Characterizing forest fragmentation: Distinguishing change in composition from configuration

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ABSTRACT

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Forest fragmentation can generally be considered as two components: 1) compositional change representing forest loss, and 2) configurational change or change in the arrangement of forest land cover. Forest loss and configurational change occur simultaneously, resulting in difficulties isolating the impacts of each component. Measures of forest fragmentation typically consider forest loss and configurational change together. The ecological responses to forest loss and configurational change are different, thus motivating the creation of measures capable of isolating these separate components. In this research, we develop and demonstrate a measure, the proportion of landscape displacement from configuration (P_y), to quantify the relative contributions of forest loss and configurational change to forest fragmentation. Landscapes with statistically significant forest loss or configurational change are identified using neutral landscape simulations to generate underlying distributions for P_y. The new measure, P_y, is applied to a forest landscape where substantial forest loss has occurred from mountain pine beetle mitigation and salvage harvesting. The percent of forest cover and six LPIs (edge density, number of forest patches, area of largest forest patch, mean perimeter area ratio, corrected mean perimeter area ratio, and aggregation index) are used to quantify forest fragmentation and change. In our study area, significant forest loss occurs more frequently than significant configurational change. The P_y method we demonstrate is effective at identifying landscapes undergoing significant forest loss, significant configurational change, or experiencing a combination of both loss and configurational change.

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Introduction

Forest loss and change in the configuration of forest land cover are often considered collectively as fragmentation. Forest loss and fragmentation are known to impact wildlife survival, habitat quality (Fahrig, 1997), and an organism's ability to navigate the landscape (Schumaker, 1996). However, species respond differently to forest loss and configurational change (Fahrig, 1997). Studies aimed at quantifying the effects of forest fragmentation frequently employ landscape pattern indices (LPIs) to measure forest loss (compositional change) and change in the arrangement (configurational change) of forest on the landscape.

Tracking changes in raw LPI values over time is frequently used to monitor forest fragmentation (e.g., Frohn & Hao, 2006); however, the comparison of raw LPI values is problematic due to interdependencies between the composition of the landscape and resulting configuration values (Gustafson & Parker, 1992; Hargis, Bissonette, & David, 1998). Current research suggests that comparison of raw LPI values should be avoided (Gergel, 2007), and new methods for comparing LPI values (e.g.,

Remmel & Csillag, 2003) or maps of land cover (e.g., Csillag, Kabos, & Remmel, 2006; Remmel & Csillag, 2006) may be useful for adding statistical context to landscape pattern analysis.

The continuing use of LPIs is a testament to their broad applicability (Cardille & Turner, 2002), ease of implementation (McGarigal & Marks, 1995; Mladenoff & DeZonia, 2004), and computational simplicity (McGarigal & Marks, 1995). Forest fragmentation studies frequently employ LPIs as a means of quantitative analysis of landscape change (e.g., Gillanders, Coops, Wulder, Gergel, & Nelson, 2008; Nagendra, Pareeth, & Ghate, 2006; Serra, Pons, & Sauri, 2008), however a statistical framework is generally absent (Csillag & Boots, 2005). Statistically significant change in fragmentation is difficult to identify with a single measure because of the interdependency between the amount forest loss and resulting change in configuration LPIs. In order to properly identify significant landscape change composition must be considered in the context of configuration to account for the dependency of configurational change on forest loss.

To illustrate the importance of considering both composition and configuration when characterizing forest fragmentation consider the following example. Edge density (ED) is a common metric used to characterize forest fragmentation. In binary simulated landscapes ED has been shown to have the relationship portrayed in Fig. 1, with edge density values peaking when the proportion of forest is 50%. If a landscape that is predominantly forest (T1 in Fig. 1) were to undergo small (T2a in Fig. 1), or large (T2b in Fig. 1), amounts of forest loss, two markedly different landscapes would result. Similar values for the configuration metric ED and similar changes in ED would be expected in both scenarios. The problem of identical LPI values is common to many LPIs frequently used in fragmentation studies and can be clearly seen using simulated landscapes (Fig. 2). In real landscapes (taken from our study area) increased variability in LPI is observed and the problem identical LPI at multiple composition levels is more apparent (Fig. 2 insets).

Trajectory analysis of LPI values, introduced by Cushman and McGarigal (2007), provides a useful framework for quantifying temporal trends in landscape pattern. Cushman & McGarigal identify four metrics for describing the trajectory of a landscape (*displacement, velocity, acceleration, and divergence*). We build upon the displacement measure, which characterizes the distance between the location of a landscape and its starting point in LPI attribute space. Displacement can be used to measure the magnitude of change a landscape has incurred, but does not describe the nature of this change. Based on displacement, we develop an approach for quantifying forest fragmentation that separately identifies landscapes undergoing significant forest loss or configurational change.

