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Relationship between landscape structure and burn severity at the landscape and class levels in Samchuck, South Korea

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ABSTRACT

Fuel treatments for reducing fire risk are necessarily tied to the landscape structure including forest composition and configuration. Thus understanding the relationships between landscape structure and burn severity is important for developing guidelines and management strategies for fire-resilient forests. The goal of this study was to investigate the relationship between landscape structure as described by spatial pattern metrics and burn severity at the landscape and class levels. In 2000, a mostly severe fire burned 16,210 ha of dense forest located in Samchuck on the east coast of the Korean peninsula. Spatial pattern metrics including patch density, largest patch index, mean shape index, area-weighted mean shape index, Euclidean nearest neighborhood distance, and Shannon's diversity index, as well as topographic characteristics of slope and elevation, were correlated with burn severity based on delta Normalized Burn Ratio (dNBR) assessments. Regression tree analysis was also carried out with the same variables to avoid spatial autocorrelation and to reveal the relative importance of variables to burn severity. The results of this study strongly suggest that both composition and configuration of the forest cover patches are closely tied to burn severity. In particular, both the correlation analysis and regression tree analysis indicated that the area of red pine tree forest cover was the most significant factor in explaining the variance of burn severity. Topography and spatial configuration of forest cover patches were also significantly related to burn severity. The heterogeneity of forests also had a significant influence on burn severity. To reduce fire risk and increase the fire resilience of forests, forest managers and agencies need to consider enhancing the heterogeneity of forests when implementing fuel treatment schemes. However, such fuel treatments for landscape structure may only be effective under moderate weather conditions.

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1. Introduction

Because fire has a profound influence on forest ecosystems and human lives (Gustafson et al., 2004; Nunes et al., 2005) it has been an important area of study for forest scientists, forest managers, land use planners, and government agencies for decades. Fire has been shown to have significant impacts on forest ecosystems, resulting in alteration of the size, arrangement, and age structure of vegetation (Collins et al., 2007; Delcourt and Delcourt, 1997; Lloret et al., 2002; Turner et al., 1994; Wimberly and Reilly, 2007). Conversely, forest composition and configuration influence fire spread and severity (Collins et al., 2007; Stephens, 2001). Other variables have been shown to influence burn severity including topography, disturbance history (Bigler et al., 2005), and weather conditions (Collins et al., 2007; Pyne et al., 1996; Rothermel, 1972). Despite the intensive investigations of those previous studies, our understanding of the interactive relationship between burn severity and environmental variables is still limited due to the complexity and dynamics of the relevant variables.

Recently, much more attention has been given to the relationship between landscape structure and characteristics of fire including burn severity and spread (e.g., Bajocco and Ricotta, 2008; Kerby et al., 2007; Nunes et al., 2005; Ryu et al., 2007; Wimberly and Reilly, 2007). For example, Ryu et al. (2007) investigated the relationship between the burned area (BA) of the Washburn Ranger District of the Chequamegon National Forest, Wisconsin, United States, and landscape structure described using spatial pattern metrics including largest patch index (LPI), mean patch size (MPS), patch density (PD), patch size standard deviation

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(PSSD), mean shape index (MSI), area-weighted mean shape index (AWMSI), and Shannon's diversity index (SHDI). They reported a strong tie between burned area (BA) and landscape structure and concluded that the forest should be composed of numerous, small, irregularly shaped, and different types of forest to mitigate fire spread. From a landscape ecology perspective, forest structure can be viewed as two-dimensional: (1) the composition and (2) the configuration (McGarigal and Marks, 1995; Turner et al., 2001). Both aspects are strongly tied to many characteristics of fire such as spread, severity, fuel types, and fuel loading (González et al., 2005; Kerby et al., 2007; Lloret et al., 2002; Nunes et al., 2005; Ryu et al., 2007). Indirectly, landscape structure is also closely associated with the composition and configuration of the post-fire forest including plant regeneration and plant mortality (Brown, 2000). Landscape structure is also tied to fuel treatments. Effective fuel treatments must consider the spatial patterns of forests that may interrupt the flow of high-intensity fire across the landscape when the entire landscape is not planned for treatments (Finney, 2001). Thus, understanding the relationship between landscape structure and the characteristics of fire is critical to managing or restoring forests that have resistance to fire ignition and spread, as well as to enhancing the recovery of the ecosystems of burned areas.

This study investigated, on a small scale, the relationship between burn severity and landscape structure and topography in South Korea. Our aim was to provide some basis for managing forests for reduced susceptibility to fire. The rationale of the study is that spatial patterns, including the composition and configuration of forests in a landscape, dictate the fire susceptibility of forests. Burn severity also partly depends on the spatial pattern of forests with high or low fire susceptibility (Cumming, 2001; Krasnow et al., 2009; Pyne et al., 1996). Furthermore, certain aspects of all fuel treatments, forest management practices, and restoration efforts are related to the spatial patterns of forests. Therefore, knowledge of the relationship between the spatial patterns of forests in landscapes and burn severity can be directly applied to fuel treatment, forest management, and restoration practices. Based on the factors and spatial patterns of forests identified as being associated with burn severity, managers and policymakers can reduce fire risks and enhance the resilience of forests to fire. With these issues in mind, our specific study question was as follows: is there a significant relationship between landscape structure described by spatial pattern metrics and burn severity derived from satellite imagery?

In 2000, a catastrophic fire burned 16,210 ha of dense forest in Samchuck on the east coast of the Korean peninsula. Although numerous studies have examined the landscape structure of forests and various fire characteristics in Europe and North America, relatively little information is available on the relationship between spatial patterns of forests and burn severity in East Asia, particularly in Korea. The fire event and subsequent collection of large amounts of data provided an opportunity to examine the complex relationship between landscape structure and burn severity, as well as the ecological consequences of severe fire.

2. Methods and data

2.1. Study site and the Samchuck fire

The study area, located in Samchuck on the eastern coast of Korea (Fig. 1a), has an annual average temperature and precipitation of 12.1 °C and 1342 mm, respectively, with dry, windy conditions in spring. The pre-fire vegetation in the area was dominated by Japanese red pine (*Pinus densiflora*) forest and mixed forest of *P. densiflora* and Mongolian oak (*Quercus mongolica*). At the time of the fire, the forests had an average age of approximately 30 years and represented secondary succession following burning during the Korean War in the early 1950s. Postwar regeneration in the area was delayed due to fuel wood collection by local people. A few rural residential areas are scattered through the lower elevations, although no densely populated areas exist in the study area. Stream systems are found mostly on the eastern and southern sides of the area.

In 2000, a fire, severe in most areas, burned about 16,151 ha of dense forest in the Samchuck area (37°7′42″–37°20′34″N, 129°11′24″–129°22′32″E, Fig. 1(a). The fire spread from a garbage-burning site near a residential area on 7 April and continued to burn for 9 days. During the day, the maximum wind speed was 26.8 m/s, and the minimum humidity was 7%. The dry and windy weather conditions accelerated fire spread and made suppression efforts ineffective. This burned area was designated as a Long-Term Ecological Research (LTER) site and has been monitored by the Korea Forest Research Institute (KFRI) since 2000 to investigate the ecological consequences of the fire and to monitor the natural recovery process.

2.2. Description of spatial layers

The National Forest Classification Map was used to measure the pre-fire landscape structure of the damaged area. This map is paper-based and was digitized into a Geographic Information System (GIS) for analysis. The National Forest Classification Map is derived from satellite imagery and field data. The forest classification is based on three criteria including tree type, age, and sub-layers. In Table 1, the forest covers on the map were initially classified into 50 categories and are now reclassified into 10 categories including mixed coniferous forest, broad-leaved forest, mixed forest, planted Japanese red pine forest, planted Korean white pine forest, planted pitch pine forest, Japanese red pine forest, open forest, and agricultural land. Forests are classified into a forest class when more than 75% of the areas are covered by a single dominant tree type. Mixed forests are covered by multiple tree types without a dominant tree type (i.e., <75% canopy cover). The forest on the eastern side of the study area is relatively homogeneous and dominated by pine trees, whereas the western side shows a variety of forest cover types, as shown in Fig. 1d.

