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Research Article

Assessing spatial uncertainty associated with forest fire boundary delineation

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Abstract

Uncertainty in managing forested landscapes arises from many sources, including complexities inherent in forest ecosystems and their disturbance processes. However, gaining knowledge about forested ecosystems at the landscape level is often impeded by limitations in collecting comprehensive, representative, as well as accurate data sets. Historical reference data sets about past disturbances are also mostly lacking. In the case of ground fires, however, records of past fires can be obtained by analyzing fire scars using dendrochronology. While the temporal series of disturbance can be determined, there is still uncertainty about the spatial limits of individual forest surface fires. Here, we investigate how a patch-based method (fuzzy set membership) and a boundary-based uncertainty method (boundary membership) can help determine the spatial uncertainty related to forest fire events and their boundary locations. We compare these methods using fire scar data from ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*) sampled at 33 1-ha plots in a 1500-ha study area within the Stein River watershed (British Columbia). Patch-based fire maps, using multiple constraints, were derived for years 1785–1937. We compared the resulting total fire event maps with the boundary-based method, finding that depending on values chosen for the patch-based method, negative correlation was present (though very modest: $r = -0.1$, $p \leq 0.05$) between some maps. However, significant positive correlation between maps (though again modest: $r = 0.22$, $p \leq 0.05$) was found under the least constrained patch-based methods, suggesting that fire patches are counted more than once in riparian zones. Our results suggest that these two methods provide complementary information about historical fire size and spatial limits. Quantifying spatial uncertainty about fire size and fire boundary location using a boundary membership method can contribute to not only understanding past fire regimes but also to providing better estimates of area burned.

Introduction

Forest management systems increasingly recognizes the importance of stochasticity in ecosystem processes, of inaccuracies in data measurement, and limitation of analytical tools to distinguish between the sources of variability (see Mitchell 1995; Kohm and Franklin 1997; Keller 1999; Edwards and Fortin 2001; Goodchild et al. 2001; Bisson et al. 2003). Consequently, uncertainty is one of the primary challenges facing landscape ecologists and managers (Naiman and Décamps 1991; Ludwig et al. 2001). Several types of uncertainty arise due to the stochastic nature of fire regime, including characteristics of fire size, frequency and location (see Lertzman et al. 1998; Armstrong 1999). The characterization of natural disturbances, as well as an understanding of spatial legacies in forested landscapes, are needed as inputs to ecosystem-based management strategies which are established on an understanding of the historical roles of fire as part of the management system (Swanson et al. 1993; Morgan et al. 1994; Galindo-Leal and Bunnell 1995; Swetnam et al. 1999; Everett et al. 2000a). While the range of natural variability is often summarized by disturbance regime as the key driver of forest ecosystem spatial dynamics, little attention has been given to the spatial configuration of the disturbed areas. More accurate and precise mapping of the fire boundary location could provide valuable insights about fire behavior and the functional role of fire boundary shape on forest regeneration (Forman 1995) as well as increase the accuracy of estimates of fire size and total area burned in a given period. Additionally, boundary location, shape and width could provide insights about forest regeneration mechanisms, successional pathways and potential refugia from fire events. Hence, a more accurate spatial delineation of ecological boundaries could provide an improved understanding of the processes which form and maintain them (Fortin and Drapeau 1995; Jordan 2002).

In general, two types of boundaries can be defined: the 'areal boundary' that encloses a relatively homogeneous area, and the 'difference boundary' which is a boundary defined by a change in a variable over space, and not necessarily enclosing an area (Greiling et al. 2002; Fagan et al. 2003). Boundaries can also be classified by how spatially definite they are: sharp boundaries are described as 'crisp' lines, whereas gradual changes in space are defined as 'fuzzy' or 'indeterminate' zones (Smith 1995; Jacquez et al. 2000). Hence, forest fire boundaries can be sharp or gradual, depending on the change of fire intensity and underlying environmental factors and conditions (e.g., soil moisture) over a given landscape. A fire that stops abruptly will have a sharper boundary than one that progressively burns out (Andison 2003; McIntire 2003).

Forest fire boundary characteristics are often driven by the data and particular nature of the research question. For example, as fire can be characterized by presence or absence, it could be therefore represented by closed areal boundaries, but not necessarily by sharp or abrupt ones, similar to other natural boundaries (Jacquez et al. 2000). The complement landscape-level feature of a closed areal boundary is manifested as a patch (Mark and Csillag 1989; Li et al. 2000; Fortin and Edwards 2001; Greiling et al. 2002; Fagan et al. 2003). Patches and boundaries can be represented in digital environments for spatial analyses (e.g., Geographic Information Systems) with a spatial data model. Two spatial data models which are often used are the raster data model and the vector data model (Goodchild 1989; Burrough and McDonnell 1998).

A patch can be represented in a raster data model by a contiguous set of pixels with the same value. For example, remote sensing imagery from satellites can be used to derive burned areas, based on pixel values which are used to derive fire information (Martin et al. 1999; Pereiva et al. 1999a, b). A patch can also be represented as a polygon within a vector data model. For instance, in a vector data model using field data of fire scar evidence, lines can be drawn to encircle similar plot data, resulting in a polygon (e.g., Wright 1996; Everett et al. 2000b; Heyerdahl et al. 2001). In these cases, burn patches (polygons) are assumed to have crisp boundaries represented by lines (vectors). If boundaries are gradual or perhaps even have unknown locations, as is prevalent in historical data arising from sample plots, methods of handling and representing uncertainty may be appropriate.

Fuzzy set theory (Zadeh 1965) is increasingly used in boundary and spatial change analyses to create raster data sets showing varying degrees of membership to a given class (e.g., Brown 1998; Dragicevic and Marceau 1999, 2000; Jacquez et al. 2000; Zhang and Stuart 2001). Possibility surfaces, or membership surfaces, based on fuzzy set theory are capable of encapsulating uncertainty (Eastman 1999) and can also be used to represent the uncertainty from vector data in a raster form (Jacquez et al. 2000).

Zhang (1998) defined components of a polygon with indeterminate boundaries: the core where the attribute of each location has full membership to a given class, the indeterminate boundary where membership at each location is fuzzy and the exterior where locations do not have membership at all. An interior and exterior component to the indeterminate boundary can also be defined (see also Zhang and Lin 2003). Edwards and Lowell (1996) showed that when interpretations of a forest scene (i.e., delineation of polygons) are made by several human subjects, differing boundary delineations result; these latter indicate the indeterminate subjective nature of a forest polygon. The zone of boundary uncertainty can indeed include more area than first reported by photo-interpretation (Edwards and Fortin 2001; McIntire 2003) which have direct effects on the area estimated by polygon delineation.