The objective of this research is to introduce a method for quantifying forest fragmentation by isolating the separate processes of forest loss and configurational change using LPIs. We introduce a metric: P_y, the proportion of landscape displacement from configuration, which identifies significant changes as either forest loss or configurational change. An application using a region in British Columbia, Canada, which has been subject to mountain pine beetle (*Dendroctonus ponderosae*) infestation, and subsequent salvage and mitigation harvest activities is used to highlight this approach. Over this region we demonstrate how the P_y approach improves interpretation of fragmentation measured with LPIs by identifying landscapes that have simply experienced forest loss or more complex configurational change.

Material and methods

An approach for characterizing forest fragmentation

Displacement (D_i*)*

Displacement (D_i), is computed by measuring the distance between T1 and T2 LPI values on a two-dimensional plane where the *x*-axis is composition, and the *y*-axis is a configuration LPI (1).

$$D_i = \sqrt{d_x^2 + d_y^2} \tag{1}$$

D_i is the displacement of the landscape for configuration index *i*, and d_x is the change in composition between the two time periods, and d_y is the change in configuration index *i*. D_i is used to measure the magnitude of overall change, but is also used
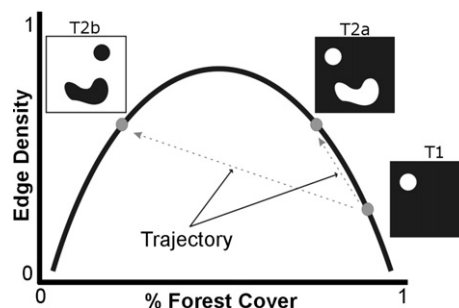

Fig. 1. Hypothetical trajectory of a landscape experiencing different amounts of forest loss but with identical changes in LPI value. For interpretation consider black – forest, and white – non-forest.
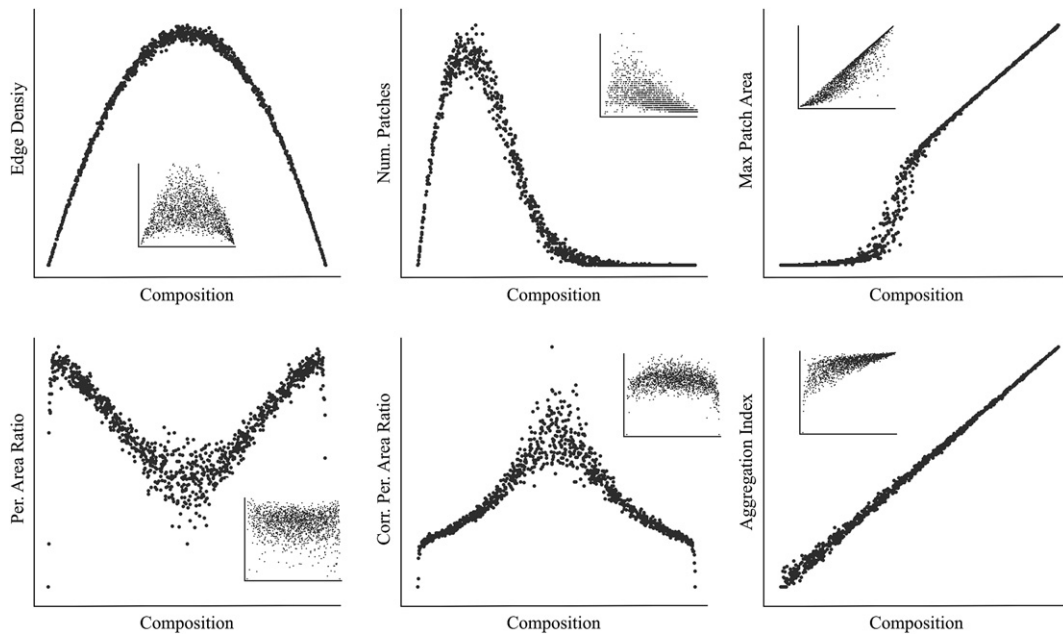
Fig. 2. Relationship between landscape composition and configuration LPI for six selected metrics. Main distributions were derived from 1000 simulated binary random landscapes. Inset distributions were derived from real landscapes in our study area.

for the derivation of P_y. D_i calculated in this manner, exclusively considers change in a configuration LPI with change in composition, as has been recommended (Gergel, 2007; Remmel & Csillag, 2003).

Proportion of displacement from configuration (P_y)
From (1) the following relationship exists:

$$D_i^2 = d_x^2 + d_y^2 \tag{2}$$

Based upon this understanding, we define the proportion of the displacement from configuration (P_y) (3), which ranges from 0 to 1:

$$P_y = \frac{d_y^2}{D_i^2} \tag{3}$$

P_y measures the relative amount of configurational change given the overall displacement (including change in forest amount). Low P_y values indicate change due primarily to forest loss, high P_y values indicate change due primarily to configurational change, and medium P_y values indicate both forest loss and configurational change have occurred.