FRAGSTATS was employed to compute landscape structure including composition and configuration before the fire (McGarigal and Marks, 1995). FRAGSTATS is a spatial pattern analysis program designed to quantify landscape patterns at the patch, class, and landscape level. Literally hundreds of spatial metrics are available. Their purpose is to obtain sets of quantitative data that allow a more objective comparison of different landscapes for grouping or differentiation (Antrop, 2000). According to McGarigal and Marks (1995), most spatial patterns can be measured with composition and configuration metrics. Composition refers to features associated with the variety and abundance of forest cover types within the forest without considering spatial character, placement, or location of forest cover patches. However, composition metrics are only applicable at the landscape level because of integration over all forest cover types. Configuration includes the spatial character and arrangement, position, or orientation of forest cover patches within the class or forest. Configuration can be quantified in terms of the spatial relationship of forest cover patches. These aspects of configuration are measures of the placement of forest cover patch types relative to other patches, other patch types, or other features of interest (Turner et al., 2001). Because many of the numerous spatial metrics are intercorrelated (McGarigal and Marks, 1995), spatial metrics selected to describe landscape structure relevant to burn severity must be based on clear study purposes and criteria.

Relevant spatial metrics associated with burn severity, as well as the ecological functions of post-fire forests, can be identified

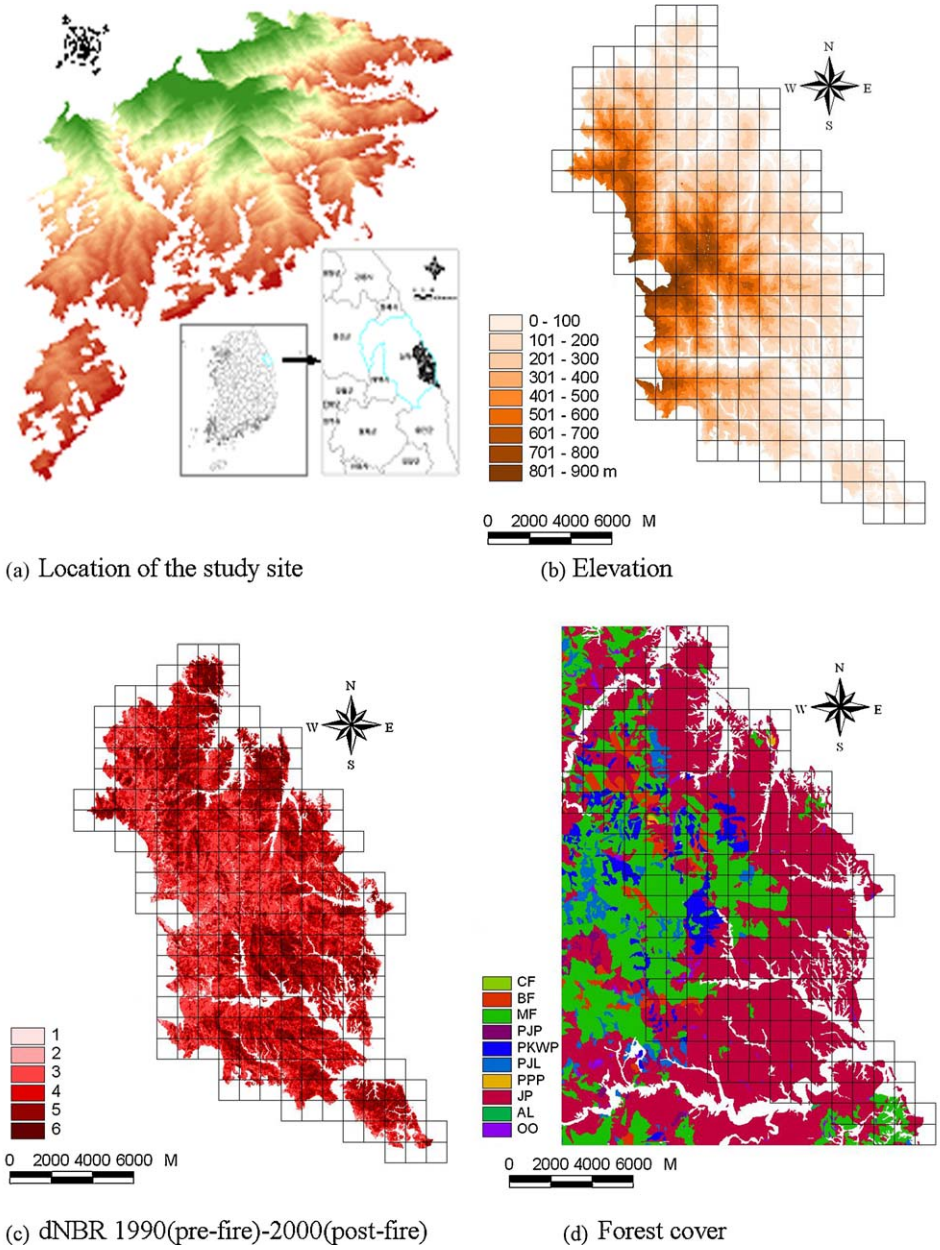

Fig. 1. Location of the study site (a), topography at the site (b), delta Normalized Burn Ratio (dNBR) values pre- and post-fire (c), and forest cover with a 1-km grid (d).

Table 1
Forest classes and the dominant trees in the study area before the fire.

Forest cover types	Dominant trees	Area (ha)	Percentage (%)
Mixed coniferous forest	Japanese red pine (*Pinus densiflora*)	0.9	0.01
	Pitch pine (*Pinus rigida*)		
	Other coniferous trees		
Broad-leaved forest	Mongolian oak (*Quercus mongolica*)	455.9	2.82
Mixed forest	Japanese red pine (*Pinus densiflora*)	2976.1	18.43
	Mongolian oak (*Quercus mongolica*)		
	Others		
Planted Japanese red pine forest	Japanese red pine (*Pinus densiflora*)	0.3	0.01
Planted Korean white pine forest	Planted Korean white pine (*Pinus koraiensis*)	867.1	5.37
Japanese larch forest	Japanese larch (*Larix leptolepis*)	264.5	1.64
Planted pitch pine forest	Pitch pine (*Pinus rigida*)	32.1	0.20
Japanese red pine forest	Japanese red pine (*Pinus densiflora*)	10 778.04	66.73
Agricultural land	Cropland	108.1	0.67
Open and other	Open fields and areas with buildings	668.2	4.14
Total		16,151	100.0

based on study objectives and the literature (e.g., Lee et al., 2008b; Lloret et al., 2002; McGarigal and Marks, 1995; Ryu et al., 2007). Selected spatial metrics include the largest patch index (LPI), patch density (PD), mean shape index (MSI), area-weighted shape index (AWMSI), Shannon's diversity index (SHDI), mean Euclidean neighborhood distance (ENNMN), aggregation index (AI), and the simple proportion of each forest cover type. All are available on both the landscape and class levels except for SHDI. The selected spatial metrics can be classified into fragmentation, size variability, patch distance, diversity, and proportion. On a broad level, all of the selected forest characteristics have been shown to be important for diverse aspects of forest ecological function such as habitat, soil erosion, energy flow, and metapopulation dynamics (Forman, 1995; Turner et al., 2001). Selected forest characteristics are also important in identifying the spatial patterns of the fuelbed (Kerby et al., 2007). The selected spatial metrics are believed to represent the forest characteristics that are most important to ecological function and burn severity, based on the study purposes, the literature, and definition of the metrics. Additionally, two topographic variables (mean slope and mean elevation) for each grid cell were calculated and associated with burn severity.

2.3. Mapping burn severity

We use the term "burn severity" to refer to the degree of environmental changes caused by fire (Key and Benson, 2006; Lentile et al., 2006; Morgan et al., 2001). Numerous environmental components, including physical and chemical changes to the soil, conversion of vegetation and fuels to inorganic carbon, and structural or compositional transformations, may be used to indicate severity. Previous remote sensing studies have found burn severity to be related to vegetation consumption (Conard et al., 2002; Miller and Yool, 2002; Zhang et al., 2003) and changes in surface reflectance (Key and Benson, 2002; White et al., 1996). The term "fire severity" has been used interchangeably with "burn severity" in many studies (Key and Benson, 2006; Lentile et al., 2006). According to Lentile et al. (2006), fire severity "integrates active fire characteristics and immediate post-fire effects on the local environment," while burn severity "incorporates both short- and long-term post-fire effects on the local and regional environments." Thus fire severity emphasizes more specific temporal and spatial effects of the fire than does burn severity. In this paper, we simply adopt the term "burn severity" to reinforce the notion of vegetation changes and to maintain consistency with the Normalized Burn Index (NBR, Key and Benson, 2006) developed to measure severity using satellite images.