Our objective in this paper is to develop and examine methods which evaluate spatial uncertainty in forest fire boundaries using dendrochronological analysis of fire scar data from ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*) sampled within the Stein River watershed (British Columbia). This area is particularly interesting because the watershed has had little impact from modern human activities aside from fire suppression, it contains a diverse range of forest types and disturbance regimes, and the forest exhibits spatial structure that is strongly conditioned by topographic variation (Dorner et al. 2002; Jordan 2002). Historical fire behavior appears to have often been constrained by topographic breaks associated with drainage channels and ridges (Wong 1999; Jordan 2002). A reasonably good estimate of past fire boundaries is important due to the fact that the location of where boundaries are drawn around the evidence of fire in a given year is a primary determinant of one's estimate of fire size, and hence area burned. However, this process of boundary determination and fire size estimation from fire scar data incorporates substantial uncertainty, especially if the distances between sampled plots are large (see Morgan et al. 1994; Jordan et al. 2001). Hence, assuming that patches of burned areas are defined by closed boundaries, we investigated how spatial uncertainties about forest fire boundary locations can be accounted for in the estimation of fire size by comparing two methods of boundary delineation. First, we developed a patch-based method where spatial uncertainty of fire patches is defined as a function of distance from known fire scar data and riparian zones. Second, we considered a boundary-based method where location uncertainty of fire boundaries is defined as a function of membership to boundary zones. In the patch-based method, we used fuzzy set theory to map the degree of fire patch membership over time. In the boundary-based method, we used location uncertainty to create a map of boundary membership over time.

Methods

Study area and field methods

The Stein River watershed is located to the west of the Fraser River in the Coast Range of Southwestern British Columbia, Canada (Figure 1). The watershed is within the Stein Valley Nlaka'pamux Heritage Provincial Park (Figure 1, watershed inset after LUCO 2000). The valley is characterized by mountainous terrain containing two major canyons and an elevation range of from 220 to 2954 m. The topography has been heavily impacted by glacial events resulting in sculpted U-shaped valleys (MWLAP 2002).

The Stein Valley contains six biogeoclimatic zones stratified over sharp topographic gradients and an east–west gradient of continental to coastal climate (Pojar et al. 1987; White 1991; MacKinnon et al. 1992): Ponderosa Pine (PP), Interior Douglas-fir (IDF), Montane Spruce (MS), Engelmann Spruce–Subalpine Fir (ESSF), Alpine Tundra (AT), and Coastal Western Hemlock (CWH). The lower valley has a dry and hot climate typical of the lower elevations of the British Columbia interior due to a strong rainshadow effect from the Coast mountains. More mesic conditions are found over an increased proportion of the landscape westward through the valley.

In addition to ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*), tree species in the portions of the watershed we studied include western red cedar (*Thuja plicata*) near streams and a variety of hardwoods in riparian zones (e.g., black cottonwood (*Populus trichocarpa*)). At higher elevations subalpine species such as Englemann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*) become dominant, and at the western end of the watershed, coastal species increase in importance (e.g., Western

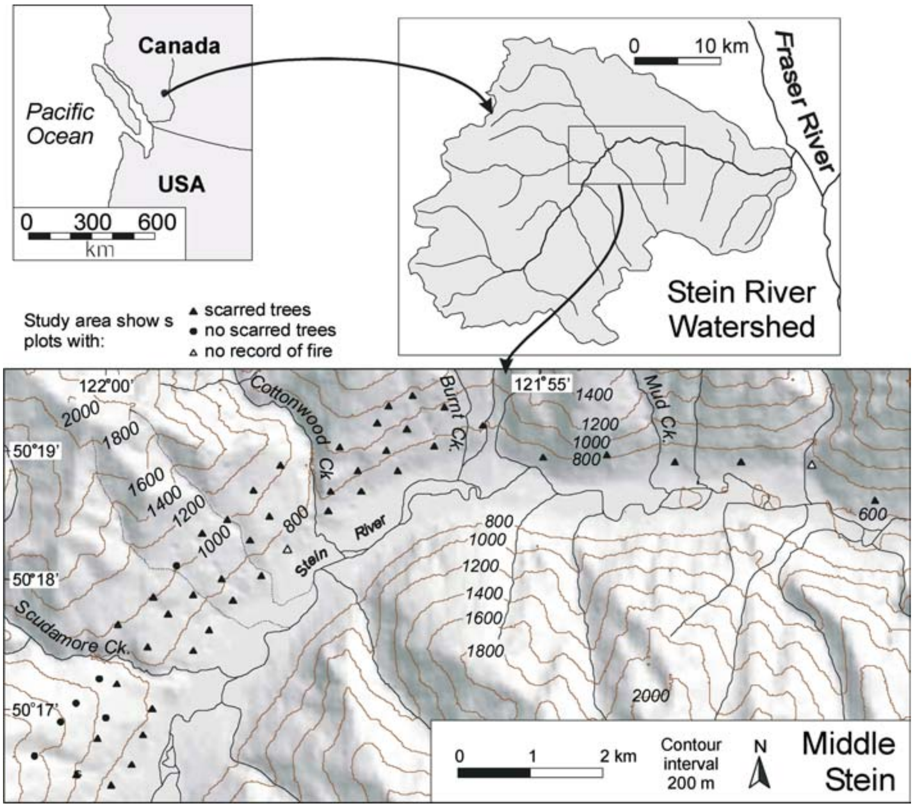

Figure 1. The study area as located within BC, Canada (upper left inset); the Nlaka'pamux Heritage Park and Stein River Valley (Watershed Inset: after MoF, LUCO 2000); and Middle Stein River valley study area (bottom).

Hemlock (*Tsuga heterophylla*), Mountain Hemlock (*Tsuga mertensiana*), and amabilis fir (*Abies amabilis*) (MWLAP 2002).