Study area

Located within the interior plateau of British Columbia, Canada, the Prince George forest district (Fig. 3) is situated primarily in the Sub-Boreal Spruce biogeoclimatic zone (Meidinger & Pojar, 1991). White spruce (*Picea glauca*), subalpine fir (*Abies lasiocarpa*), and lodgepole pine (*Pinus contorta*) are the dominant forest species within this region. The Prince George forest district has experienced extensive timber losses due to mountain pine beetle infestation, and an increased annual allowable cut was prescribed as a salvage and spread mitigation strategy (British Columbia Ministry of Forests and Range, 2007). A 40 by 40 km study area that was subject to infestation by mountain pine beetle and related management activities is the basis of our case study.

Data

A land cover dataset for 2000 was obtained from the Earth Observation for Sustainable Development of forests (EOSD) program (Wulder et al., 2003; Wulder, White, Cranny, et al., 2008). These data, derived from Landsat-7 ETM + imagery with land cover products resampled to a spatial resolution of 25 m, represent an applicable spatial resolution for monitoring forest disturbance (Healey, Cohen, Yang, & Kennedy, 2007). The EOSD data consist of 23 detailed land cover classes that are
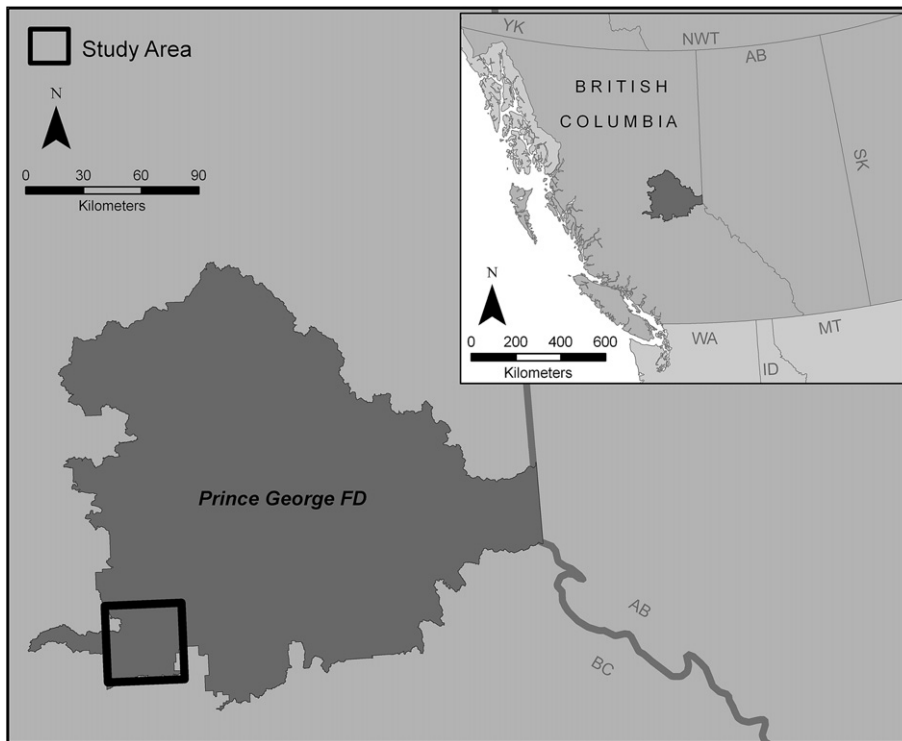
Fig. 3. Study area (40 by 40 km) located within the Prince George forest district, British Columbia, Canada.

developed through a logical hierarchy that enables aggregation into three base generalized land cover classes: forest, non-forest and other (see Wulder & Nelson, 2003) to support the generation of LPI. To monitor forest loss and fragmentation, an analogous year 2006 forest, non-forest, other classification was generated from Landsat imagery. The enhanced wetness difference index (EWDI) change-detection method (Franklin, Lavigne, Moskal, Wulder, & McCaffrey, 2001; Franklin, Lavigne, Wulder, & McCaffrey, 2002) was used to derive a binary forest change map for 2006 following Han et al. (2007). The 2000 EOSD data were updated to 2006 conditions, converting the forest class to non-forest where forest loss was detected based on the EWDI method. An independent 2006 land cover classification was not created thereby avoiding error propagation related to the comparison of separate land cover classifications representing different dates (Fuller, Smith, & Devereux, 2003).

The validity of the 2000 land cover dataset created under the EOSD program has been assessed in three separate studies (Remmel, Csillag, Mitchell, & Wulder, 2005; Wulder et al., 2006; Wulder, White, Magnussen, & McDonald, 2007). Over all applicable EOSD classes (e.g., 23 class generalization to cover types) a target accuracy of over 80% was obtained using the mode class of a 3 × 3 spatial neighbourhood of the EOSD data (Wulder et al., 2007), which contains more detail than was used in this study. Accuracy was found to increase as class generalization is undertaken (Remmel et al., 2005). We performed an accuracy assessment on the 2006 land cover dataset. Visual interpretation of 0.5 m digital imagery was used as validation data based upon an existing framework used in the EOSD program (Wulder et al., 2007). An overall accuracy of 91.3% was obtained, with high user (100%) and producer (87.5%) accuracies for the forest class.