To adequately characterize the spatial pattern of a large fire, massive amounts of spatial information are needed. Remote sensing appears to be an effective tool for the characterization of the effects of fire (Key and Benson, 2002). Burn severity can be derived from the spectral signature following the fire (Wimberly and Reilly, 2007), and a burn severity map can provide crucial information about fire effects. In many studies, Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) have been very effective in delineating the pattern of burn severity (e.g., Collins et al., 2007; Kushla and Ripple, 1998; Turner and Romme, 1994). A single remote sensing image taken soon after a fire is sometimes sufficient for mapping burn severity. However, multi-date imagery is more beneficial in mapping burn severity as it can account for both the pre- and post-fire condition of the damaged forests (Wimberly and Reilly, 2007). Although there is some criticism regarding its ability to delineate burn severity (Roy et al., 2006), the delta Normalized Burn Ratio (dNBR) is particularly promising for mapping burn severity in different forest types and geographical locations (e.g., Cocke et al., 2005; Collins et al., 2007; Wimberly and Reilly, 2007). The dNBR is derived from different reflectances in bands 4 and 7 in pre- and post-fire Landsat imagery. The NBR is defined as (band 4 − band 7)/(band 4 + band 7) and the dNBR representing burn severity is defined as the difference between the $NBR_{pre\text{-}fire}$ and the $NBR_{post\text{-}fire}$. NBR values range between −1 and +1, while dNBR ranges between −2 and +2. Previous studies have found a strong correlation between ground-based data and the dNBR derived from satellite imagery (Epting et al., 2005; Roy et al., 2006; van Wagtendonk et al., 2004). The delta Normalized Difference Vegetation Index (dNDVI) derived using band 4 and 5 data is a similar index to dNBR and has also been widely used to map burn severity. Studies have shown, however, that dNBR results are a better fit (Key and Benson, 2006; Lentile et al., 2006; van Wagtendonk et al., 2004).

The burn severity of the study area was mapped using dNBR values derived from two Landsat multi-spectral images with 30-m resolution. The images were taken on 7 May 1999 and 5 May 2000 to capture pre- and post-fire landscape structure. The dNBR values ranging from −2 through +2 were converted to 1 through 255, and then the dNBR values were classified into six categories: extreme, very high, high, moderate, low, and unburned (Table 2, Fig. 1c, RSAC, 2005). The dNBR map (Fig. 1c) shows that about 65% of the area was severely damaged (high to extreme), particularly on the eastern side of the area, while the western side was relatively less damaged.

A few previous studies have used NBR methods to examine forest fires in Korea (Lee et al., 2008a; Won et al., 2008). The results of those studies and others indicated that NBR derived from satellite imagery could capture the burn severity of forests in Korea, as well as elsewhere (Epting et al., 2005; Rogan and Yool, 2001; Roy et al., 2006). In this study, we collected field assessment data for burn severity from 30 plots in the burned areas; after elimination of incomplete data, 20 field assessments remained. Because the Composite Burn Index (CBI; Key and Benson, 2002, 2006) was released after this fire event, the field assessment used here did not exactly follow the CBI method. The data for the 25 field assessments were used to validate the dNBR. We selected 25 plots, 30 m × 30 m in size, from a random sample of homogeneous areas within the dNBR classification. The field survey method simply assessed the burn severity based mainly on the consumptions of litter, duff, shrubs, and intermediate and tall trees. The field-assessed burn severity was classified into three categories of low, moderate, and high severity. In low severity (surface fire) plots, fire consumed only light fuels including litter, small dead branches, or ground covers, with scorching of the crowns of medium-sized trees. In areas of moderate severity, some fuels remained on the forest floor and there was mortality of small trees with scorching of the crowns of large trees. High severity (crown fire) was typified by nearly complete combustion of all litter, duff, and small logs, mortality of small trees, and consumption of large tree crowns. The severity classes were then encoded as 1 (low severity), 2 (moderate

Table 2
Burn severity classes in the study area determined using delta Normalized Burn Ratio (dNBR) values.

Severity	Intervals[a]	Threshold[b]	Damaged area (ha)[c]	Percentage (%)
Unburned	$x < \mu - 2\delta$	76	93	0.6
Low	$\mu - 2\delta \le x < \mu - 1\delta$	114	811	5.0
Moderate	$\mu - 1\delta \le x < \mu$	152	4743	29.3
High	x	190	5421	33.5
Very high	$\mu \le x < \mu + 1\delta$	228	3894	24.0
Extreme	$\mu + 1\delta \le x < \mu + 2\delta$	255	1238	7.6

[a] x = observed dNBR value, μ (mean) = 171.1, and δ (standard deviation) = 37.99.
[b] A distinct value of dNBR at which the upper interval and lower interval are split, ranging from 1 through 255.
[c] Total damaged area is 16,201 ha.

severity), and 3 (high severity) to validate the dNBR. Although 25 is not a sufficient number of field assessments, correlation analysis indicated that dNBR was able to capture the burn severity effectively in the study areas ($r = 0.832$, $p < 0.01$).

We used a 1-km grid as the base unit for the analysis of the relationship between burn severity and landscape structure and the analysis of topographic characteristics. We arranged 2321-km grids covering the entire damaged area (Fig. 1b). This grid size has been shown to be effective in delineating the spatial pattern of burn severity (e.g., Lloret et al., 2002). We computed the mean burn severity for each 1-km grid and associated this mean with elevation, slope, and a few selected spatial pattern metrics within the same grid.

2.4. Analysis of spatial database

In our analysis, we investigated the possible relationships of burn severity with landscape metrics, as well as elevation and slope. We employed Pearson correlation analysis to gain an overview of the general relationships among variables. However, many previous studies have reported spatial autocorrelation problems in dealing with burn severity (Collins et al., 2007; Haining, 2003; Lloret et al., 2002; Wimberly and Reilly, 2007). Neighboring pixels may have similar values for burn severity due to similarities in climate, topography, or other spatially dependent factors (Lloret et al., 2002). Typical correlation analysis cannot exclude the inherent spatial autocorrelation problems of spatial datasets. According to Collins et al. (2007), one possible way to avoid such spatial autocorrelation issues is to perform the analysis on a subset of the data that are separated by a distance greater than the range of similarity in observed values. A semivariogram analysis on a reclassified dNBR map of the study area indicated that the effective distance of spatial autocorrelation for burn severity in the Samchuck area was 690 m. However, a subset of data separated by 690 m (i.e., by 1 grid cell) from all neighborhood grids allowed only 53 observations, or one-third of all observations. Another way to handle the spatial autocorrelation problem is to use regression trees (Calbk et al., 2002; Collins et al., 2007). Regression tree analysis has been demonstrated to effectively model correlative relationships even if autocorrelation is present in the dataset (Calbk et al., 2002), and the results of regression trees are easy to interpret (Collins et al., 2007). Compared with conventional generalized linear models, regression trees provide better predictions because they are well suited for analysis of complex ecological data that may include lack of balance, missing values, non-linear relationships between variables, and high-order interactions (Breiman et al., 1984; De'ath, 2002; De'ath and Fabricius, 2000; Ripley, 1996). In the model, a tree is grown by repeated binary splitting of the data. Each split is defined based on a single explanatory variable, forming two nodes. Cross-validation is used to select the tree size, with the chosen tree having the smallest predicted mean square error (Breiman et al., 1984). This tree is considered to be the best predictive tree (De'ath, 2002). In addition to correlation analysis, therefore, we used regression tree analysis to solve the spatial autocorrelation problems inherent in the dataset and to keep the maximum number of observations.

3. Results

3.1. Descriptive statistics

Table 3 lists the burn severity classes mapped after the Samchuck fire. Severity ranged from low (surface fire) to moderate (mixed surface fire and scorching) to high to extreme (stand-replacing fire). The mean fire severity was 3.8 for 65% of the classified area, representing high to extreme severity. The areas of most forest cover types varied greatly from grid to grid. Mixed forest, planted Korean white pine forest, and Japanese red pine forest showed especially large standard deviations, while mixed coniferous forest and planted Japanese red pine forest showed relatively small standard deviations, with relatively small occupied areas of 38.79 and 11.6 m^2, respectively. The mean occupied area of mixed forest and Japanese red pine was 128,308.2 m^2 and 464,628.9 m^2 within a grid, respectively. The mean elevation was 257 m and the maximum elevation of the site was 840 m. The slope analysis suggested that the study area is hilly (with a mean slope of 21.4%).

All selected spatial pattern metrics were measured at both the landscape and class level. Preliminary analysis, however, indicated that only pine and mixed forest exhibited significant relationships

Table 3
Descriptive statistics of selected variables.