We examined fire history in the middle valley (see Figure 1). The study area is entirely within the Interior Douglas-fir zone, includes subzones: IDFdk – dry cool and IDFun – undifferentiated (Meidinger and Pojar 1991; MoF 2003) and is centred near 50°18′ N, 121°55′ W. Evidence of low severity fires and trees scarred by multiple fires are present throughout the study area. As part of a larger study, E. Heyerdahl collected fire-scar samples to reconstruct a spatially-explicit history of surface fire occurrence and extent (Heyerdahl and Lertzman, in preparation). In the middle valley, 44 plots of approximately 1 ha were sampled over a 1500 ha area to the north of the Stein River. In each 1 ha plot, an average of 5 trees (range: 1–6), of either ponderosa pine or Douglas-fir, were sampled per plot (Arno and Sneck 1977). The fire dates were derived from a total of 154 fire-scarred trees; the majority of these were ponderosa pine trees (94%). Chainsaws were used to remove scarred sections from dead or living trees. Samples were prepared and cross-dated using standard dendrochronological methods. Sample cross-dating was done by E. Heyerdahl; cross-dating could not be done on some samples (5%), which were excluded from further study. The calendar year for each fire scar was noted, as well as any substantial changes in growth associated with fire injuries. The scar dates from all the samples in a 1 ha plot were combined to provide an area-based record of fire occurrence for that hectare. The tree-ring record extends from 1562 to 1937.

For illustration purposes, we used a subset of the data to compare the two methods to determine the spatial uncertainty related to fire events. For each year in the record, each plot can be assessed as having evidence of a fire (scarring for that year), no evidence of fire, or no record. We can only infer that a fire did not occur if there were trees present in a plot which were likely to have recorded a fire that year, but did not do so. This requires that there be trees with previous scars that are sensitive recorders of fire (e.g., Fall 1998). Where the trees in a plot are all young or there are no previously scarred trees, no inference can be made about the incidence of fire: thus, there is no record (e.g., Fall 1998). Our period of record for the analyses begins when all the plots in the dataset are capable of recording fires. Plots with no record in a given year during the period of analysis were not used in making inferences about the extent of fire for that year. This selection procedure reduced the number of sampled plots by 11 and also shortened the data set temporally. We therefore used a subset of 33 plots, at which 48 fires were recorded between 1785 and 1937.

Analytical methods

First, we developed a method to create maps of fire-patch membership over time. By adjusting parameters (explained below), cumulative fire maps were created and subsequently compared with each other. Next, we used location uncertainty analysis to create maps of fire boundary membership over time. Last, we compared the resulting maps sets from the two methods.

Patch membership: fuzzy set mapping

When a fire event is mapped using crisp lines, with the delineated patch assigned an attribute 'burned' while the surrounding landscape is considered 'not burned,' a Boolean map results. The attribution of space in a Boolean map can be illustrated by a cross-section (z) over a boundary (Figure 2a). No membership (0) is allotted to areas outside of patch membership, the matrix ($z < b_1$ and $> b_2$), whereas full membership (1) is allotted to a patch ($b_1 < z < b_2$). In contrast, uncertainty can be incorporated by using fuzzy set membership functions that allow partial membership to a burned area (Figure 2b). Fuzzy set membership allows the possibility of belonging to a set, taking on values between 0 and 1 (Zadeh 1965; Burrough and McDonnell 1998). For example, membership can be modeled by a linear function that increases, starting from 0 at a_1, with a value of 1 at c. The 'cross-over' point occurs when the degree of membership level is greater than 0.5, here shown at b_1. Other functions can be specified, such as sinusoidal functions (c to a_2). Of importance in all the functions are the relationships between the parameters a_1, a_2, b_1 and b_2 (Burrough and McDonnell 1998). In fuzzy set maps, manipulating these, as well as the type of function selected can greatly alter the results.

We used fuzzy set theory (Zadeh 1965; Burrough and McDonnell 1998) to develop a method for creating fire patch membership maps for each fire year (1785–1937). We calculated the fuzzy maps for each year as follows (in IDRISI32, Clark Labs 2000):

We created a map showing locations where we assumed fire membership to be low: riparian zones and areas at or near plots with no fire evidence. We buffered the Stein River to 360 m (approximate distance across the floodplain, as interpreted from a digital elevation model) and the creeks to 180 m (half the distance of the Stein River buffer). The plots with no fire evidence were also buffered to 280 m (approximately half the mean distance between plots). These three sources of buffers were then overlaid to create a map that showed distances from the edges of the buffer to its interior. We used this as a type of friction map to 'impede' fire from known fluvial features.

The friction map was then used in a calculation reflecting the resistance effort of moving across the landscape (Clark Labs 2000). This calculation represented the assumption that it is increasingly difficult to confidently assign fire membership in proximity to plots that had no evidence of fire. A fuzzy set membership was then assigned to this map with values between 1 and 0, with a value of 1 at point c where fire evidence was recorded, using the one-sided sinusoidal function (see Figure 2b). For a, where the function falls to zero, we tested three different distance constraints: approximately half-way, three-quarters, and full (mean) distance between plots, corresponding to 280, 420 and 560 m. We therefore generated three different maps in each year.

Last, we reclassified each map into one of three new Boolean maps expressing the degree of belief in the membership: upper 0.05, 0.10 and 0.15 of the fuzzy set membership maps. This reclassification generated nine different maps in each year.

We produced cumulative fire maps for each constraint combination by adding the maps for each year together. To test the sensitivity of our

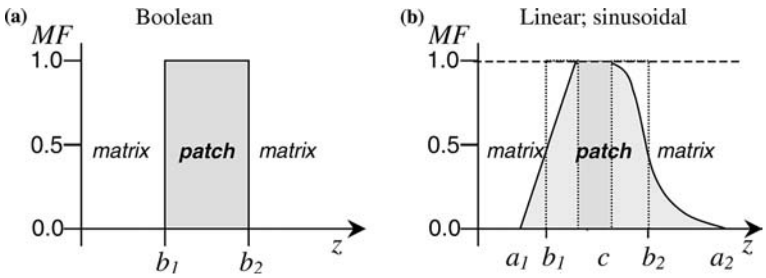

Figure 2. Membership functions (MF) along a distance (z) for (a) Boolean membership compared to fuzzy membership functions, (b) linear and sinusoidal (after Burrough and McDonnell 1998).

methods, we used a Kappa (κ) measure of agreement between a predefined area on each cumulative map (Congalton and Mead 1983; Lillesand and Kiefer 1994). Kappa is a measure of agreement between classifications, as generated by an error matrix for each category. We compared all nine cumulative maps with each other. We expected that the least conservative maps, with less constraint in distance and in fuzzy-thresholds would result in more area assigned to fire patches. Conversely, we expected that more conservative constraints would produce maps in which less area is assigned to fire patches. We expected maps with large distances and small values for the fuzzy constraint to be similar to maps with smaller distances and larger fuzzy constraints.

