be directly computed from attribute tables of forest inventory polygons (Cumming and Vernier, 2002). Landscape pattern metrics, on the other hand, were developed to measure patch shape, core area, and spatial distribution of habitat (McGarigal and Marks, 1995). Landscape pattern metrics derived from spatial data layers in a geographic information system (GIS) are the preferred methods for characterizing landscape composition and structure because of the spatial elements they reflect (e.g. Jaeger, 2000; Wang and Cumming, 2011). Nevertheless, many predictive models depend on non-spatial stand table metrics (e.g. Cumming and Vernier, 2002; Linke et al., 2008).

Due to their complex nature, landscape configurations cannot be measured with just one metric, and a group of landscape pattern metrics are usually used in landscape pattern analysis (e.g. Cumming and Vernier, 2002; Remmel and Csillag, 2003). Even then, one important remaining problem is that many metrics are highly correlated with habitat abundance (Andren, 1994; Fahrig, 1998; Neel et al., 2004). As a consequence, when comparing different study sites, configuration metrics cannot be easily interpreted if levels of habitat abundance are different. In order to reduce correlation between landscape metrics and habitat abundance,

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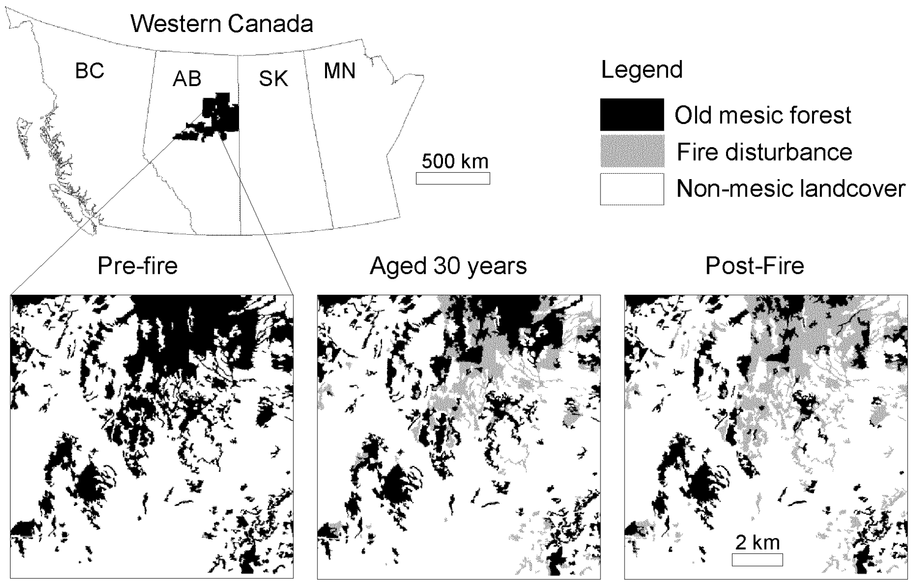

Fig. 1. Study area in north central Alberta and an example township (~10 km × 10 km) at different stages of simulated fire disturbance used for calculating landscape configuration metrics for old mesic forest.

various approaches have been employed. Li and Reynolds (1994) and Riitters et al. (1995) recommend selection of independent configuration metrics, based on a large set of candidate metrics. McGarigal and McComb (1995) use principal component analysis to remove multi-collinearity configuration metrics. Gustafson (1998) builds on this idea and proposes the development of configuration metrics that optimally measure these independent principal components. Another common practice is to eliminate the impact of habitat abundance, either by controlling the total amount of habitat (McGarigal and Marks, 1995; With and King, 2001), or by taking linear or quadratic regression model residuals of a metric versus abundance as the real configuration measurements (Trzcinski et al., 1999; Villard et al., 1999; Flather and Bevers, 2002), which we hereafter call "detrended". The approach, however, has been criticized by Koper et al. (2007). They have shown that regression residuals cannot be used to differentiate the ecological effects of habitat amount and fragmentation even within a fixed landscape population.