Variables		Min.	Max.	Mean	Std. Dev.
Burn severity		2.1	5.4	3.8	0.5
Composition (forest cover area)	CF (m^2)	0.0	9000	38.79	590
	BF (m^2)	0.0	530,000	19,000	75,000
	MF (m^2)	0.0	892,000	128,000	214,000
	PJP (m^2)	0.0	20,700	11.0	177
	PKWP (m^2)	0.0	864,000	37,000	109,000
	PJL (m^2)	0.0	522,000	11,000	52,000
	PPP (m^2)	0.0	141,000	1000	11,000
	JP (m^2)	0.0	1040,000	464,000	334,000
	AL (m^2)	0.0	143,000	4000	15,000
	OO (m^2)	0.0	417,000	28,000	53,000
Topography	Elevation (m)	25.6	840.2	257.0	206.6
	Slope (%)	6.4	31.5	21.4	4.94
Configuration	PD (L/P/M)[a]	1.0/1.0/1.0	15.3/10.2/7.1	6.5/2.6/2.1	3.3/1.7/1.4
	LPI (L/P/M)	22.4/0.09/0.3	100/100/100	68.2/49.8/31.7	20.7/32.4/27.6
	MSI (L/P/M)	1.0/1.0/1.0	2.3/3.2/3.0	1.4/1.4/1.5	0.2/0.3/0.3
	AWMSI (L/P/M)	1.0/1.0/1.0	3.6/4.1/3.0	1.7/1.6/1.6	0.4/0.4/0.4
	ENNMN(L/P/M)	0.0/60/60	690.0/1050/918	139.7/142.3/186.7	114.5/114.2/155.5
	AI	83/63/67	100/100/100	94.4/93.2/91.5	3.6/5.8/7.2
	SHDI	0.0	1.3	0.6	0.3

CF: coniferous forest, BF: broad-leaved forest, MF: mixed forest, PJP: planted Japanese red pine, PKWP: planted Korean white pine, PJL: planted Japanese larch, PPP: planted pitch pine, JP: Japanese red pine, AL: agricultural land, and OO: open and other. PD: patch density, LPI: largest patch index, MSI: mean shape index, AWMSI: area-weighted mean shape index, ENNMN: Euclidean nearest neighborhood distance mean, AI: aggregation index, SHDI: Shannon's diversity index.

[a] L: landscape level ($n = 232$), P: pine tree forest ($n = 230$), and M: mixed forest ($n = 115$).

with burn severity and spatial pattern metrics at the class level. Patch density (PD) measures the number of patches including all forest cover types per 100 ha. The mean number of forest cover patches in a grid was 6.5, and the standard deviation of PD was 3.3 at the landscape level. The mean PD for pine and mixed forests was somewhat smaller, 2.6 and 2.1, respectively. The mean percent of a grid that the largest forest cover patch comprises (i.e., LPI) was 68.2 at the landscape level, and pine forest and mixed forest showed smaller mean LPI values (49.8 and 31.7, respectively). Some grids had only a single large forest cover patch (i.e., LPI = 100) at both the landscape and class level. The shape index is the simplest and perhaps the most straightforward measure of overall shape complexity. The MSI equals 1 when the patch is maximally compact (McGarigal and Marks, 1995). The mean and minimum shape indices of the area at the landscape level were 1.4 and 1.0, respectively, indicating that forest cover patches in the study area were relatively simple. Mixed forest had a slightly higher MSI (1.5) than pine forest (1.4). The area-weighted mean shape index (1.7) at the landscape level was slightly higher than the simple mean shape index (1.4), suggesting that larger forest cover patches are only slightly more complex than small forest cover patches. The ENNMN of the same forest cover type patches was 139.7 m, with a very large standard deviation (114.5 m) at the landscape level. Mixed forests had more distance between patches (186.7 m) compared to pine forests (142.3 m). SHDI measures the proportion of the grid occupied by forest cover patch types and is available only at the landscape level. Considering that SHDI can theoretically range from 0 (i.e., no diversity) with no upper limit, the mean SHDI in the study area (0.6) suggests that the forest in the study area was relatively homogeneous.

3.2. Effects of forest cover composition and topography on burn severity

Burn severity was negatively correlated with grid topographic characteristics including elevation ($r = -0.36$) and slope ($r = -0.14$) in Table 4. Specifically, burn severity was more likely to be low if elevation or slope was high. Some forest cover types also had significant relationships with burn severity. In particular, Japanese red pine was positively correlated with, and mixed forest was negatively related to, burn severity ($r = 0.58$ and -0.25, respectively). Thus, fire is more likely to be severe if an area contains more Japanese red pine. Fire is likely to be less severe if an area includes more mixed forest. Other forest cover types including coniferous, broad-leaved, planted Japanese red pine, Korean white pine, Japanese larch, pitch pine, and agricultural lands had insignificant relationships with burn severity. This select relationship between many fire characteristics, including burn severity and fire behavior, and certain forest cover types has been reported in previous studies suggesting that fire size is significantly tied to land-cover types (Bajocco and Ricotta, 2008; Gustafson et al., 2004; Moreira et al., 2001; Ryu et al., 2007). Recently, Nunes et al. (2005) reported that fire spread is very selective and that some land-cover types effectively constrain fire spread over landscapes. Their data suggest that shrub cover burns more readily, whereas agricultural land and olive groves are mostly avoided. As reported elsewhere (e.g., Cardille and Ventura, 2001; Ryu et al., 2007), certain tree types such as pine, aspen, and birch showed the strongest correlation with burn severity. A positive relationship ($r = 0.67$) between slope and elevation indicated that uplands are steeper than lowlands. More broad-leaved forest ($r = 0.35$), mixed forest ($r = 0.61$), Korean white pine ($r = 0.39$), and Japanese larch ($r = 0.19$) occurred in uplands, whereas red pines ($r = -0.29$) were located in lowland areas. Similarly, broad-leaved forest ($r = 0.29$), mixed forest ($r = 0.45$), Korean white pine ($r = 0.32$), and Japanese larch ($r = 0.15$) were present in steeper areas. Mixed forest cover was more likely to be present if the topography was steep in upland areas. Mixed forest cover occupied areas neighboring Korean white pine ($r = 0.17$) and Japanese larch ($r = 0.22$) but was not found in areas neighboring red pine ($r = -0.39$). In general more upland mixed forests were expected in areas of high elevation and steep slope in the Samchuck area. These forests tend to burn at low severity. In contrast, Japanese red pines were more common in the lowlands, and severe ecological effects are expected when red pine burns. In terms of the strength of correlations with burn severity, the area of Japanese red pine cover appeared to be the most significant variable, followed by elevation, area of mixed forest, and slope.

3.3. Effects of forest cover configuration on burn severity

The correlations between measured spatial pattern metrics and burn severity at the landscape and class level shown in Table 5 indicate that the spatial pattern of forest cover prior to the fire event was tied to burn severity. Specifically, at the landscape level, burn severity was negatively correlated with PD ($r = -0.14$), ENNMN ($r = -0.18$), and SHDI ($r = -0.23$) and positively correlated with LPI ($r = 0.14$). However, MSI, a measure of shape complexity of forest cover patches, was not related to burn severity at the landscape level. Similar patterns were observed at the class level in pine forest. For example, burn severity was negatively related with ENNMN ($r = -0.26$) and positively related with LPI ($r = 0.23$) and AI

Table 4
Pearson correlation analysis between forest cover and topography and burn severity.

	BS[a]	Elev.	Slope	CF	BF	MF	PJP	PKWP	PJL	PPP	JP	AL
Elev.	−0.36**											
Slope	−0.14*	0.67**										
CF	−0.01	−0.01	0.01									
BF	−0.07	0.35**	0.29**	0.01								
MF	−0.25**	0.61**	0.45**	−0.03	0.22**							
PJP	−0.06	0.02	0.10	−0.01	−0.01	−0.01						
PKWP	−0.11	0.39**	0.32**	−0.02	−0.11	0.17**	−0.01					
PJL	0.03	0.19**	0.15*	−0.01	−0.04	0.22**	−0.01	−0.03				
PPP	0.06	0.01	0.06	−0.01	−0.02	0.03	−0.01	−0.03	−0.01			
JP	0.58**	−0.29**	−0.08	−0.10	0.10	−0.39**	−0.06	−0.20**	−0.09	−0.01		
AL	−0.04	−0.01	0.12	−0.05	0.05	0.05	−0.02	0.05	−0.03	−0.03	0.07	
OO	0.23*	−0.37**	−0.42**	−0.03	0.03	−0.19**	−0.03	−0.15*	−0.11	0.02	0.08	−0.04

$n = 232$. CF: coniferous forest, BF: broad-leaved forest, MF: mixed forest, PJP: planted Japanese red pine, PKWP: planted Korean white pine, PJL: planted Japanese larch, PPP: planted pitch pine, JP: Japanese red pine, AL: agricultural land, and OO: open and other.

[a] Burn severity.

* $p < 0.05$.

** $p < 0.01$.

Table 5
Pearson correlation analysis of spatial pattern metrics of pre-fire forest cover types with burn severity at the landscape and class levels.