Boundary membership: location uncertainty mapping

While attributing degrees of patch membership is one method to address spatial uncertainty, uncertainty can also be modeled by examining the boundary itself. Location uncertainty of boundaries can be determined by randomization using spatially restricted procedures (Fortin and Jacquez 2000). To retain structure, regional spatial randomization redistributes plot location within the study area. Boundary membership values (BMV) can be calculated at each location on a map by reassigning the point data to other locations, calculating the boundary, and repeating these reassignments to create a spatial distribution of boundary membership (TerraSeer 2001; Greiling et al. 2002). This process generates a map of boundary membership. Combination of spatial data models (i.e., vector and raster) allows each location in a study area to be assigned a value of boundary membership (see Greiling et al. 2002). For aggregate data, or sampled data, where polygonal areas are defined by one value, boundary membership allows the degree of uncertainty between polygons to be assessed and reported as rasterized results (Greiling et al. 2002).

To compute BMV, data values of scar and of no scar evidence were reassigned within a network of polygons which were created from the original distribution of plots (i.e., Voronoi polygons, using BoundarySeer by TerraSeer 2001). Location uncertainty was generated by first randomly re-allocating the position of plots within their respective polygons. The random allocation was performed using a uniform distribution. Boundaries were then determined for the new locations of the plots. The top 20% of boundaries were retained. We used 999 randomizations of the data set. We used this number of randomizations and all yearly data to produce cumulative BMV maps. We reclassified the data into ranges comparable to the patch membership maps.

Comparison of methods

Using Pearson's correlation, we compared the cumulative fire patch membership maps with the cumulative fire boundary membership maps. We expected that since the patch approach defines membership *to* fire events, such maps would be inversely related to boundary membership maps, which define zones *between* fire events.

Results

Patch membership: fuzzy set maps

Fuzzy maps were generated for the study area (Figure 3). Maps a, d and g depict smaller burned areas (i.e., more circular ones) reflecting our lower belief that fire would be found far from the fire scar. The tightest constraints are found in (g). The middle column of maps (b, e, and h) and the end column (c, f, and i) show less restriction on fire possibilities. Row-wise in the map sets, more restriction is found in the bottom row, where we only retained 0.05 of the fuzzy function (i.e. 0.95–1). The small histograms show the distribution of pixels with similar fire frequency (low frequency on the left, high on the right). In particular, for the distance constraint of 280 m and the fuzzy constraint of 0.05, the annual area attributed to fire events had a distribution of many small events and fewer larger events (Figure 3a). Maps in Figure 3c and g appeared most different from each other. Maps in Figure 3a and i, where constraints have been manipulated in opposing directions appeared similar. Notably, the map in Figure 3g had higher frequencies of zero where no fire membership occurs. The results from the Kappa values for agreement between images quantitatively supported observations of the maps (Table 1). Maps in highest agreement, at 0.886, are Figure 3d (distance = 280, fuzzy = 0.10) and Figure 3h (distance = 420, fuzzy = 0.05).

Boundary membership: location uncertainty maps

The area of location uncertainty with BMV greater than zero was 238 ha, or 16% of the study area (with pre-classified ranges between 0 and 0.083) (Figure 4). The highest amount of boundary membership was located near Cottonwood Creek. A high degree of membership was also observed near Scudamore and Mud Creeks.

BMVs detected locations in which membership was most likely. Conversely, low membership occurred in areas in which no boundary generating process was active (such as areas of uniform terrain located between creeks) as well as in locations in the study area which would not be useful in detecting boundaries (i.e., at the margins of the study area). Thus, high BMV indicates fire boundary membership, whereas low BMV does not necessarily indicate membership to fire patches.

The results of the correlation between patch membership maps and boundary membership maps were generally low (Table 2), though both significant positive and negative correlation were present ($p = 0.05$). Significant negative correlations were found for low value fuzzy thresholds and small distance constraints (Figure 3d, g, and h). Highest positive correlation occurred when fuzzy values had high values and distance constraints were large Figure 3c and f). The positive correlation suggests that the parameterization for the patch-based method does not always produce the inverse of the boundary-based method. We elaborate these results in the following section.

Comparison of maps

The results of the cumulative patch membership maps showed that when constraints were more conservative (e.g., 0.05 for fuzzy threshold and small distance constraints), less area was assigned to fire events (Figure 3g, h and i). As we would have expected from lowering the value of distance constraints and having included our assumption regarding fire impedance at streams, less patch membership occurred near riparian zones. However, in contrast, the maps with the higher values of distance constraints, fire patch membership increasingly overlapped, with higher membership at riparian zones of Scudmore and Cottonwood Creeks, despite the riparian zone constraint (especially for Figure 3c, f, and i). The results of the boundary location uncertainty revealed high degree of boundary membership in riparian zones, in particular, Scudamore, Cottonwood and Burnt Creeks. The highest values were located at Cottonwood Creek.

Correlations between patch-based maps and the boundary-based map were generally low, and mostly negative, as expected (i.e., methods seeking to define areas would be the inverse of those seeking boundaries). However, in the middle Stein, some correlation (r) values were positive when using the largest distant constraint in terms of distance (560 m). As we observed in the maps Figure 3c, f, and i, also observed to a lesser degree in (Figure 3b and e), the effect of tributaries