A new set of normalized landscape configuration metrics was recently developed by Wang and Cumming (2011). These normalized configuration metrics were made largely independent from habitat abundance by dividing a raw metric by its theoretical maximum value. For example, the configuration metric "total core area" distinguishes between buffer and habitat core area (McGarigal and Marks, 1995). Within a landscape, the theoretical maximum total core area for a given amount of habitat would be a single circle. The normalized core area metric can be thought of as a relative measurement to this maximum, comparable across landscapes with any amount of habitat.

We use the above configuration metrics to evaluate fragmentation as a result of forest fires. Fire is the driving force of boreal forest landscape dynamics. It alters species composition (Cammeraat and Imeson, 1999), changes soil properties (Certini, 2005), affects species dispersal and dynamics (Green, 1989; Parisien and Sirois, 2003), and fire also changes habitat amount and configuration (McRae et al., 2001). To quantify what effect fire disturbance has on landscape fragmentation, and by implication species habitat, we need suitable configuration metrics.

In this paper we test the suitability of landscape configuration metrics to quantify fragmentation. Our two primary objective are: (1) to compare the widely used detrending approach with a new set of three normalized configuration metrics and evaluate their suitability to detect changes to forest fragmentation as a result of fire disturbance, and (2) to examine whether spatial configuration metrics can be directly predicted from non-spatial surrogates that describe the initial habitat structure and the disturbance regime. This has practical value, because many models that guide forest management and conservation are non-spatial. If spatial configuration metrics are predictable from stand table metrics, they may be used as criteria to evaluate different management options in such models.

2. Methods

2.1. Study area and data preparation

Our study area is an approximately 80,588 km^2 region in central Alberta, Canada (Fig. 1). This section of the boreal forest is managed by Alberta-Pacific Forest Industries Inc. (Al-Pac), who provided digital Alberta Vegetation Inventory (AVI) data, containing stand level information including land cover, species composition, and soil attributes. We chose old mesic forest (≥90 years) as focal habitat because of its importance in boreal song birds' conservation (Cumming, 2001). Old mesic forest stands in our study area mainly consist of habitats with soils derived from glacial till or lacustrine deposits, and are typically dominated by trembling aspen (*Populus tremuloides* Michx.) and white spruce (*Picea glauca* (Moench) Voss).

Fire disturbance in the simulated landscape was implied by stand age recorded in the Alberta Vegetation Inventory database, after removing harvesting. Harvesting is a major disturbance factor for this study area, but most harvesting occurred after the year 2000 in old mesic forests and occasionally in younger mesic and pine forests over 60 years old (Cumming and Armstrong, 2001). Following the rules of assigning closest-permitted alternative values, we isolated the wildfire effect by applying a standard raster GIS tool, `nibble` (ESRI, 2009), to refill the harvested blocks with their surrounding major harvested forest classes. Hereafter, we called this restored landscape the "post-fire landscape".

In order to obtain a realistic sequence of landscape configurations prior to fire disturbance, we aged each stand of the post-fire landscape in decadal intervals from 10 to 90 years, and subsequently reclassified the landscapes after each aging step. After

Table 1
Definitions, selected formulas, and unit of measurement (if applicable) for spatial configuration metrics used in this study. For more details refer to Wang and Cumming (2011) for the normalized metrics and to McGarigal and Marks (1995) for all other metrics.

Code	Description of metric	Selected metric formula[c]	
Shape indices			
s	Normalized shape index	$s = \frac{msi_{\max} - msi}{msi_{\max} - 1}$	where $msi_{\max} = \frac{1}{2}(\sqrt{\bar{x}} + 1)$
*l*msi	Log of mean shape index[a]	$msi = \frac{\sum_{j}^{n} p_j/(\pi a_j)}{n}$	where p_j is the perimeter of patch a_j and n is the number of patches
mpf	Area-weighted mean patch fractal dimension		
dlf	Double log patch fractal dimension		
Core area indices			
c	Normalized core area index	$c = \frac{tca}{tca_{\max}}$	where $tca_{\max} = \pi(\sqrt{A/\pi} - b)^2$ buffer width b
*l*tca	log of total core area (ha)[a]	$tca = \sum_{j}^{n} a_j^c$	where a_j^c is the core area of patch a_j and n is the number of patches
*l*mca	log of mean disjunct core area[a]		
*l*cas	Core area standard deviation (casd)[a]		
Spatial indices			
d	Normalized inter-patch distance	$d = \frac{mnn}{mnn_{\max}}$	where $mnn_{\max} = \frac{\sqrt{A_0}}{\sqrt{N-1}} - (2/3)\sqrt{\bar{x}}$
*l*mnn	Log mean nearest neighbor distance[a]	$mnn = (\sum_{j}^{n} h_j)/n$	where h_j is the nearest distance to patch a_j and n is the number of patches
*l*mpi	Log mean proximity index[a]		
*l*nsd	Log nearest neighbor standard deviation (nnsd)[a]		
Matrix indices			
cwe	Contrast weighted edge density (cwed)[b]		
mec	Area-weighted mean edge contrast index (awmeci)[b]		
Iji	Interspersion and juxtaposition index		