	Spatial pattern metrics	Correlation coefficient
Landscape level[a]	PD	−0.14*
	LPI	0.14*
	MSI	0.04
	AWMSI	−0.01
	ENNMN	−0.18*
	AI	−0.04
	SHDI	−0.23**
Class level (pine tree cover)[b]	PD	−0.03
	LPI	0.46**
	MSI	−0.07
	AWMSI	−0.01
	AI	0.29**
	ENNMN	−0.26**
Class level (mixed forest cover)[c]	PD	−0.03
	LPI	−0.44**
	MSI	−0.05
	AWMSI	−0.11*
	AI	−0.13*
	ENNMN	−0.10

PD: patch density, LPI: largest patch index, MSI: mean shape index, AWMSI: area-weighted mean shape index, ENNMN: Euclidean nearest neighborhood distance mean, AI: aggregation index, SHDI: Shannon's diversity index.
[a] $n = 232$.
[b] $n = 230$.
[c] $n = 115$.
* $p < 0.05$.
** $p < 0.01$.

($r = 0.29$) in areas with pine forest cover. The relationship among PD, MSI, and AWMSI of pine tree forest cover was not significantly correlated with burn severity. In contrast, LPI of mixed forest cover was negatively related to burn severity ($r = -0.44$). Overall, burn severity is more likely to be low if forests are patchy with diverse tree cover. Conversely, burn severity is more likely to be high when forests are occupied by a few large patches located close together. Small patches of mixed species forests are more likely to burn with low severity while large patches of pine forests are more likely to burn with severe effects.

3.4. Regression tree analysis

Regression tree analysis at the landscape level indicated that the area of Japanese pines within a grid was the most significant variable explaining burn severity (Fig. 2). The area of Japanese red pine trees was split at 36.1 ha into two groups in the regression tree. In the regression tree, the <36.1 ha group was associated with lower burn severity while the >36.1 ha group was associated with higher burn severity. Elevation was the second most important factor explaining burn severity for areas of Japanese red pine <36.1 ha (left side of the tree). Higher elevation (>699 m) was associated with lower burn severity. In areas of Japanese red pine >36.1 ha, AWMSI appeared to be the second most important variable explaining burn severity (right side of the tree). Complex large forest patches were associated with lower burn severity. Regardless of elevation, SHDI was the third most important variable on the left side of the regression tree, while slope appeared to be the third most important factor explaining burn severity on the right side of the tree. Although some variables did not appear in the regression trees, the overall order of relative importance to burn severity at the landscape level was as follows: area of Japanese red pines > elevation > area of mixed forests > slo-slope > AWMSI > SHDI > LPI. Overall, most variance in burn severity was explained by forest composition and topography, while a relatively small proportion of the burn severity variance was explained by forest configuration at the landscape level. The R^2 of the regression tree model at the landscape level was 49.8%, and the mean standard error was 0.16.

Fig. 3 presents regression trees for both Japanese red pine forests and mixed forests at the class level. In the regression trees for Japanese red pine forests, a large proportion of burn severity variance was explained by LPI at the class level. Higher burn severity was associated with the high LPI value (>28.2) of Japanese red pine forests, which is consistent with regression trees at the landscape level (Fig. 2). The aggregation index of Japanese red pine forests appeared to be the second most important factor explaining the variance of burn severity. When LPI of Japanese red pine forests was greater than 28.2, a high value of the aggregation index was related to high burn severity. Although some variables did not appear in the regression trees, the overall order of relative importance to burn severity at the class level was as follows:

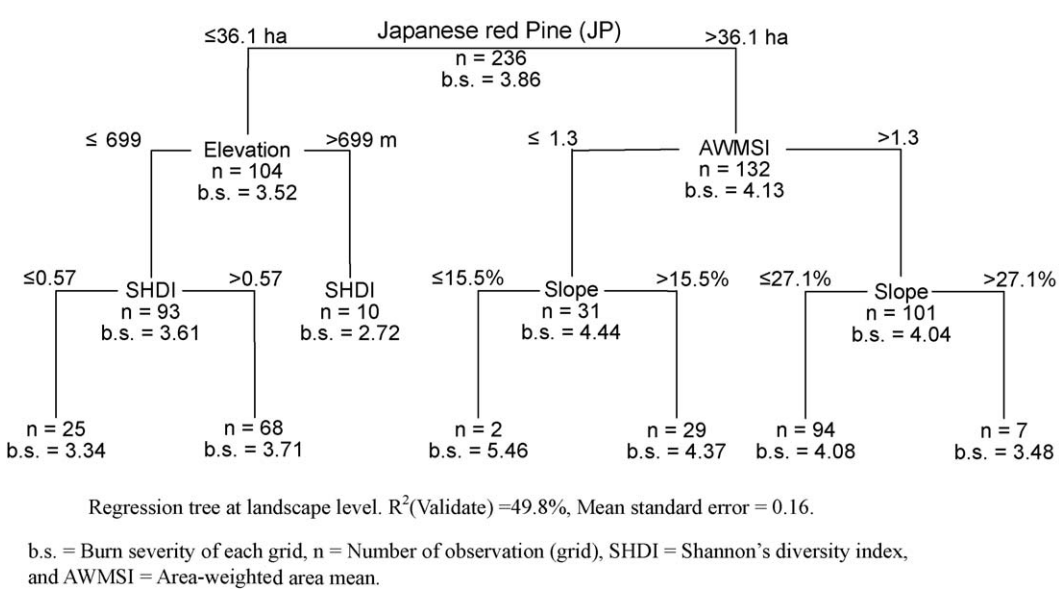

Fig. 2. Regression tree explaining the spatial distribution of burn severity in the study areas at the landscape level. Variables in higher nodes explain a greater proportion of burn severity variance. The number of observations and the mean burn severity in each group are reported for each node.

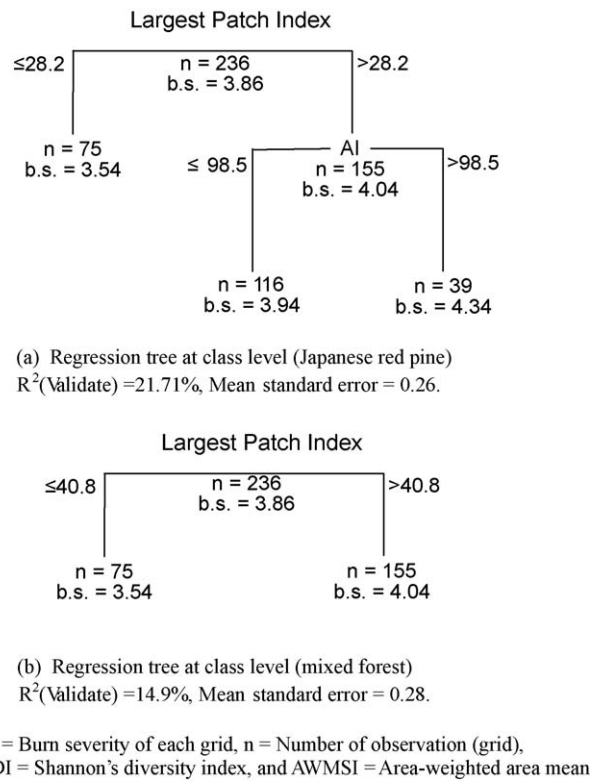

Fig. 3. Regression trees for Japanese red pine forests (a) and mixed forests (b) at the class level. In both regression trees, LPI is the most significant variable explaining burn severity at the class level.

largest patch index > aggregation index > Euclidian nearest neighborhood distance > patch density of Japanese red pine forests. The regression trees for mixed forests in Fig. 3b show that the only effective variable was LPI. A small LPI value for mixed forests was tied to a high value of burn severity. The order of relative importance to burn severity at the class level was largest patch index > mean shape index > area-weighted mean shape index > Euclidian nearest neighborhood distance of mixed forest. The R^2 values and mean standard errors of regression trees for Japanese red pine forests and mixed forests were 21.71% and 14.9% and 0.26 and 0.28, respectively.

4. Discussion

The spatial heterogeneity of forests has a significant impact on burn severity. The present study demonstrated that topographic characteristics, forest composition, and forest configuration have significant relationships with burn severity. Forest heterogeneity was shown to be associated with low burn severity. The present results also confirmed the findings of previous studies that have suggested a strong tie between forest heterogeneity and fire characteristics including the behavior, spread, severity, number, and size of fires (Duguy, 1998; Farina, 1998; Li and Wu, 2004; Ryu et al., 2007; Stephens, 2001).