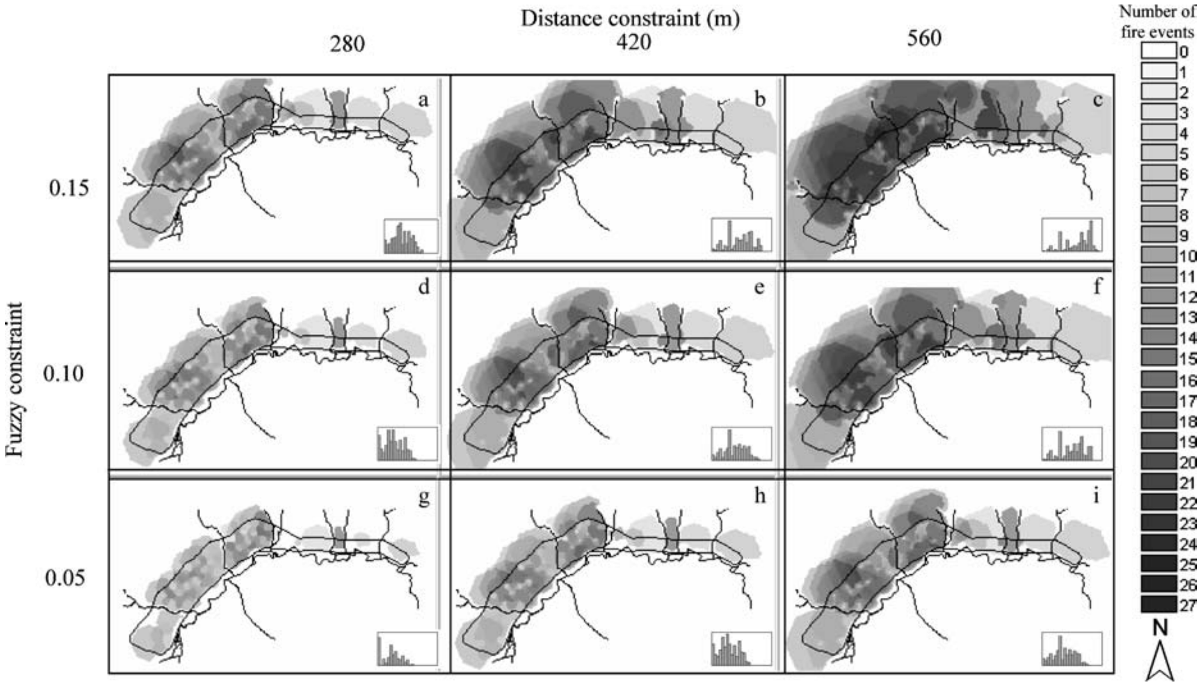

Figure 3. Cumulative results from the fuzzy methods approach (1785–1937; 48 fire events). The horizontal axis, distance constraint, shows the distance (from a fire scarred plot) to which the sigmoidal function falls to zero. The vertical axis (fuzzy constraint) shows three different thresholds at which we retained fire possibility areas, i.e. top 0.15, 0.10 and 0.05 from the area with values between 0 and 1 as defined by the fuzzy function. Histograms show the distribution of pixels with similar fire frequency (low frequency on the left, high on the right).

Table 1. Kappa (κ) values for agreement between maps derived from patch-based method.

Map			a	b	c	d	e	f	g	h	i
	Fuzzy threshold	Distance (m)	280	420	560	280	420	560	280	420	560
a	0.15	280	1.000	0.308	0.109	0.532	0.548	0.250	0.219	0.616	0.671
b		420		1.000	0.456	0.164	0.531	0.803	0.063	0.191	0.443
c		560			1.000	0.047	0.224	0.568	0.024	0.057	0.179
d	0.1	280				1.000	0.278	0.132	0.428	0.886	0.339
e		420					1.000	0.429	0.115	0.323	0.819
f		560						1.000	0.052	0.153	0.360
g	0.05	280							1.000	0.363	0.141
h		420								1.000	0.399
i		560									1.000

appeared to be overcome when distance constraints were relaxed (i.e., large), effectively permitted a ‘doubling-up’ of fire event membership in riparian zones. Thus, evidence of fire events from two different years, burning spatially asynchronously, may have been counted twice in overlap areas. This is not impossible given the predominance of surface fires in our study area and the fact that only surface fires are represented in the dataset.

The fuzzy area analyses were complemented by the BMV fire events analyses, quantifying uncertainty in area burned and uncertainty in boundary location of a burned area. The results of the study consequently showed that the two methods of estimating spatial fire parameters provided

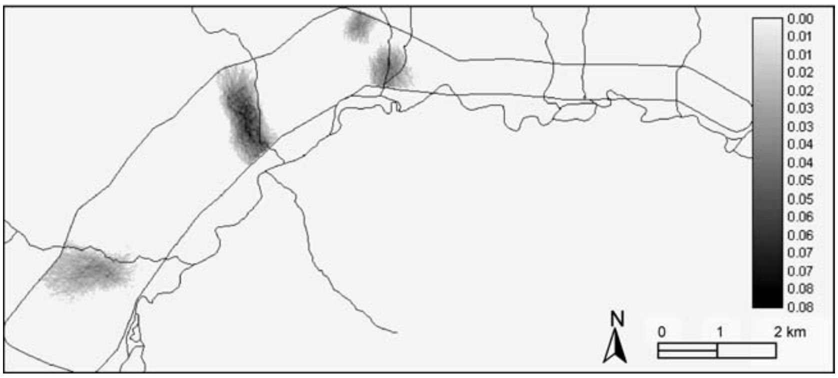

Figure 4. Middle Stein boundary membership surface (1785–1937).

Table 2. Correlation (r) of maps from the patch membership (Maps listed in first column) with boundary membership map (n = 37825); *P = 0.05 (two-tailed).

Map	Fuzzy threshold	Distance (m)	r
a	0.15	280	−0.002
b		420	0.229*
c		560	0.266*
d	0.10	280	−0.061*
e		420	0.119*
f		560	0.255*
g	0.05	280	−0.082*
h		420	−0.056*
i		560	0.082*

complementary results although the fuzzy methods were flexible. Thus, in our study, we controlled fuzzy membership, with respect to the distance away from plots, and riparian zones as the possibility, not a certainty, of fire extent.

When topographic constraints were lower, the results of the patch-based analyses revealed patch membership in upland areas between riparian zones, which is expected, given that one of the input constraints included streams. Compellingly, boundary-based results, which involved no additional data input other than the fire scar data, showed high membership areas near and in riparian zones. We will compare the results of the two methods below, with a focus on issues arising from study area shape and from sampling intensity. The results have ecological implications related to a better understanding of fire boundary persistence, and implications for forest and fire management based on the spatial nature of fire regimes.

Discussion

Knowledge of the spatial and temporal extents of the data is a critical factor in understanding the fire regimes and landscape heterogeneity (Lertzman et al. 1998). Both the spatial and temporal component of surface fire regimes can contain uncertainties. While temporal uncertainties in fire return interval, as determined from fire scars, have been documented elsewhere (see Baker and Ehle 2001), our study focuses on the spatial boundary components of surface fire disturbance. We discuss three points related to spatial uncertainty from our results: sampling uncertainty, uncertainty in ecological boundaries, and the implication of spatial uncertainty in the decision-making process and management.

Sampling uncertainty

As this data set was used for illustration purposes, the way it was sampled did affect the fire maps obtained by the two methods in comparable ways. First, the original source of uncertainty was largely a result of sampling scale and study area shape (see Fortin and Edwards 2001; Dungan et al. 2002). Uncertainty arising from sampling scale reflects the distance between sampling sites and the size of the sampling plot (Fortin and Edwards 2001). Finer scale sampling will determine more precisely nature of the fire event boundary. In our case, since boundaries were strongly associated with riparian corridors (see also Jordan 2002), allocation of more sampling effort to riparian zones would have made the most difference to spatial uncertainty in fire boundaries. With more intensive sampling, the ability of riparian zones to act as firebreaks could be assessed at more detailed scales. Indeed, additional fire events and extents would likely be detected with increased sample size.