[a] Log transformation following to Cumming and Vernier (2002).
[b] Edge contrast matrix adapted from Vernier et al. (2001).
[c] A = habitat area (ha), A_0 = total area of the landscape, N = number of patches, $\bar{x}$ = Mean patch size (ha), tca = total core area (ha), mnn = mean nearest neighborhood (m), and msi = mean shape index.

all mesic forests were converted to old forests in this simulation, we referred to this landscape as the “pre-fire landscape”. Although we referred to this landscape as pre-fire, forest stands were retrospectively simulated to estimate pre-disturbance landscape conditions. Configuration metrics were calculated for 573 townships (approximately 10 km × 10 km quadrats) within the study area. An example for the simulated landscape of a township quadrat is shown in Fig. 1.

2.2. Configuration metrics

We computed 12 landscape pattern metrics following Cumming et al. (1996) and Cumming and Vernier (2002) to measure patch shape, core area, spatial distribution, and matrix of the landscape, and refer to them as “raw metrics” (Table 1). Because most metric–abundance relationships are non-linear, the residuals of linear (Trzcinski et al., 1999) or quadratic (Flather and Bevers, 2002) regression models can introduce bias. We therefore used a generalized additive model (GAM, see Hastie and Tibshirani, 1990) to obtain unbiased abundance-independent configuration metrics for the landscapes that we studied. We refer to the residuals of GAM as the measurements of landscape configurations as “detrended metrics”. The individual detrended metrics were denoted as *gam*(*metrics*), e.g. *gam*(*ltca*) for GAM residuals of total core area (TCA) where “*l*” indicates log transformation in order to reduce the positive skew in their distributions (Cumming and Vernier, 2002). All metrics were computed from landscapes rasterized at 30 m resolution with FRAGSTATS v3.3 (McGarigal et al., 2002).

The second approach for obtaining configuration metrics that are independent of habitat abundance was through normalization (Wang and Cumming, 2011): normalized total core area (*c*), normalized mean nearest neighbor distance (*d*), and normalized mean shape index (*s*) (Table 1). These metrics were calculated by dividing their raw metric measurements, the total core area (tca), mean nearest neighbor distance (mnn) and mean shape index (msi), by a theoretical maximum and then were further scaled to the values ranging from 0 to 1. Following Wang and Cumming’s (2011) convention, the core area value *c* approaching 1 implies a less fragmented landscape with respect to core area, a distance value *d* increasing towards 1 implies patches becoming increasingly isolated, and a shape value *s* approaching 1 indicates that habitat patches are maximally compact.

2.3. Evaluation of metrics

Our criteria for a good configuration metric include: (1) the metrics should be independent of habitat abundance; (2) the metrics should clearly distinguish between the different simulated landscapes; (3) the metrics should reflect the non-spatial stand table metrics, such as mean patch size or number of patches. Since there are only three normalized configuration metrics, three equivalent detrended metrics were used in the comparisons: for core area we compared *c* versus the detrended *ltca*, for nearest neighbor distance we compared *d* versus the detrended *lmnn*, and for a measure of patch shape we compared *s* versus the detrended *lmsi* (see Table 1 for explanation of these metrics).