Analysis

Selection of LPIs

Six LPI (Table 1); edge density (ED), number of forest patches (NPF), area of largest forest patch (FMAX), mean landscape perimeter area ratio (PAR), corrected mean landscape perimeter area ratio (CPAR), and aggregation index for the forest class (AI), were selected based on principles of forest fragmentation (Haines-Young & Chopping, 1996) and to provide examples of LPIs with varying relationships between composition and configuration (see Fig. 2). Two analysis scales (landscapes) were chosen: 1 km ($n = 1600$) and 10 km ($n = 16$) non-overlapping square units. The 1 and 10 km analysis units represent typical scales used for examining landscape trends at the regional level (Wulder, White, Han, et al., 2008).

Standardization of LPI values

When comparing multiple LPIs it is advantageous to standardize (normalize) values due to differences in measuring units and scale. LPI values were standardized to zero mean and unit variance using (4), outlined in Kaufman and Rousseeuw (1990).

Table 1
Six selected LPIs and their formulation. LPIs were calculated using APACK version 2.23 (see Mladenoff and DeZonia, 2004).

LPI	Formulation	Notes
Edge density (ED)	$ED = \frac{P}{A}$	$P = total\ perimeter$
Number of forest patches (NPF)	$NPF = n_f$	$A = landscape\ area$
Area of largest forest patch (FMAX)	$FMAX = \max[a_f]$	$n = number\ of\ patches$
Mean landscape perimeter area ratio (PAR)	$PAR = \frac{(\sum_{j=1}^{n} \frac{p_j}{a_j})}{n}$	$f = forest\ patch$
		$a = area\ of\ patch$
Corrected mean landscape perimeter area ratio (CPAR)	$CPAR = \frac{(\sum_{j=1}^{n} \frac{p_j}{\sqrt{4\pi a_j}})}{n}$	$p = perimeter\ of\ patch$
		$e_{ff} = adjacent\ edges\ of\ class\ f\ and\ itself$
Aggregation index forest class (AI)	$AI = \frac{e_{ff}}{\max[e_{ff}]}$	

$$z_{ki} = \frac{x_{ki} - m_i}{s_i} \tag{4}$$

Here, z_{ki} is the standardized LPI value for observation k of LPI i, x_{ki} is the original LPI value for observation k of LPI i, m_i is the mean of LPI i, and s_i is a measure of dispersion for LPI i. We use the mean absolute deviation as the measure of dispersion as it is more robust than the typically used standard deviation (Kaufman & Rousseeuw, 1990).

Identifying high and low P_y values

In order to identify high P_y values, which indicate the dominance of configurational change, and low P_y values, which indicate the dominance of forest loss, thresholds for defining high and low P_y must be determined. Neutral (random) landscape simulations provide a logical starting point for generating distributions of P_y to assist in delineating high and low P_y values. Alternatively, distributions for P_y could be generated using a large database of real landscapes that have undergone change. Landscape simulation has previously been used with LPIs to examine topics such as the relationship between landscape composition and configuration (Gustafson & Parker, 1992), statistically compare LPI values (Remmel & Csillag, 2003), and to develop spatially local measures (Boots, 2006).

We simulated 9999 random binary landscapes (coded 1, 0) to represent forest/non-forest conditions. The T1 composition of each simulated landscape was drawn from a frequency distribution of landscape composition levels observed in our study area (where landscape composition was conditioned to be >5% forest). The amount of loss was simulated by randomly drawing from the frequency distribution of observed forest loss in our study area (forest loss was conditioned to be >0%). The drawn amount of loss was then randomly removed from each simulated landscape to generate 9999 T2 landscapes of forest change. This simulation procedure is analogous to the change-detection method used for creating the real T1 and T2 forest/non-forest data. This procedure was repeated for both 1 km (40×40 pixel) and 10 km (400×400 pixel) analysis units.

Simulated $T1$ and $T2$ landscapes were used to generate distributions of P_y for each configuration LPI. The randomly generated distribution of P_y values can be used to identify statistically unexpected high or low P_y values. Based on percentiles from random distributions of P_y, thresholds to define unexpectedly high or low P_y are defined using a two-tailed test and $\alpha = 0.10$.

Results

Distributions of P_y and selection of threshold values

Distributions for P_y from random simulated landscapes were used to derive threshold values for denoting significant P_y results. Distributions for the 9999 random landscapes for the 1 km analysis unit are presented (Fig. 4), along with the distributions of P_y for the real landscapes at the 1 km scale (insets, Fig. 4). The distributions for P_y for the 10 km analysis unit are not given, but are comparable to those for the 1 km case. The distributions of P_y show obvious peaks at $P_y = 0$, except with the metric AI. $P_y = 0$ represents landscapes where forest loss has occurred but no configurational change has been measured. Landscapes where $P_y = 0$ are frequently associated with small levels of change. As we are using P_y in an exploratory role, we separated $P_y = 0$ into a unique class and derive thresholds for significant high and low P_y from the distribution with these cases removed. Thus, four classes are reported: $P_y = 0$, significant low P_y, significant high P_y, and not significant.