Uncertainty also arises from the shape of our study area. Its elongated shape promotes a substantial 'edge effect,' that is, possible boundaries and patches extending near or beyond the study area margin are not detected. The existing or historical fire processes likely did not have such restrictions as fires burned upslope, thus in our data, we capture only boundaries that occurred within the study area. In areas more central to in the data set, zero values of BMVs were observed in the regions between creeks. We interpreted these areas as zones where boundaries were not likely to form. Therefore, uncertainty increases towards the edge of the study area, but we can be more certain of boundary membership and stability more centrally within the study area.

Uncertainty of ecological boundaries

There is a need for better understanding the links between topography, riparian corridors and fire disturbance (Bisson et al. 2003; Dwire and Kauffman 2003). Riparian zones are typically distinct from the adjoining uplands in such attributes as vegetation composition, hydrology, and fuel loading (Dwire and Kauffman 2003). As a result, emulation of disturbances, i.e., using the natural disturbance regime as a template for management, must consider to a large degree site-specific topography. (Note, however, that topographic influence can be overwhelmed by climate during periods with weather conducive to more extreme fire behavior (Gavin et al. 2003; Whitlock et al. 2003)).

Boundary membership and boundary location stability are affected by the nature of ecological functions, disturbance processes, and of physiographic control. Edge stability is not only a product of its generation process, but also of continuing synergy between edge and its environment (Fagan et al. 2003). Boundary membership values under uncertainty are applicable for determining whether, in historical disturbances, a given riparian zone has been the location of fire boundaries or of fire continuity. Understanding the interactions between fire disturbance boundaries, topography and riparian landscape elements can improve our ability to locate riparian late serial refugia (as in Camp et al. 1997) and the accuracy of delineating historical surface fire extents (as in Wright 1996; Everett et al. 2000b).

Incorporating boundary uncertainty in historical fire disturbance analysis improves techniques from rule-based, exact fire delineation approaches to incorporating lack of data between sampled plots. The improvement resides in the applications such as fire extent estimation, and not merely in the fact that the lack of data between plots is represented. Historical fire extents, as determined from fire scars, are typically drawn using Voronoi polygons methods or rules based on topography (e.g., ridges, creeks, aspect) (Wright 1996; Everett et al. 2001) without determining certainty of boundary location. Fire sizes can be substantially over- or under-estimated using such methods, and these errors may then propagate into calculations such as the natural range of variation.

One of the more compelling implications from our study of methods is that the location of boundary membership values (BMV) can be determined from fire scar data alone (i.e., using the boundary-based approach). In our attempt at assigning membership from a patch-based method, we imposed fire growth 'restriction,' assuming that fire would not cross riparian zones readily. In fact, the patch-based approach (which indeed helps us determine areas burned) could, in future studies, be informed by BMV. That is, the BMV method would substantiate assumptions of using riparian zones as impedances. Area burned in each year could be given a margin of error, depending on the flexing of the other known constraints (distance from plot and fuzzy constraint). Such a calculated value of spatial fire extent error would then allow a measure of spatial uncertainty to be incorporated into the procedure of determining fire sizes. Our methods can be used to provide a degree of spatial uncertainty, area-based, either on each fire size calculated, or on a desired cumulative statistic to inform management decisions.

Uncertainty and management

Knowledge of size, shape, frequency and legacies of past disturbances can inform forest fire management (Hunter 1993; Galindo-Leal and Bunnell 1995; Swetnam et al. 1999). Thus providing a reliable estimate of the spatial characteristics of past events is critical. If knowledge of these attributes is important, then quantifying boundary uncertainty in them is equally so, but has rarely been accomplished (Baker and Ehle 2001). Indeed, an ecological boundary perspective, incorporating uncertainty, can provide a new dimension to management (Naiman and Décamps 1991). In general, though shorter records are more likely to provide a biased estimate of disturbance characteristics, the further back in time one extrapolates the historical landscape, the greater the uncertainty due to the records having been erased by subsequent disturbances (Schuum and Lichty 1965; Morgan et al. 1994). Meaningfully incorporating estimates of uncertainty into decision-making can turn management actions into desirable experiments (see Walters 1997). As more management decisions incorporate information about historical disturbance regimes, building in estimates of uncertainty will become increasingly important.

Addressing boundary uncertainty is important for a variety of applications in forest management and conservation. If the current landscape differs substantially from the historical spatial configuration of boundary membership, a management treatment should be applied to restore fire to the landscape using the historical boundaries as a guide. Our study shows where historical boundaries hypothetically have had, in the past, higher membership values than at other locations on the landscape. Boundary uncertainty improves historical disturbance analysis that is typically rule-based fire delineation by incorporating lack of data between sampled plots. Applying boundary uncertainty is important for management operations which use fire size and shape based on perimeter.

Conclusion

Exploring methods for better characterization of the spatial uncertainty about historical forest fire boundaries has implications for both forest and fire management. The first is that delineation of fires from historical records is affected by sampling uncertainty due to generally tenuous extrapolation of complex surface data from point data. Thus, understanding the ramifications of uncertainty in boundary placement can contribute to acknowledging potentially even greater variability in past fire regimes than currently quantified.

Second, we are more certain of, and better able to delineate, historical disturbances boundaries as topography changes. In riparian zones, where topography changes with drainage channels, higher boundary membership is found than on less varied upland areas.

The third implication of our findings is that management decisions should be improved when spatial uncertainties can be better quantified. We have illustrated this by application to the location of historical fire boundaries, which are relevant in making decisions about forest and fire management. These methods can be applied for types of disturbances that leave a spatially explicit record, and indeed to a variety of other ecological problems where the reconstruction of past boundaries exhibits spatial uncertainty.

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References

Andison D. 2003. Boundary zones, or islands with a twist? Natural Disturbance Program Quicknote, Foothills Model Forest 23: 1–2.

Armstrong G.W. 1999. A stochastic characterization of the natural disturbance regime of the boreal mixedwood forest with implications for sustainable forest management. Can. J. Forest Resour. 29: 424–433.

Arno S.F. and Sneck K.M. 1977. A Method for Determining Fire History in Coniferous Forest of the Mountain West. Intermountain Forestry and Range Experiment. Ogden, Utah.