To test whether a configuration metric meets the first criterion, independence from habitat abundance, we computed the adjusted coefficient of determination (r^2_{adj}) of the GAMs that model the relationship between each configuration metric and the habitat abundance *p*. Between each pair of the configuration metrics, the core area (*c* and *gam*(*ltca*), distance (*d* and *gam*(*lmnn*), and shape metrics (*s* and *gam*(*lmsi*), the lower r^2_{adj} indicates the weaker dependency on *p* and thus is a better configuration metric.

Secondly, we quantified the difference in configuration metrics between the landscapes with increasing amount of simulated fire disturbance (larger differences in metrics indicate more statistical power in detecting fragmentation). For the detrended metrics, we collated all the simulated landscapes to represent a full sample set of the natural landscapes. We then fitted the GAM models between the 12 raw configuration metrics and *p* respectively, and computed the detrended metric values. Configuration metrics that show significant differences between landscapes of a disturbance sequence were considered superior.

The third criterion, correlation with non-spatial stand table metrics, was tested by fitting the GAMs between each of the spatial configuration metrics and number of patches (N_p), patch size ($\bar{z}$), and standard deviation of patch size (s_z). We also used a multiple

Table 2
Definition of the non-spatial stand table variables used to evaluate configuration metric and to predict spatial configuration metrics post-fire.

Symbols	Descriptions
Initial stand configuration	
x_i	Patch sizes
$\bar{x}$	Mean patch size
z_i	$\log(x_i)$
$\bar{z}$	Mean of z_i
s_z	Standard deviation of z_i
N_p	Log of number of patches of pre-fire focal habitat
Disturbance parameters	
f_i	Log of burned focal habitat patch sizes (e.g. log of young mesic forest patch sizes)
$\bar{f}$	Mean of f_i
s_f	Standard deviation of f_i
N_f	Log of number of patches for burned focal habitat
p_f	Proportion of burned focal habitat to the total area of the landscape
m_i	The initial metric values for the pre-fire focal habitat

linear regression model between each configuration metric and the stand table metrics collectively (N_p, $\bar{z}$ and s_z). Adjusted coefficient of determination (r^2_{adj}) for single and multiple predictor variables were used again to evaluate the strength of correlation between the dependent and independent variables. A regression model with a higher r^2_{adj} value indicates a stronger relationship and a better configuration metric.

2.4. Predictive models for configuration metrics

Finally, we applied multiple linear regression models (MLM) with every detrended and normalized configuration metric as dependent variable (Table 1) and a set of stand table metrics representing initial stand configuration and a set of disturbance parameters as predictor variables (Table 2). We built multiple linear regression models to predict the post-fire habitat configurations based on the pre-fire habitat patch structure and the non-spatial quantification of fire disturbance. Fire disturbance was measured by taking current young mesic patches as the burned focal habitats (see definitions in Table 2). The pre-fire configuration metric corresponding to the dependent variable was included as a predictor variable denoted as m_i following Linke et al. (2008). To evaluate its contribution to the regression model, we calculated partial coefficients of determination for each predictor variable.

3. Results

3.1. Configuration metrics compared

Our criteria for a good configuration metric in this study were independence from habitat abundance, sensitivity to simulated landscapes, and correspondence to non-spatial stand table metrics, such as mean patch size or number of patches. With respect to the first criterion the detrended metrics are ideal simply because they are the regression residuals between the raw configuration metrics and p (Table 3). The normalized configuration metrics, on the other hand, were still correlated with p but the variance explained (r^2_{adj}) was reduced compared to their raw versions (*ltca*, *lmnn*, and *lmsi*) except for the normalized shape index *s*.

With respect to the second criterion, all normalized configuration metrics were able to differentiate landscape configurations when the extent of fire disturbance increases (Fig. 2). The response of normalized metrics over the disturbance sequence was largely linear and monotonic, whereas this was not the case for detrended metrics. Further, the power to detect significant differences between landscapes with different disturbance regimes was much larger for the normalized metrics (compare 95% confidence intervals, Fig. 2). Comparing the pre- and post-fire values of normalized metrics (Fig. 3, top row), in the majority of samples the post-fire landscapes were more fragmented in core area and shape, and less isolated in patch spatial distances. The detrended metric counterparts (Fig. 3, bottom row), on the other hand, showed a much weaker ability in differentiating landscapes before and after the fire disturbance for the core area and shape changes.