A liberal α value ($\alpha = 0.10$) was chosen for illustrative purposes. Values in the upper 5% of the distribution are denoted as significant high P_y and those in the lower 5% of the distribution are denoted as significant low P_y. The threshold values for $\alpha = 0.10$ along with threshold values for $\alpha = 0.05$ and $\alpha = 0.20$ are given, to show the impact of this parameter (Table 2) for both the 1 km and 10 km analysis scales. Across scales of analysis, significant thresholds for P_y do not differ greatly.

P_y results

Results for P_y are reported for each of the six selected LPI at the 1 km (Fig. 5) and 10 km (Fig. 6) analysis scales. At the 1 km scale it is interesting to compare the number of significant results for different LPI. 1231 out of 1600
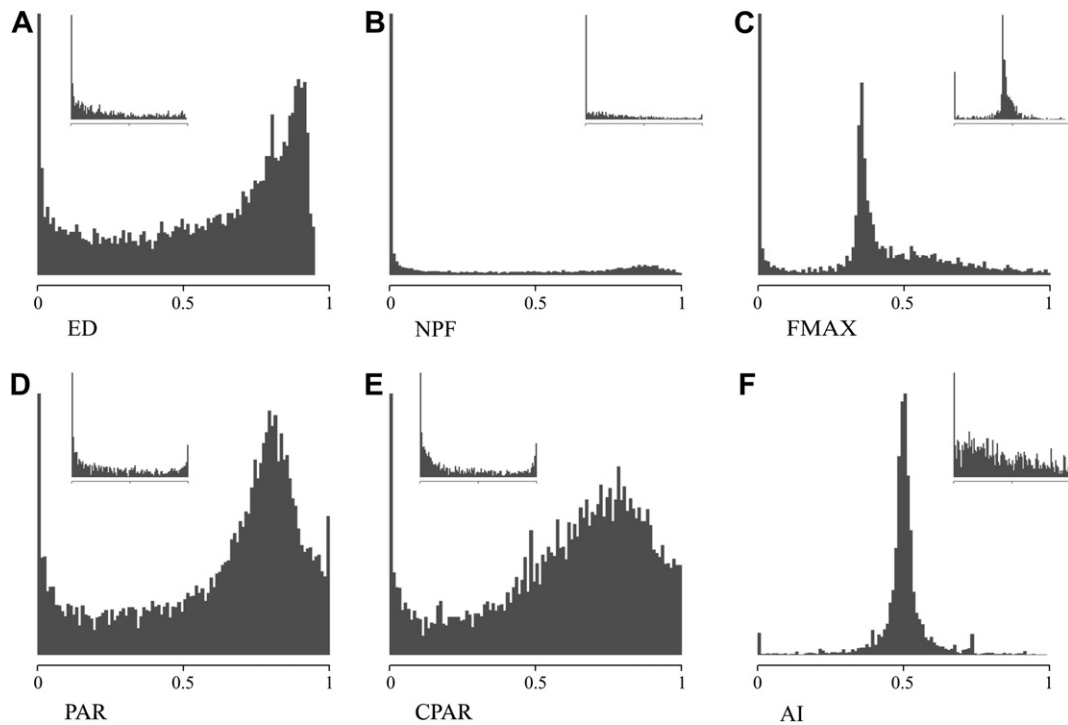
Fig. 4. Distribution of P_y for each of the six selected LPIs using 9999 simulated binary random landscapes undergoing random change. Inset distributions are from 1231 real landscapes in our study area that have undergone change. A) edge density – ED, B) number of forest patches – NPF, C) area of largest forest patch – FMAX, D) mean landscape perimeter area ratio – PAR, E) corrected mean landscape perimeter area ratio, and F) aggregation index forest class – AI.

1 km analysis units experienced change. AI had the largest number of significant results, and FMAX the lowest (Table 3).

Areas where P_y is significantly high in all or most of the selected metrics are associated with configurational change (Fig. 7). Areas where $P_y = 0$ or P_y is significantly low in all or most of the selected metrics indicate areas simply experiencing forest loss (Fig. 7). Areas where P_y is predominantly not significant are interpreted to be undergoing a combination of forest loss and configurational change.

Discussion

Empirical studies have demonstrated explicit links between wildlife occurrence and forest fragmentation (e.g., habitat uptake by American marten, Hargis, Bissonette, & Turner, 1999). Increasingly, conservation research relies on implicitly

Table 2
Comparison of threshold values for denoting significant P_y using $\alpha = 0.05$, 0.10, and 0.20, for 1 km (top) and 10 km (bottom) analysis units. Note: $\alpha = 0.10$ was used in this study.