Correlation analysis of elevation and slope with burn severity indicated that both are negatively related to burn severity. However, scatter plots of elevation and slope versus burn severity suggest that a non-linear relationship may exist between them. Estimated quadratic models of both slope and elevation were better than linear models at explaining the variances of burn severity (Fig. 4, Table 6). Other studies have reported non-linear relationships between topographic characteristics and burn severity (González et al., 2005; Schoenberg et al., 2003). As shown in Fig. 4, burn severity increased with slope in the range of 0–18.4%, beyond which burn severity decreased with slope. A similar relationship was found between elevation and burn severity. Burn severity increased between 0 and 241.6 m but decreased at elevations above 241.6 m.

It is not clear why slope and elevation exhibit non-linear relationships with burn severity. Possible explanations include differences in fuel moisture, temperature, precipitation, canopy bulk density (González et al., 2005; Hall and Burke, 2006; Van Wagner, 1977), and the compounding effects of fuels. Additionally, the chimney effect (Pyne et al., 1996) and water potential (Foster, 1983) might play important roles in the relationships between fire spread and topography. A topographic chimney is formed from a steep narrow chute with three walls. The chimney effect occurs when unstable air conditions at the surface create a convection current through the chimney area, drawing air in at the base and exhausting it at the top. Normal upslope air flow becomes rapid and funnels into the chimney (Dickinson and Johnson, 2001; Pyne et al., 1996).

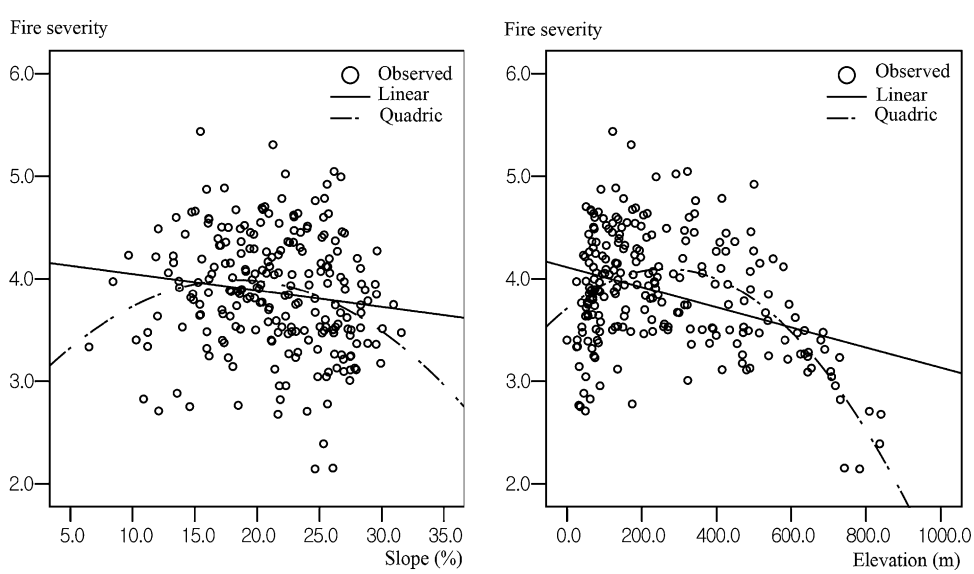

Fig. 4. The relationships of elevation and slope with burn severity.

Table 6
Estimated linear and quadric models of elevation and slope.

	Model	*R*-square	*F*-value	b_0	b_1	b_2
Elevation	Linear	0.12	33.54**	4.11	−0.001	–
	Quadric	0.29	47.59**	3.70	−0.0029	−6.E−06
Slope	Linear	0.01	4.60*	4.20	−0.0161	–
	Quadric	0.05	6.71**	2.73	−0.1362	−0.0037

d.f. = 231.
* $p < 0.05$.
** $p < 0.01$.

The findings of this study reveal only a small part of the complex relationships between topology and burn severity, and large aspects of the relationships remain unresolved. Notably, a negative relationship ($r = -0.29$) was found between the area of red pine and elevation. Japanese red pines are more likely to be present at lower elevation and scarce at higher elevations. The results of regression tree analysis suggest that the most significant factor explaining the variance of burn severity was the area of red pine forest patches at the landscape level. From the results of correlation analysis between elevation and area of red pines as well as the regression tree analysis, a reasonable explanation for the non-linear relationship between topology and burn severity might be that red pines are quite susceptible to fire and this susceptibility overrides the influence of topology. Fuel moisture, fuel loads, and the bulk crown density tend to vary with elevation in non-linear patterns (Miller and Urban, 2000).

The results of this study also suggest that burn severity in Samchuck, Korea, depends on forest cover type, similar to the selective effects of forest composition on burn severity reported from many other geographic locations (e.g., Bigler et al., 2005; Collins et al., 2007; Lloret et al., 2002; Nunes et al., 2005; Ryu et al., 2007; Wimberly and Reilly, 2007). In the present study, burn severity was positively correlated with the area of pine cover and negatively related to the area of mixed forest cover. In general, pine forests are positively associated with fire spread, ignition, and severity due to their susceptibility to fire (Bigler et al., 2005; Cardille and Ventura, 2001; Collins et al., 2007; Nunes et al., 2005; Ryu et al., 2007). The results of regression tree analysis also strongly support the susceptibility of red pines to fire. Furthermore, this study supports previous observations that have suggested a negative relationship between mixed forest cover and fire spread and severity (Ryu et al., 2007). The negative relationship between SHDI and burn severity in this study strongly suggests that homogenization of forest composition may increase burn severity, again confirming previous findings (Lloret et al., 2002). Regression tree analysis at the landscape level also showed that the compositional heterogeneity (i.e., SHDI) and shape complexity of large forest patches (i.e., AWMSI) impact burn severity. Presumably, forests dominated by one to a few types of tree cover, particularly pine, are more susceptible to fire than forests consisting of many different tree covers. However, it is noteworthy that the effects of compositional homogeneity are significantly reduced for very large catastrophic fires usually driven by weather conditions (Bajocco and Ricotta, 2008; Nunes et al., 2005). The results of the present study and others noted above strongly suggest that compositional heterogeneity is a key factor in managing and restoring forests that are resilient to small or less intensive fires.

Configuration of forest patches was strongly tied to burn severity in the Samchuck area at both the landscape and class level. Results of correlation analysis indicated that PD, patch size, and distance appeared to be particularly important variables in explaining burn severity at the landscape level. This confirms previous findings that have suggested a strong tie between fragmented forests and less severe fire damage (e.g., Lloret et al., 2002; Ryu et al., 2007). In regression trees, landscape heterogeneity appeared as an important factor explaining burn severity, especially for forests with less red pine. The shape complexity of forest cover patches was also an important variable in regression trees when there was larger coverage by red pines.

However, correlation analysis at the class level showed a somewhat different relationship with burn severity depending on forest cover types. Specifically, burn severity was positively tied to LPI and AI and negatively correlated with the patch distance of pine tree patches. Regression trees for Japanese red pines suggested that LPI was the most significant variable explaining burn severity, while AI was the second. The spatial metrics of mixed forest cover exhibited a somewhat different relationship with burn severity. LPI of mixed forest cover had a negative relationship with burn severity. Regression tree analysis provided consistent results. In the mixed forest regression trees, only LPI made a significant contribution to burn severity.

Consistent with the above results, the sizes of both pine and mixed forest cover patches were key factors in understanding burn severity. This is quite interesting, as most previous studies have investigated the relationship between forest heterogeneity and burn severity at the landscape level. The spatial pattern of forest cover may function differently with regard to burn severity depending on the fire susceptibility of different forest cover types.

5. Conclusions

This study measured the heterogeneity in both composition and configuration of forests at the landscape and class level in Samchuck, Korea and related them to burn severity with dNBR derived from satellite images taken pre- and post-fire in 1999 and 2000. The results confirm the findings of previous studies dealing with landscape structure and fire spread and severity (Li and Wu, 2004; Stephens, 2001). The present findings highlight the relationship between forest heterogeneity and burn severity. Both the composition and configuration of forest cover are strongly tied to burn severity. Specifically, burn severity is very dependent on forest cover type. Pine forest cover results in high severity, whereas mixed forest does not. Also, burn severity is sensitive to the configuration of forest cover patches. Patch density, distance among patches, and shape complexity of large patches are particularly important characteristics of spatial configuration. However, spatial configuration may result in different effects on burn severity depending on the susceptibility of cover type to fire. Both elevation and slope had significant non-linear relationships with burn severity, possibly due to local climate and weather conditions. To improve fire prevention and resilience, forest managers and agencies need to consider both the composition and configuration of forest cover, and recognize the important differences among forest cover types. By enhancing the heterogeneity of forests, burn severity may be substantially reduced.