Table 3
Variance explained (r^2_{adj}) in configuration metrics through non-linear regression models (GAM) with non-spatial stand table metrics (predictor variables): habitat abundance (p), number of patches (N_p), patch size ($\bar{z}$), and standard deviation of patch size (s_z). The last column gives the r^2_{adj} for the multiple linear regression models (MLM) between the configuration metrics and all patch structural variables (N_p, $\bar{z}$, and s_z).

Metric	GAM				MLM
	p	N_p	$\bar{z}$	s_z	
Detrended					
gam(*l*tca)	0.00	0.16	0.08	0.14	0.38
gam(*l*mnn)	0.00	0.17	0.03	0.06	0.20
gam(*l*msi)	0.00	0.11	0.26	0.13	0.33
Normalized					
c	0.69	0.04	0.11	0.67	0.67
d	0.18	0.74	0.19	0.09	0.74
s	0.45	0.04	0.17	0.41	0.45
Raw					
*l*tca	0.92	0.19	0.11	0.66	0.82
*l*mnn	0.60	0.42	0.02	0.22	0.63
*l*msi	0.43	0.03	0.28	0.54	0.65

Evaluating the third criterion, correspondence to non-spatial stand table metrics, r^2_{adj} values of the multiple linear regression models indicated that the three normalized metrics reflected changes of the testing covariates better than their detrended equivalents (variance explained by MLM, Table 3). In fact, detrended metrics did not strongly correlate with any of the testing covariates individually (variance explained by GAMs, Table 3). Detrended metrics are therefore less sensitive to landscape fragmentation. The normalized metrics, *c* and *s* primarily represent patch size standard deviation (s_z), and *d* primarily represents the number of patches (N_p). In contrast, none of the three detrended metrics were correlated well with any of the testing covariates (Table 3). With respect to the third criterion, normalized metrics also better characterized landscape changes due to simulated fires.

3.2. Habitat fragmentation predicted by the normalized metrics

All three normalized metrics were moderately predictable based on initial configuration and disturbance regime according to the regression model results (Table 4). Among all the predictor variables, the initial (pre-fire) value of the configuration measure (m_i) and habitat abundance (p) of the pre-fire landscapes, and the proportion of habitat lost to fires (p_f) were consistently significant in all three regression models. For the normalized core area and shape metrics (*c* and *s*), these three variables were the only significant predictor variables. For the normalized distance metric (*d*), a number of stand table metrics (N_p, N_f, $\bar{f}$, and s_f) were also significant, indicating that spatial distribution of patches could be altered not only by habitat loss but also by the way habitat was lost. Evaluated by the overall variance explained (r^2_{adj}), the predictive power for core area as dependent variable *c* was notably higher than that of *d* and *s*, respectively (Table 4).

For all three detrended metrics (*gam*(*ltca*), *gam*(*lmnn*), and *gam*(*lmsi*)) corresponding to the normalized metrics (*c*, *d*, and *s*), the predictive models were very weak, with $r^2_{\text{adj}} \leq 0.25$ (Table 4). However, the other detrended matrix indices (for which we could not develop a normalized equivalent) were moderately high, and