|	$\alpha = 0.05$		$\alpha = 0.10$		$\alpha = 0.20$	
	low	high	low	high	low	high
1 km						
ED	0.0064	0.9254	0.0218	0.9165	0.0811	0.8997
NPF	0.0012	0.9629	0.0026	0.9386	0.0076	0.9044
FMAX	0.0016	0.8815	0.0094	0.8104	0.0854	0.7059
PAR	0.0073	0.9790	0.0290	0.9550	0.1103	0.9118
CPAR	0.0145	0.9752	0.0498	0.9521	0.1692	0.9063
AI	0.2915	0.7248	0.3747	0.6390	0.4322	0.5685
10 km						
ED	0.0019	0.8678	0.0090	0.8612	0.0331	0.8447
NPF	0.0003	0.9713	0.0005	0.9499	0.0010	0.9276
FMAX	0.0111	0.8985	0.0397	0.8919	0.1265	0.8817
PAR	0.0048	0.9268	0.0188	0.9145	0.0690	0.8872
CPAR	0.1344	0.9401	0.3206	0.9287	0.3210	0.8953
AI	0.4918	0.5084	0.4936	0.5065	0.4951	0.5048
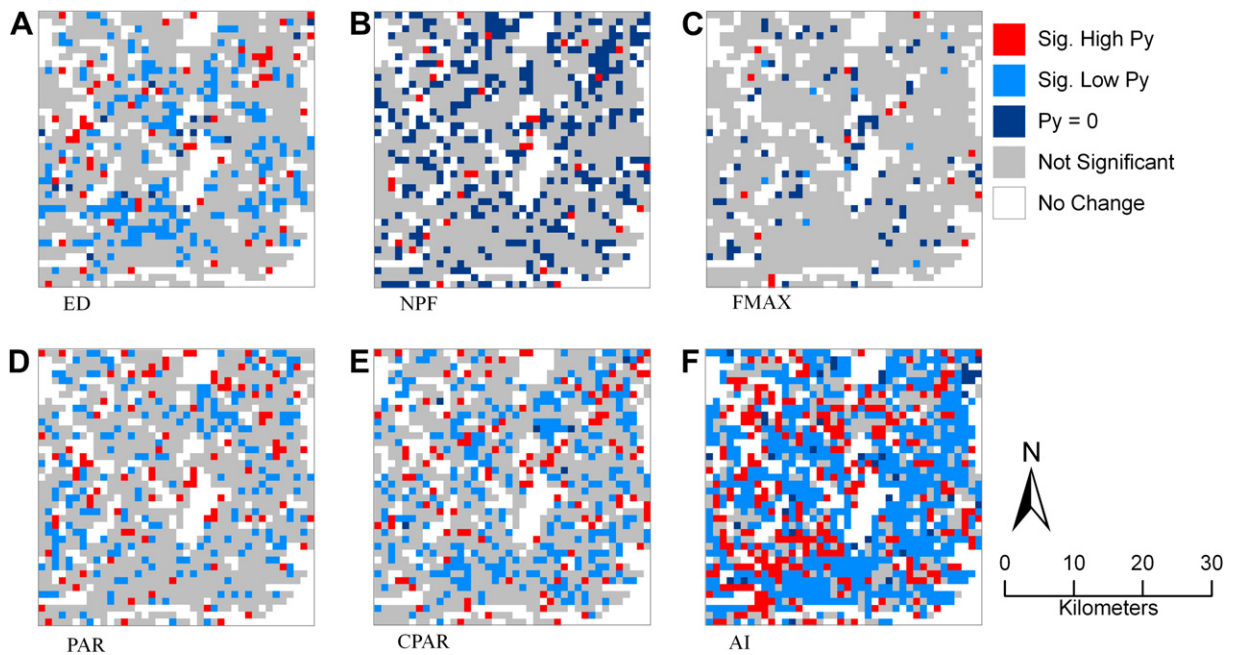
Fig. 5. Maps of significant P_y values with 1 km analysis unit. Significant values were identified using simulated distribution for P_y and $\alpha = 0.10$. A) edge density – ED, B) number of forest patches – NPF, C) area of largest forest patch – FMAX, D) mean landscape perimeter area ratio – PAR, E) corrected mean landscape perimeter area ratio, and F) aggregation index forest class – AI.