Baker W.L. and Ehle D. 2001. Uncertainty in surface-fire history: the case of ponderosa pine forests in the western United States. Can. J. Forest Res. 31: 1205–1226.

Bisson P.A., Rieman B.E., Luce C., Hessburg P.F., Lee D.C., Kershner J.L., Reeves G.H. and Gresswell R.E. 2003. Fire and aquatic ecosystems of the western USA: current knowledge and key questions. Forest Ecol. Manage. 178(1–2): 213–229.

Brown D.G. 1998. Classification and boundary vagueness in mapping presettlement forest types. Int. J. Geograp. Inform. Sci. 12(2): 105–129.

Burrough P.A. and McDonnell R.A. 1998. Principles of Geographic Information Systems. Oxford University Press, Inc, New York.

Camp A., Oliver C.D., Hessburg P. and Everett R. 1997. Predicting late-successional fire refugia pre-dating European settlement in the late Wenatchee Mountains. Forest Ecol. Manage. 95(1): 63–77.

ClarkLabs 2000. The Idrisi Project. Clark Labs, Worcester, MA.

Congalton R.G. and Mead R.A. 1983. A quantitative method to test for consistency and correctness in photointerpretation. Photogrammet. Eng. Remote Sens. 49(1): 69–74.

Dorner B., Lertzman K. and Fall J. 2002. Landscape pattern in topographically complex landscapes: issues and techniques for analysis. Landscape Ecol. 17: 729–743.

Dragicevic S. and Marceau D.J. 1999. Spatio-temporal interpolation and fuzzy logic for GIS simulation of rural-urban transition. Cartograph. Geograph. Inform. Sci. 26: 125–137.

Dragicevic S. and Marceau D.J. 2000. A fuzzy logic approach for modeling time in GIS. Int. J. Geograph. Inform. Sci. 3: 225–245.

Dungan J.L., Perry J.N., Dale M.R.T., Legendre P., Citron-Pousy S., Fortin M.-J., Jakomulska A., Miriti M. and Rosenberg M.S. 2002. A balanced view of scale in spatial statistical analysis. Ecography 25: 626–640.

Dwire K.A. and Kauffman J.B. 2003. Fire and riparian ecosystems in landscapes of the western USA. Forest Ecol. Manage. 178(1–2): 61–74.

Eastman R. 1999. Decision Support Tools for Effective Use of Spatial Data Resources. Clark University, Clark Lab, Worchester, MA.

Edwards G. and Fortin M.-J. 2001. Cognitive view of spatial uncertainty. In: Goodchild M., Friedl M., Case T. and Hunsaker C. (eds), Spatial Uncertainty in Ecology. Implications for Remote Sensing and GIS Applications. Springer-Verlag, New York, pp. 158–174.

Edwards G. and Lowell K. 1996. Modelling uncertainty in photointerpreted boundaries. Photogrammet. Eng. Remote Sens. 62(4): 337–391.

Everett R., Townsley J. and Baumgartner D. 2000a. Inherent disturbance regimes: A reference for evaluating the long-term maintenance of ecosystems. J. Sustain. Forest. 11(1/2): 265–288.

Everett R.L., Schellas R., Keenum D., Spurbeck D. and Olson P. 2000b. Fire history in the ponderosa pine/Douglas-fir forests on the east slope of the Washington Cascades. Forest Ecol. Manage. 129: 207–225.

Everett R.L., Schellhass R., Ohlson P., Spurbeck D. and Keenum D. 2001. Continuity in fire disturbance between riparian and adjacent sideslopes in the Douglas-fir forest series. URL: http://www.fs.fed.us/pnw/pubs/journals/riparian.pdf

Fagan W.F., Fortin M.-J. and Soykan C. 2003. Integrating edge detection and dynamic modeling in quantitative analyses of ecological boundaries. BioScience 53: 730–738.

Fall J. 1998. Reconstructing the historical frequency of fire: a modeling approach to developing and testing methods. M.R.M. Thesis. Simon Fraser University, Burnaby, BC, 93 pp.

Forman R.T.T. 1995. Land Mosaics: The Ecology of Landscapes and Regions. Cambridge University Press, Cambridge.

Fortin M.-J. and Drapeau P. 1995. Delineation of ecological boundaries: a comparison of approaches and significance tests. Oikos 72: 323–332.

Fortin M.-J. and Edwards G. 2001. Delineation and analysis of vegetation boundaries. In: Goodchild M., Friedl M., Case T. and Hunsaker C. (eds), Spatial Uncertainty in Ecology. Implications for Remote Sensing and GIS Applications. Springer-Verlag, New York, pp. 158–174.

Fortin M.-J. and Jacquez G.M. 2000. Randomization tests and spatially autocorrelated data. Bull. ESA 81: 201–206.

Galindo-Leal C. and Bunnell F.L. 1995. Ecosystem management: implications and opportunities of a new paradigm. Forest. Chronicle 71(5): 601–606.

Gavin D.G., Brubaker L.B. and Lertzman K. 2003. Holocene fire history of a coastal temperate rain forest based on soil charcoal radiocarbon dates. Ecology 84: 186–201.

Goodchild M. 1989. Modeling error in objects and fields. In: Goodchild M. and Gopal S. (eds), Spatial Accuracy of Spatial Databases. Taylor and Francis Inc., Bristol, PA, pp. 107–114.

Goodchild M., Friedl M., Case T. and Hunsaker C. (eds) 2001. Spatial Uncertainty in Ecology. Implications for Remote Sensing and GIS Applications. Springer-Verlag, New York.

Greiling D., Hall K., Maruca S. and Jacquez G. 2002. BoundarySeer Help. TerraSeer Inc.

Heyerdahl E.K., Brubaker L.B. and Agee J.K. 2001. Spatial controls of historical fire regimes: a multiscale example from the interior west, USA. Ecology 82(3): 660–678.

Hunter M.L. Jr. 1993. Natural fire regimes as spatial models for managing boreal forests. Biol. Conserv. 65: 115–120.

Jacquez G.M., Maruca S. and Fortin M.-J. 2000. From fields to objects: a review of geographic boundary analysis. J. Geograph. Syst. 2: 221–241.

Jordan (Bergmans) G., Heyerdahl E. and Lertzman K. 2001. A comparison of methods for estimating historical fire extents. In: Natural Disturbance and Forest Management Symposium, March 5–7, Edmonton, Alberta.

Jordan G.J. 2002. Space, time and uncertainty: detecting and characterizing boundaries in forest fire disturbances. Ph.D. Thesis. Simon Fraser University, Burnaby, 246 pp.