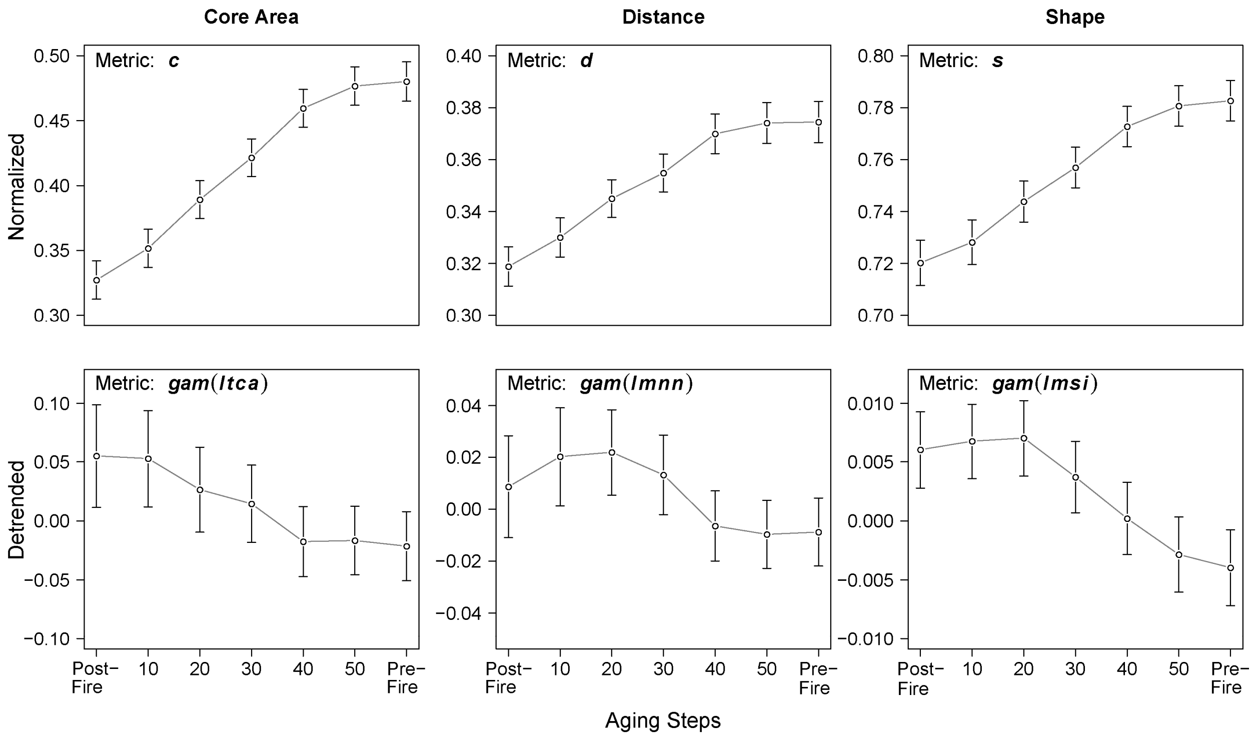

Fig. 2. Power of detrended versus normalized configuration metrics to distinguish landscape configurations under simulated levels of fire disturbance. The graphs show means and 95% confidence intervals of all townships within the study area.

appear to be as useful in configuration predictions as the normalized metrics. For all these three detrended metrics, the initial configuration measures (m_i) were the major predictors to the models. However, the number of disturbance patches (N_f) and proportion of habitat lost to fires (p_f) also played contributing roles in these predictive models.

4. Discussion

4.1. Use of detrended metrics

Detrended metrics can differentiate the pre-fire landscapes from the post-fire landscapes in terms of core area and patch shape,