defined relationships between wildlife processes and fragmentation (e.g., whether an organism is positively or negatively impacted by fragmentation). Current international forest management policy now requires reporting on forest fragmentation, as it is considered an indicator of biological diversity (Montreal Process Liaison Office, 2000). The desire to use forest cover and pattern information as a quantitative indicator of forest biodiversity originates from a lack of consensus on ideal indicator species and the cost effectiveness of remote sensing methods (Noss, 1999). Single time LPI measurements have been used for
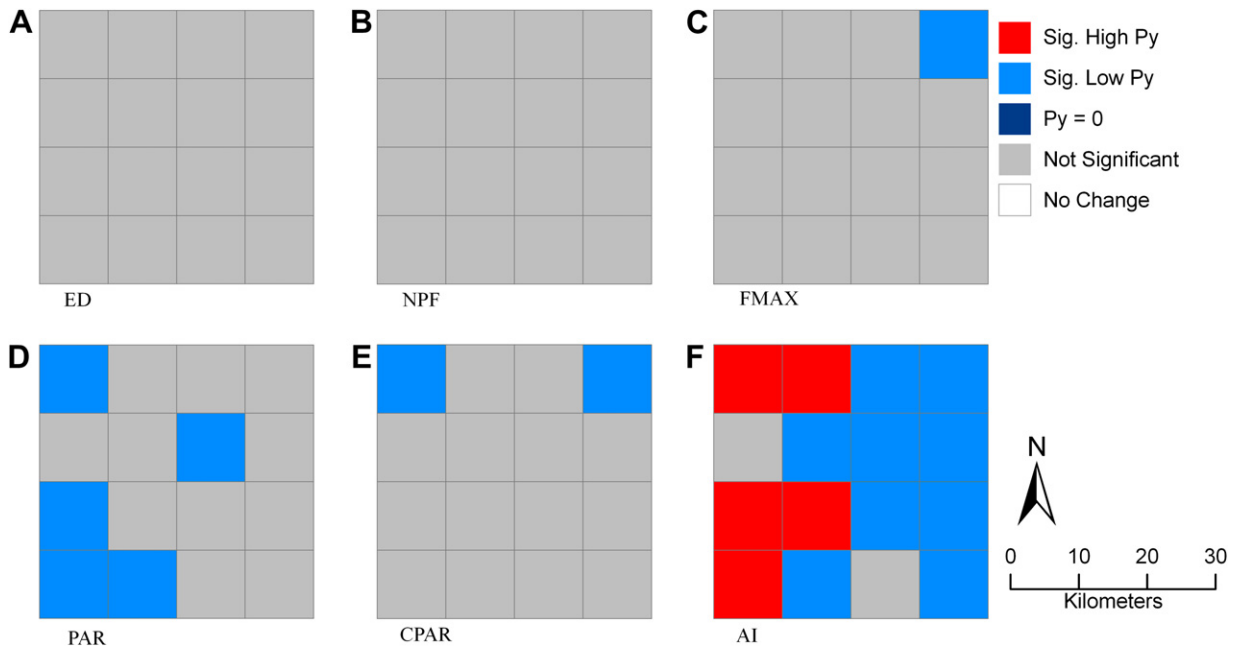

Fig. 6. Maps of significant P_y values with 10 km analysis unit. Significant values were identified using a simulated distribution for P_y and $\alpha = 0.10$. A) edge density – ED, B) number of forest patches – NPF, C) area of largest forest patch – FMAX, D) mean landscape perimeter area ratio – PAR, E) corrected mean landscape perimeter area ratio, and F) aggregation index forest class – AI.

Table 3
Number of results where $P_y = 0$, P_y significantly low, and P_y significantly high for each selected LPI using a 1 km analysis unit.

Metric	$P_y = 0$	Sig. low	Sig. high
ED	17	215	59
NPF	333	0	33
FMAX	75	11	15
PAR	0	211	95
CPAR	6	296	110
AI	39	645	262

initial reporting (Riitters, Wickham, & Coulston, 2004; Wulder, White, Han, et al., 2008), but effective methods for monitoring the temporal changes in forest loss and fragmentation, such as P_y, are required to evaluate forest management practices and change.

Research has shown that the environmental response to habitat loss and fragmentation are different (Fahrig, 1997). Forest loss can lead to reduced species diversity (Hill & Curran, 2001), while configurational changes have been linked to increased wildlife-vehicle collisions (Gonser, Jensen, & Wolf, 2009). Separating the components of *loss* and *configurational change* is difficult given that, in general, configurational change is driven by some form of habitat (e.g., forest) loss. This has led researchers to explore the use of density (composition) based indicators for monitoring forest fragmentation (e.g., Wickham, Riitters, Wade, & Homer, 2008). However, these indicators are insensitive to properties related to configurational change (e.g., increased edge and number of patches, decreasing patch areas and connectivity). Distinct configurational changes resulting from deforestation imply different landscape altering processes, not detectable by simply monitoring forest loss (Mertens & Lambin, 1997). Using the mountain pine beetle case study, we demonstrate the ability of the metric P_y to differentiate between landscapes primarily experiencing forest loss ($P_y = 0$ and significantly low P_y), concurrent forest loss and configurational change (P_y not significant), and those primarily experiencing configurational change (significantly high P_y).

Landscape simulation was used to generate distributions for P_y for six LPI at two analysis scales. For five of the six LPI the distribution from 9999 simulated landscapes was comparable to the observed distribution (see Fig. 4). For the AI metric however, the simulated distribution of P_y was noticeably different from the observed distribution. It is likely that the randomization approach used for selecting thresholds is inappropriate for use with AI as the distribution in the real case was markedly different from the simulated landscapes.