Fuel treatments must also be considered in managing fire-resilient forests (Agee and Skinner, 2005; Finney, 2001; Schmidt

et al., 2008; Stephens and Ruth, 2005). Although fuel treatments will not necessarily be able to stop or eliminate all risks of damages to natural and human resources (Finney and Cohen, 2003), reducing fire severity may be best achieved by identifying place-specific fuel treatments such as prescribed burning, mechanical thinning, or a combination of the two (Arno and Allison-Bunnell, 2002; Graham et al., 2004). Fuels are defined as the physical characteristics of live and dead biomass that contribute to the spread, intensity, and severity of forest fire (Andrews and Queen, 2001; Burgan et al., 1998). Knowledge of the spatial pattern of fuels is important to developing management strategies for fire-resilient forests (Arroyo et al., 2008), and manipulating the structure of forests in landscapes may reduce fire risks by controlling fuel patterns to some extent. The amount and continuity of live and dead vegetation limits fire spread and severity (Green, 1983; Minnich et al., 2000; Rollins et al., 2002; Turner and Romme, 1994) and the patterns of fuels depend in part on forest composition and configuration. Applying fuel-reduction treatments in individual stands without addressing the overall spatial configuration may result in little change in the spread and severity of fires at landscape scales (Gustafson et al., 2004). Thus, the effectiveness of surface and canopy fuel treatments may be enhanced by considering the landscape heterogeneity identified in this study. However, such fuel treatments with considerations of forest composition and configuration may be effective only under moderate weather conditions (Bessie and Johnson, 1995; Turner and Romme, 1994), because extreme temperature and wind speed can override the influence of fuels (Schoennagel et al., 2004).

As discussed elsewhere (Collins et al., 2007), forest heterogeneity is not the primary factor affecting many fire characteristics, including severity, frequency, and behavior, all of which are affected by numerous factors, such as available fuels, weather, and topography (Collins et al., 2007; Pyne et al., 1996; Rothermel, 1972). Our regression tree analysis results indicated that forest composition, which is strongly tied to fuel types (Minnich et al., 2000; Rollins et al., 2002), is a more significant factor explaining fire severity than other factors such as topology and spatial arrangement. However we were not able to integrate weather conditions or fuels into the present analysis. Collins et al. (2007) reported that weather conditions such as relative humidity, temperature, and wind speed are the primary factors explaining the distribution of dNBR. However, because our study was carried out at one fire site, weather variables were assumed to be the same across the damaged areas. We also could not examine fuels in the present study because of a lack of sufficient field data regarding pre-fire fuels at the study site. Integrating these variables with forest structure might lead to better guidelines and management plans for fire-resilient forests.

Despite numerous studies, including the present one, the relationship between forest heterogeneity and burn severity remains unclear because of the complex and dynamic interactions among the relevant variables, such as topography, disturbance history (Bigler et al., 2005), and weather conditions (Collins et al., 2007; Pyne et al., 1996; Rothermel, 1972). Our study examined only simple relationships between forest heterogeneity and burn severity, not the interactions between variables or their combined effects on burn severity. For example, non-linear relationships between elevation and slope with burn severity were observed, but it is not clear how these characteristics interact with forest heterogeneity. Furthermore, do elevation and slope have direct and indirect effects on burn severity through the shaping of landscape structure? These interesting questions are beyond the scope of this study and remain unanswered. Thus, a more sophisticated study with a wider ranging data set including soils, weather, and climate is needed to answer these questions. It is also important to note that implementation of the findings of this study may be limited because of the difficulty in applying the present results, based on an analysis unit of 1 km, to the relationship between landscape structure and burn severity on a larger scale.

References

Agee, J.K., Skinner, C.N., 2005. Basic principles of forest fuel reduction treatments. For. Ecol. Manage. 211, 83–96.

Andrews, P.L., Queen, L.P., 2001. Fire modeling and information system technology. Int. J. Wildland Fire 10, 343–352.

Antrop, M., 2000. Background concepts for integrated landscape analysis. Agric. Ecosyst. Environ. 77, 17–28.

Arno, S.F., Allison-Bunnell, S., 2002. Flames in Our Forest: Disaster or Renewal. Island Press, Washington, DC.

Arroyo, L.A., Pascual, C., Manzanera, J.A., 2008. Fire models and methods to map fuel types: the role of remote sensing. For. Ecol. Manage. 256, 1239–1252.

Bajocco, S., Ricotta, C., 2008. Evidence of selective burning in Sardinia (Italy): which land-cover classes do wildfires prefer? Landsc. Ecol. 23, 241–248.

Bessie, W.C., Johnson, E.A., 1995. The relative importance of fuels and weather on fire behavior in subalpine forests. Ecology 76, 747–762.

Bigler, C., Kulakowski, D., Veblen, T.T., 2005. Multiple disturbance interactions and drought influence fire severity in Rocky Mountain subalpine forests. Ecology 86, 3018–3029.

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.G., 1984. Classification and Regression Trees. Wadsworth International Group, Belmont, CA.

Brown, J.K., 2000. Ecological principles, shifting fire regimes and management considerations. In: Brown, J.K., Smith, J.K. (Eds.), Wildland Fire in Ecosystems—Effects of Fire on Flora, USDA Forest Service, Rocky Mountain Research Station, RMRS-GTR-42-volume 2, pp. 185–203.

Burgan, R., Klaver, R., Klaver, J., 1998. Fuel model and fire potential from satellite and surface observations. Int. J. Wildland Fire 8, 159–170.

Calbk, M.E., White, D., Kiester, A.R., 2002. Assessment of spatial autocorrelation in empirical models of ecology. In: Scott, J.M., Heglund, P.J., Morrison, M.L., Haufler, J.B., Raphael, M.G., Wall, W.A., Samson, F.B. (Eds.), Predicting Species Occurrences: Issues of Scale and Accuracy. Island Press, Washington, DC, pp. 429–440.

Cardille, J.A., Ventura, S.J., 2001. Occurrence of wildfire in the northern Great Lakes region: effects of land cover and land ownership assessed at multiple scales. Int. J. Wildland Fire 10, 145–154.

Cocke, A.E., Fule, P.A., Crouse, J.E., 2005. Comparison of burn severity assessments using differenced normalized burn ratio and ground data. Int. J. Wildland Fire 14, 189–198.

Collins, B.M., Kelly, M., van Wagtendonk, J.W., Stephens, S.L., 2007. Spatial patterns of large natural fires in Sierra Nevada wilderness areas. Landsc. Ecol. 22, 545–557.

Conard, S.G., Sukhinin, A.I., Stocks, B.J., Cahoon, D.R., Davidenko, E.P., Ivanova, G.A., 2002. Determining effects of area burned and fire severity on carbon cycling and emissions in Siberia. Climatic Change 55, 197–211.

Cumming, S.G., 2001. Forest type and wildfire in the Alberta boreal mixedwood: what do fires burn? Ecol. Appl. 11, 97–110.

De'ath, D., Fabricius, K.E., 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology 81 (11), 3178–3192.

De'ath, D., 2002. Multivariate regression trees: a new technique for modeling species–environment relationships. Ecology 83 (4), 1105–1117.

Delcourt, H.R., Delcourt, P.A., 1997. Pre-Columbian Native American use of fire on southern Appalachian landscapes. Conserv. Biol. 11, 1010–1014.

Dickinson, M.B., Johnson, E.A., 2001. Fire effects on trees. In: Johnson, E.A., Miyanishi, K. (Eds.), Forest Fire: Behavior and Ecological Effects. Academic Press, San Diego, p. 503.

Duguy, B., 1998. Reconstrucción de los cambios en los usos del suelo y en la estructura del paisaje (1956–1994), Interacción con los incendios. Caso de una zona piloto en la provincia de Alicante, Ph.D. Thesis, Centro Internacional de Altos Estudios Agronómicos.

Epting, J., Verbyla, D., Sorbel, B., 2005. Evaluation of remotely sensed indices for assessing burn severity in interior Alaska using Landsat TM and ETM+. Remote Sens. Env. 96, 328–339.

Farina, A., 1998. Principles and Methods in Landscape Ecology. Chapman & Hall, London, UK.

Finney, M.A., Cohen, J.D., 2003. Expectation and evaluation of fuel management objectiveness. In: Omi, P.N., Joyce, L.A. (Eds.), Fire, Fuel Treatments, and Ecological Restoration. USDA Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-29, pp. 353–366.

Finney, M.A., 2001. Design of regular landscape fuel treatment patterns for modifying fire growth and behavior. For. Sci. 47, 219–228.

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

Foster, D.R., 1983. The history and pattern of fire in the boreal forest of southeastern Labrador. Can. J. Botany 61, 2459–2471.

González, J.R., Palahí, M.P., Pukkala, T., 2005. Integrating fire risk consideration in forest management planning in Spain—a landscape level perspective. Landsc. Ecol. 20, 957–970.