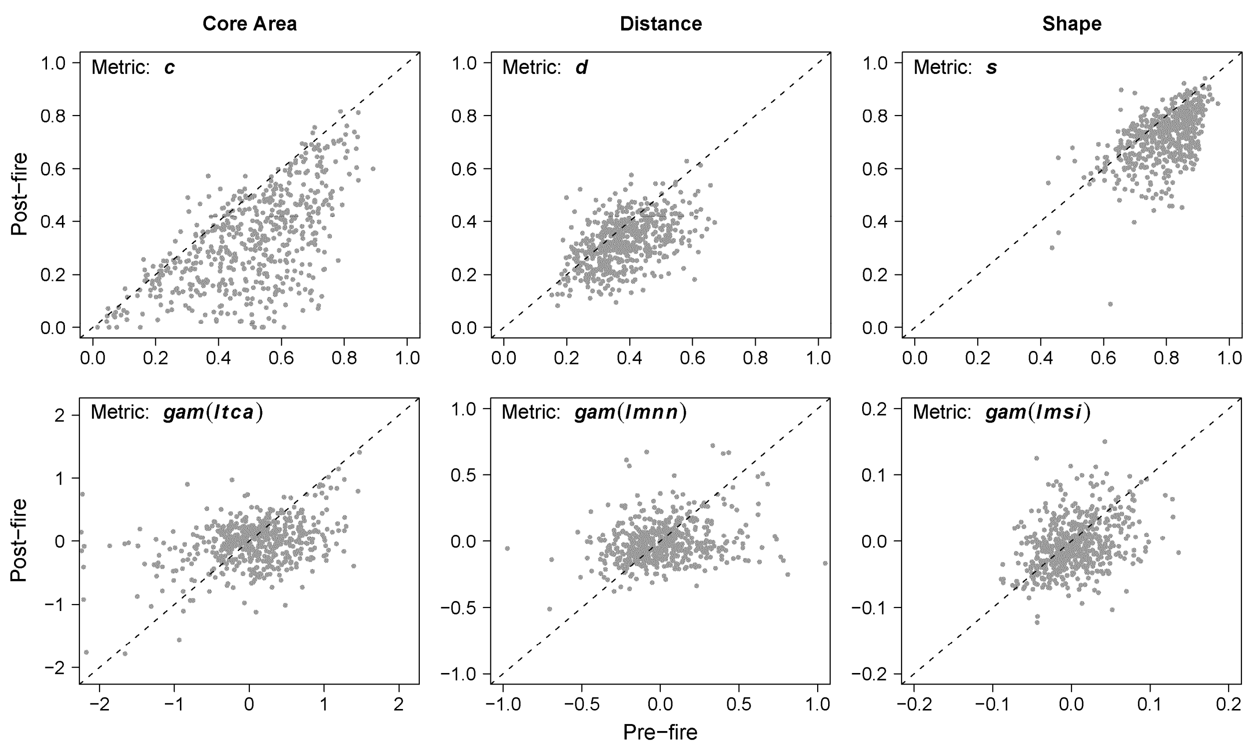

Fig. 3. Changes between pre- and post-fire configuration metrics for all townships of the study area (represented by dots). The null model of no effect ($y = x$) is shown by the dashed diagonal line.

Table 4
Multiple linear regression models to predict post-fire spatial configuration metrics based on the pre-fire landscapes and non-spatial measurement of the levels of fire disturbance. Partial r^2 represent the contribution of each independent variable to the regression model. "–" = no entry. Significant codes: 0 '***', 0.001 '**', and 0.01 '*'. r^2_{adj} = adjusted coefficient of determination values for each regression model.

Metrics	m_i	$\bar{z}$	s_z	N_p	p	$\bar{f}$	s_f	N_f	p_f	r^2_{adj}
Shape indices										
s	0.162***	–	–	–	0.062***	–	–	–	0.092***	0.454
gam(*lmsi*)	0.062***	–	–	0.019**	–	0.011*	–	0.009*	–	0.251
gam(*mpf*)	0.094***	0.007*	–	0.016**	–	0.017**	–	–	0.024***	0.153
gam(*dlf*)	0.180***	–	–	–	–	0.010*	–	–	0.009*	0.193
Core area indices										
c	0.248***	–	–	–	0.159***	–	–	–	0.280***	0.697
gam(*ltca*)	0.113***	–	–	–	–	–	–	–	–	0.178
gam(*lmca*)	0.142***	–	–	–	–	–	–	–	–	0.227
gam(*lcas*)	0.160***	–	–	–	–	–	–	–	–	0.240
Spatial indices										
d	0.027***	–	–	0.034***	0.114***	0.010*	0.009*	0.025***	0.033***	0.439
gam(*lmnn*)	0.055***	0.008*	–	–	–	–	–	–	–	0.054
gam(*lmpi*)	0.090***	0.007*	–	0.021***	–	0.008*	–	0.008*	0.011*	0.212
gam(*Lnsd*)	0.047***	–	–	–	–	–	–	–	–	0.052
Matrix indices										
gam(*cwe*)	0.270***	–	–	0.020**	0.008*	–	–	0.045***	0.063***	0.418
gam(*mec*)	0.647***	0.008*	–	0.040***	0.014**	0.008*	–	0.044***	0.056***	0.687
gam(*iji*)	0.417***	0.031***	–	–	–	0.014**	–	0.074***	0.053***	0.493

but normalized metrics performed better in distinguishing levels of fragmentation (Figs. 2 and 3). Our results confirm that the detrending method is not an ideal solution to measure landscape configuration as pointed out by Koper et al. (2007). It should be noted that the detrending approach is still valid when p is held constant and when the sampled landscapes cover the full range of configuration variation at all levels of p. A critical requirement for detrending is that the regression model needs to be properly fitted. If the sampled landscapes are biased i.e. either very fragmented or compacted at different p levels, the fitted regression models between the raw metrics and p would be biased.