Using a large database of changed landscapes at multiple scales, or simulating spatial aggregation in the randomization procedure (see Remmel & Csillag, 2003), could improve significance threshold selection. For example, use of the AI metric here was limited due to the extreme differences in the distribution of P_y in the real and random scenarios. If the selection of
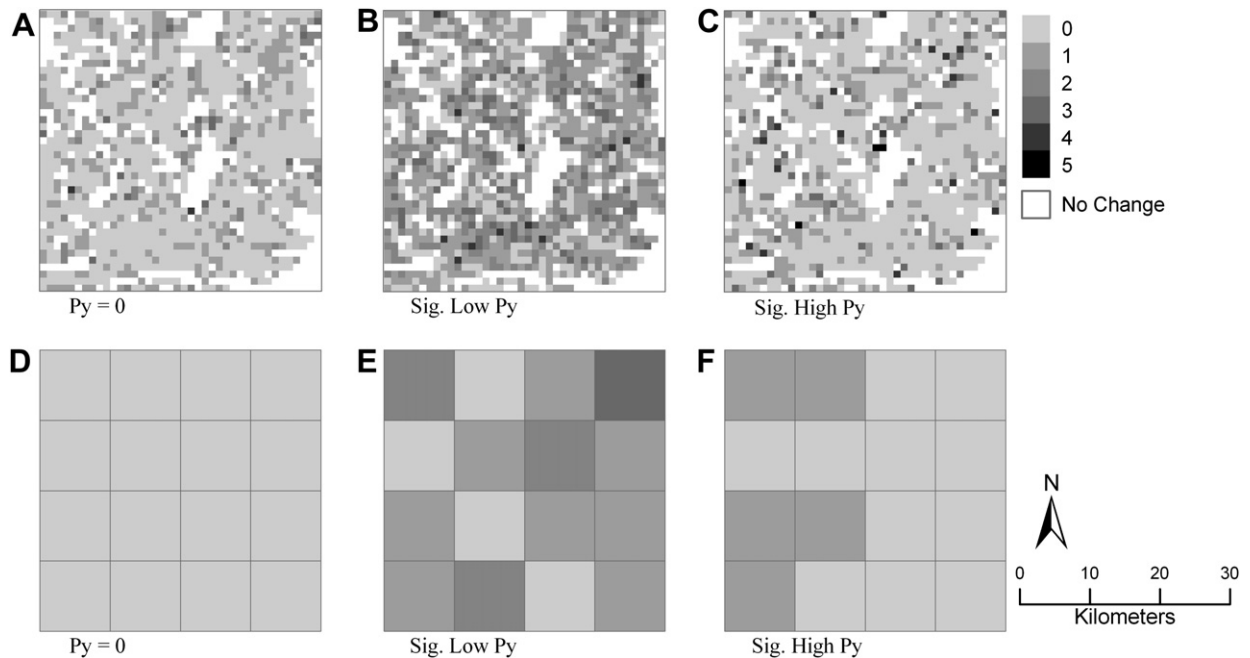

Fig. 7. Counts of $P_y = 0$, significantly low P_y, and significantly high P_y, for the 1 km (top) and 10 km (bottom) analysis units. A value of 0 indicates that P_y was not significant in any of the selected LPIs, a value of 5 indicates that P_y was significant in five of the selected LPI. There were no instances of P_y significant for all six selected LPI.

significant P_y was based on a more realistic distribution for the metric AI, significant results would be less frequent and have more relevance.

This research implemented two analysis scales (1 and 10 km) suitable for regional monitoring of forest loss and fragmentation. Using the selected data grain (25 m), analysis units smaller then 1 km tend towards forest patch or no patch, while those larger then 10 km offer reduced interpretability due to various landscape altering processes occurring simultaneously within the analysis unit (e.g., road creation and forest harvest). The size of the analysis unit impacts resulting values and interpretation of P_y. The discrepancy in results shown originates from a common problem in spatial analysis methods known as the modifiable areal unit problem (MAUP) (Jelinski & Wu, 1996; Openshaw, 1984). LPIs are well known to be impacted by the MAUP through choices of data grain and analysis unit (Lausch & Herzog, 2002; Wu, 2004) and as it is derived from LPIs, P_y is too impacted by the MAUP. Their currently exists no solution to the MAUP, however a multi-scale approach is warranted when implementing P_y to improve interpretation of results and limit scale related bias.

Conclusions

Testing for significance with P_y is appropriate using neutral landscapes when the relationship between configuration and composition (e.g., Fig. 2) of real landscapes is similar to simulated landscapes. When this is not the case, such as with the AI metric, P_y results are less useful. Our example focused on six LPIs, and we tried to select those with unique distributional properties (see Fig. 2). Future work should explore P_y with other LPIs to further examine its usefulness. In the interim, P_y can still be a useful measure of change enabling hypothesis testing against an expectation of random change.

As land cover datasets increase in availability, methods that extract relevant information from categorical data are required. LPIs are useful in characterizing land cover patterns, and methods that improve temporal comparisons of LPIs are necessary. P_y is successful at distinguishing landscapes impacted by forest loss and/or configurational change. Density based indicators of forest fragmentation may be appropriate in landscapes where P_y is small; however, are limited in capturing important configurational changes. In a mountain pine beetle case study we demonstrate the ability of P_y to identify landscapes suffering primarily from forest loss and those experiencing more complex configurational change. Raw LPI values are difficult to interpret when substantial forest loss has occurred (e.g., with salvage harvesting). The P_y approach is able to identify those regions that have undergone significant forest loss which will have different ecological consequences from those undergoing significant configurational change.

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