Graham, R.T., McCaffrey, T.S., Jain, T.B., 2004. Science basis for changing forest structure to modify wildfire behavior and severity, USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-120.

Green, D.G., 1983. Shapes of simulated fires in discrete fuels. Ecol. Model. 20, 21–32.

Gustafson, E.J., Zollner, P.A., Sturtevant, B.R., He, H.S., Mladenoff, D.J., 2004. Influence of forest management alternatives and land type on susceptibility to fire in northern Wisconsin, USA. Landsc. Ecol. 19, 327–342.
Haining, R., 2003. Spatial Data Analysis: Theory and Practice. Cambridge University Press, Cambridge.
Hall, S.A., Burke, I.C., 2006. Considerations for characterizing fuels as inputs for fire behavior models. For. Ecol. Manage. 227, 102–114.
Kerby, J.D., Fuhlendorf, S.D., Engle, D.M., 2007. Landscape heterogeneity and fire behavior: scale-dependent feedback between fire and grazing processes. Landsc. Ecol. 22, 507–516.
Key, C.H., Benson, N.C., 2002. Fire effects monitoring and inventory protocol—landscape assessment. USDA Forest Service Fire Science Laboratory, Missoula, MT.
Key, C.H., Benson, N.C., 2006. Landscape assessment: sampling and analysis methods. USDA Forest Service, Rocky Mountain Research Station General Technical Report RMRS-GTR-164-CD, Ogden, UT.
Krasnow, K., Schoennagel, T., Veblen, T.T., 2009. Forest fuel mapping and evaluation of LANDFIRE fuel maps in Boulder County, Colorado, USA. For. Ecol. Manage. 257, 1603–1612.
Kushla, J.D., Ripple, W.J., 1998. Assessing wildfire effects with Landsat thematic mapper data. Int. J. Remote Sens. 19, 2493–2507.
Lee, B.D., Won, M.S., Jang, K.M., Lee, M.B., 2008a. Relationship between topology and fire severity. J. Korean Assoc. Geogr. Inform. Stud. 11 (1), 58–67 (in Korean).
Lee, S.-W., Ellis, C.D., Kweon, B.-S., Hong, S.-K., 2008b. Relationship between landscape structure and neighborhood satisfaction in urbanized areas. Landsc. Urban Plan. 85, 60–70.
Lentile, L.B., Holden, Z.A., Smith, A.M.S., Falkowski, M.J., Tudak, A.T., Morgan, P., Lewis, S.A., Gessler, P.E., Benson, N.C., 2006. Remote sensing techniques to assess active fire characteristics and post-fire effects. Int. J. Wildland Fire 15, 1–27.
Li, H.B., Wu, J.G., 2004. Use and misuse of landscape indices. Landsc. Ecol. 19, 389–399.
Lloret, F., Calvo, E., Pons, X., Díaz-Delgado, E., 2002. Wildfires and landscape patterns in the eastern Iberian Peninsula. Landsc. Ecol. 17, 745–759.
McGarigal, K., Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA Forest Service, Pacific Northwest Research Station, Portland, OR, PNW-GTR-351.
Miller, C., Urban, D.L., 2000. Connectivity of forest fuels and surface fire regimes. Landsc. Ecol. 15, 145–154.
Miller, J.D., Yool, S.R., 2002. Mapping forest post-fire canopy consumption in several overstory types using multi-temporal Landsat TM and ETM data. Remote Sens. Environ. 82, 481–496.
Minnich, R.A., Barbour, M.G., Burk, J.H., Sosa-Ramirez, J., 2000. Californian mixed-conifer forests under unmanaged fire regimes in the Sierra San Pedro Martir, Baja California, Mexico. J. Biogeogr. 27, 105–129.
Moreira, F., Rego, F.C., Ferriera, P.G., 2001. Temporal (1958–1995) pattern of change in a cultural landscape of northwestern Portugal: implications for fire occurrence. Landsc. Ecol. 16, 557–567.
Morgan, P., Hardy, C.C., Swetnam, T., Rollins, M.G., George, L.G., 2001. Mapping fire regimes across time and space: understanding coarse and fine-scale fire patterns. Int. J. Wildland Fire 10, 329–342.
Nunes, M.C.S., Vasconcelos, M.J., Pereira, J.M.C., Dasgupta, N., Alldredge, R.J., Rego, F.C., 2005. Land cover type and fire in Portugal: do fires burn land cover selectively? Landsc. Ecol. 20, 661–673.
Pyne, S.J., Andrews, P.L., Laven, R.C., 1996. Introduction to Wildland Fire. John Wiley & Sons Inc., New York, NY, pp. 51–63.
Ripley, B.D., 1996. Pattern recognition and neural networks. Cambridge University Press, Cambridge, UK.
RSAC, 2005. Remote sensing application center burned area emergency response (BAER) imagery support, Salt Lake City, Utah: US Department of Agriculture Forest Service, Remote sensing Application Center, http://www.fs.fed.us/eng/rsac/baer/.
Rogan, J., Yool, S.R., 2001. Mapping fire-induced vegetation depletion in the Peloncillo Mountains, Arizona and New Mexico. Int. J. Remote Sens. 22, 3101–3121.
Rollins, M.G., Morgan, P., Swetnam, T., 2002. Landscape-scale control over 20th century fir occurrence in two large Rocky Mountain (USA) wilderness areas. Landsc. Ecol. 17, 539–557.
Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. General technical report INT-115. U.S. Department of Agriculture, Forest Service, Ogden, UT, 40 pp.
Roy, D.P., Boschetti, L., Trigg, S.N., 2006. Remote sensing of fire severity: assessing the performance of the Normalized Burn Ratio. IEEE Geosci. Remote Sens. Lett. 3 (1), 112–116.
Ryu, S.-R., Chen, J., Zheng, D., Lacroix, J.L., 2007. Relating surface fire spread to landscape structure: an application of FARSITE in a managed forest landscape. Landsc. Urban Plan. 83, 275–283.
Schmidt, D.A., Taylor, A.H., Skinner, C.N., 2008. The influence of fuels treatment and landscape arrangement on simulated fire behavior, Southern Cascade range, California. For. Ecol. Manage. 255, 3170–3184.
Schoenberg, F.P., Peng, R., Huang, Z., Rundel, P., 2003. Detection of non-linearities in the dependence of burn area on fuel age and climatic variables. Int. J. Wildland Fire 12, 1–6.
Schoennagel, T., Veblen, T.T., Romme, W.H., 2004. The interaction of fire, fuels and climate across Rocky Mountain forests. BioScience 54, 661–676.
Stephens, S.L., Ruth, L.W., 2005. Federal forest-fire policy in the United States. Ecol. Appl. 15, 532–542.
Stephens, S.L., 2001. Fire history of adjacent Jeffrey pine and upper montane forests in the eastern Sierra Nevada. Int. J. Wildland Fire 10, 161–176.
Turner, M.G., Romme, W.H., 1994. Landscape dynamics in crown fire ecosystems. Landsc. Ecol. 9, 57–77.
Turner, M.G., Hargrove, W.W., Gardner, R.H., Romme, W.H., 1994. Effects of fire on landscape heterogeneity in Yellowstone National Park, Ywoming. Journal of Vegetation Science 5, 731–742.
Turner, M.G., Gardner, R.H., O'Neill, R.V., 2001. Introduction to landscape ecology. In: Turner, M.G., Gardner, R.H., O'Neill, R.V. (Eds.), Landscape Ecology in Theory and Practice. Springer-Verlag, NY, pp. 1–23.
Van Wagner, C.E., 1977. Conditions for the start and spread of crown fire. Can. J. For. Res. 7, 23–24.
van Wagtendonk, J.W., Root, R.R., Key, C.H., 2004. Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. Remote Sens. Environ. 92 (3), 92–115.
White, J.D., Ryan, K.C., Key, C.C., Running, S.W., 1996. Remote sensing of forest fire severity and vegetation recovery. Int. J. Wildland Fire 6, 125–136.
Wimberly, M.C., Reilly, M.J., 2007. Assessment of fire severity and species diversity in the southern Appalachians using Landsat TM and ETM+ imagery. Remote Sens. Environ. 108, 189–197.
Won, M.S., Koo, K.S., Lee, M.B., Son, Y.M., 2008. Estimation of non-CO_2 greenhouse gases emission from biomass burning in the Samchuck large-fire area using Landsat TM imagery. Korean J. Agric. For. Meteorol. 10 (1), 17–24 (in Korean).
Zhang, Y.-H., Wooster, M.J., Tutabalina, O., Perry, G.L.W., 2003. Monthly burned area and forest fire carbon emission estimates for the Russian Federation from SPOT VGT. Remote Sens. Environ. 87, 1–15.