To predict detrended metric changes, the sampled landscapes on which the regression models were built must be sufficient to cover the full range of configuration variations at all levels of p and the metrics must be highly predictable. While the three detrended metric prediction models for the matrix indices are strong (Table 4), the predictive power depends greatly on the processes (e.g. fire or harvesting) that shaped the landscapes. Consequently, these models may not be easily applicable to landscapes with different harvesting and fire regimes.

4.2. Evaluation of normalized metrics

The normalized metrics are independent from the sampling methods and sample size because their values do not rely on regression models. These metrics accurately reflect changes in patch number, mean patch size, and spatial arrangement of habitat patches associated with simulated fire disturbance (Table 3). Although it is probably not possible to have a metric that measures all aspects of landscape configuration, we consider spatial metrics that are clearly related to one or more stand table metrics as superior. Results in our study showed that among the three normalized configuration metrics, d responds well to patch numbers, and c is best represents variation in patch size. Their combination covers configuration dynamics very well. For example, a high d value indicates high number of more isolated patches, and if c is low, together they indicate more small patches in the landscape after disturbance. Habitat fragmentation (leading to smaller, more isolated, and increased numbers of habitat patches) is therefore well described with these two normalized metrics.

For the purpose of predicting spatial configuration metrics after disturbance, non-spatial models are widely used in forest management and land use planning. These models use stand table metrics, such as number of polygons or mean and standard deviation of polygon size, that are widely available from forest inventory databases to predict spatial configuration metrics that characterize critical wildlife habitat (e.g. Cumming and Vernier, 2002; Linke et al., 2008). We found that normalized metrics were always more predictable than their detrended equivalents. Nevertheless, between 30 and 55% of the variance remains unexplained and a large portion of the variance explained by the initial (pre-fire) configuration metric itself (Table 4). We conclude that random or spatial elements within the normalized metrics cannot be comprehensively captured by the non-spatial predictor variables, and therefore configuration metrics cannot be completely replaced by stand table metrics.

Lastly, we point out that even though the normalized metrics are conceptually independent measurements of landscape configurations, they still showed correlations with habitat abundance in a real-world landscape (Table 3).

4.3. Habitat fragmentation after fire

Concepts of "pre-fire habitat structure" and "pre-fire landscape" allowed us to compare habitat configurations after disturbance to their initial undisturbed state. Habitat configuration changes depend on how the disturbance agent acts. For example, under different fire conditions fires may indiscriminately burn different types of forest patches, or propagate only selectively through vulnerable stand types. Landscape configurations can become more compacted after small residual patches were eliminated, or they may become more fragmented when bigger patches are split. Comparing configurations of pre- and post-fire landscapes, both approaches indicated that fires changed the core area and shape of the old mesic forest patches. Normalized metrics also detected that habitat patches became spatially more aggregated, while detrended metrics did not find significant differences in patch distribution. Moreover, normalized metrics changed monotonically with levels of fragmentation, and have a constrained value range that allows comparisons of spatial landscape configurations among different areas.

In this paper, we contributed a new set of configuration metrics that provide a more consistent measure of habitat fragmentation, and that are largely independent of measures of habitat loss.

Normalization also showed improvement over other widely used detrending methods in accurately reflecting changes in patch number, mean patch size, and spatial arrangement of habitat patches. Habitat fragmentation is an important cause of decline or extirpation of species populations (Rosenzweig, 1995), and an accurate assessment and monitoring of habitat fragmentation is important for wildlife management and conservation planning. Our case study of simulated fire disturbance in a boreal forest environment indicates that normalized configuration metrics are a promising new tool to monitor and predict habitat fragmentation under different disturbance regimes.

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