Keller C.P. 1999. Designing of decision support capable of managing and visualizing uncertainty in multiple source forestry data. FRBC Ref#: HQ96078-RE; SRBC Ref#: FR-96/97–191, Forest Renewal BC Research Program and Science Council of BC.

Kohm K.A. and Franklin J.F. 1997. Introduction. In: Kohm K.A. and Franklin J.F. (eds), Creating a Forestry for the 21st Century. Island Press, Washington, DC, pp. 1–5.

Lertzman K., Fall J. and Dorner B. 1998. Three kinds of heterogeneity in fire regimes: at the crossroads of fire history and landscape ecology. Northwest Sci. 72: 4–22.

Li Z., Li L. and Chen Y.-Q. 2000. Basic topological models for spatial entities in 3-dimensional space. GeoInformatica 4(4): 419–433.

Lillesand T.M. and Kiefer R.W. 1994. Remote Sensing and Image Interpretation. John Wiley and Sons, New York.

LUCO 2000. GIS Data. Government of British Columbia.

Ludwig D., Mangel M. and Haddad B. 2001. Ecology, conservation, and public policy. Annu. Rev. Ecol. Syst. 32: 481–517.

MacKinnon A., Meidinger D. and Klinka K. 1992. Use of the biogeoclimatic ecosystem classification system in British Columbia. Forest. Chronicle 68: 100–120.

Mark D.M. and Csillag F. 1989. The nature of boundaries on 'area-class' maps. Cartographica 26:65–78.

Martin M.P., Ceccato O., Flasse S. and Downey I. 1999. Fire detection and fire growth monitoring using satellite data. In: Chuvieco E. (ed.), Remote Sensing of Large Wildfires in the European Mediterranean Basin. Springer-Verlag, New York, pp. 101–129.

McIntire E. 2003. Wildfire and mountain pine beetle boundary zones: spatial pattern, boundary creation and successional consequences. Ph.D. Thesis. University of British Columbia, Vancouver, 143 pp.

Meidinger D. and Pojar J. 1991. Ecosystems of British Columbia. British Columbia Ministry of Forests. Crown Publications, Victoria, BC.

Mitchell B. 1995. BEATing conflict and uncertainty in resource and environmental management. In: Mitchell B. (ed.), Resource and Environmental Management in Canada: Addressing Conflict and Uncertainty. Oxford University Press, Toronto, ON, pp. 406–425.

MoF 2003. Biogeoclimatic Subzone Variant Mapping. Research Branch, Ministry of Forests, Government of British Columbia.

Morgan P., Aplet G.H., Haufler J.B., Humphries H.C., Moore M.M. and Wilson W.D. 1994. Historical range of variability: a useful tool for evaluating ecosystem change. J. Sustain. Forest. 2: 87–111.

MWLAP 2002. British Columbia Parks: Stein Valley Nlaka'pamux Heritage Provincial Park, 2002.

Naiman R.J. and Décamps H. 1991. Landscape boundaries and restoration of changing environments: a summary. In: Holland M.M., Naiman R.J. and Risser P.G. (eds), Ecotones: The Role of Landscape Boundaries in the Management and Restoration of Changing Environment. Chapman & Hall, Inc., New York, pp. 130–137.

Pereiva J.M.C., Sa A.C.L., Sousa A.M.O., Silva J.M.N., Santos T.N. and Carreiras J.M.B. 1999a. Spectral characterization and discrimination of burnt areas. In: Chuvieco E. (ed.), Remote Sensing of Large Wildfires in the European Mediterranean Basin. Springer-Verlag, New York, pp. 123–157.

Pereiva J.M.C., Sousa A.M.O., Sa A.C.L., Martin M.P. and Chuvieco E. 1999b. Regional-scale Burnt Area Mapping in Southern Europe using NOAA-AVHRR 1 km Data. In: Chuvieco E. (ed.), Remote sensing of large wildfires in the European Mediterranean Basin. Springer-Verlag, New York, pp. 139–153.

Pojar J., Klinka K. and Meidinger D. 1987. Biogeoclimatic ecosystem classification in British Columbia. Forest Ecol. Manage. 22: 119–154.

Schuum S. and Lichty R. 1965. Time, space and causality in geomorphology. Am. J. Sci. 263: 110–119.

Smith B. 1995. On drawing lines on a map. In: Frank A.U., Kuhn W. and Mark D.M. (eds), Proceedings in Spatial Information Theory: Proceedings of COSIT '95. Springer-Verlag, New York, pp. 475–484.

Swanson F.J., Jones J.A., Wallin D.O. and Cissel J.H. 1993. Natural variability – implications for ecosystem management. In: Jensen M.E. and Bourgeron P.S. (eds), Eastside Forest Ecosystem Health Assessment, Ecosystem Management: Principles and Applications, Vol. II. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR, pp. 89–103.

Swetnam T.W., Allen C.D. and Betancourt B.L. 1999. Applied historical ecology: using the past to manage for the future. Ecol. Appl. 9(4): 1189–1206.

TerraSeer. 2001. BoundarySeer. Environmental Insight Software, Ann Arbor, MI.

Walters C. 1997. Challenges in adaptive management of riparian and coastal systems. Conservation Ecology [online] 1(2):1. Available from the internet. URL: http://www.consecol.org/vol1/iss2/art1/

White G. 1991. Stein Valley Wilderness Guidebook. Stein Wilderness Alliance, Vancouver.

Whitlock C., Shafer S. and Marlon J. 2003. The role of climate and vegetation change in shaping past and future fire regimes in the Northwestern U.S. and the implications for ecosystem management. Forest Ecol. Manage. 178: 5–21.

Wong C. 1999. Memories of natural disturbances in ponderosa pine – Douglas-Fir age structure, Southwestern British Columbia. M.R.M. Thesis. Simon Fraser University, Burnaby, BC, 96 pp.

Wright C.S. 1996. Fire history of the Teenaway River drainage, Washington. M.Sc. Thesis, University of Washington, Seattle, 190 pp.

Zadeh L.A. 1965. Fuzzy sets. Inform. Control 8(3): 338–353.

Zhang F.B. 1998. Approximate analysis of binary topological relations between geographic regions with indeterminate boundaries. Soft Comput. 2: 28–34.

Zhang F.B. and Lin H. 2003. Overlay of two simple polygons with indeterminate boundaries. Trans. GIS 7(1): 67–81.

Zhang J. and Stuart N. 2001. Fuzzy methods for categorical mapping with image-based land cover. Int. J. Geograp. Inform. Sci. 15(2): 175–195.