Characterizing Fire-Related Spatial Patterns in the Arizona Sky Islands Using Landsat TM Data

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Abstract
This research investigates the use of Landsat Thematic Mapper data to characterize spatial patterns in forests experiencing different fire severities and frequencies between 1943 and 1996. Spectral vegetation indices (SVIs) were used to compare spectral characteristics and spatial patterns for four categories of fire history: once burned, twice burned, multiple burned, and unburned. We quantified spatial patterns by calculating spatial statistics from several SVIs for each plot. These statistics were used in Spearman’s Rank Correlation Analysis with fire history characteristics. We found significant relationships (p < 0.05) between many of the spatial measures (mean patch size, patch size coefficient of variation, mean patch fractal dimension, Shannon’s Diversity Index, and Shannon’s Evenness Index) and fire occurrence in the past ten, thirty, fifty, and fifty-four years, average fire-free interval, most recent fire-free interval, and time since the most recent fire.

Introduction
Over the last 100 years, fuels have accumulated to dangerous levels in conifer forest communities of the southwestern United States. Aggressive fire suppression that dominated forest and range management for most of the 20th century is considered largely responsible for the current magnitude of fuel loads (Covington et al., 1997). Prior to fire exclusion, frequent, low intensity lightning-ignited fires burned throughout the late spring and summer, removing dead, decaying plant material. In conifer forest communities, fire return intervals of less than 20 years were common (Swetnam and Baisan, 1996). However, in the absence of fire, leaves, branch-wood, logs, and other plant debris collect in unnaturally high amounts, creating volatile conditions. A significant number of recent fires have been more intense and uncontrollable than the natural, moderate fires of the past, destroying entire forest stands (Covington et al., 1997; Dahms and Geils, 1997). Fuels continue to increase until they are removed by fire or mechanical clearing.

Prescribed burning has been implemented in many areas in an effort to remove those excess fuels (Hurley, 1965; Swetnam and Baisan, 1996; Pibili et al. 2001). To determine which areas are best-suited (and most critical) for prescribed burning, it is extremely important to assess fuel conditions. Variations in fuel are determined by species composition, fire history, as well as a host of topographically related factors, including site productivity. Fuel amounts are modified each time a fire burns through an area, because some portion (or all) of the fuel is removed. Frequently burned forests have less fuel and often have a more open appearance than forests that have not burned (Romme, 1982). These fire-induced changes are spatially variable in ways that have not been clearly defined (i.e., how are variations in fire severity distributed over space?) and at scales that are not well known (Pyne et al., 1996). Many ecologists cite the importance of spatial patterns in understanding forest structure and function (Turner, 1989), but much related research has been field-based (Romme, 1982). Remote-sensing-based research on fire-related spatial patterns (Minnich et al., 2000) has been conducted in only a few areas, such as Yellowstone National Park (Turner et al., 1994) and the Mediterranean Basin (Chuvieco, 1999; Ricotta and Retzlaff, 2000). These studies demonstrate that the broad perspective afforded by satellite-based remote sensing is appropriate for examining spatial patterns over larger areas than are practical with field work (Schlesnower, 1994). While the field-based studies are vital to understanding the fundamental effects of anthropogenic fire regime changes, spatially unbiased field sampling is extremely intensive and time-consuming, and it is often difficult to extrapolate these findings to a scale useful for forest managers (Whelan, 1995). For this reason, remote sensing may be the optimal technique for monitoring fire-related landscape dynamics in both a spectral and spatial context.

In this study we extracted landscape metrics from several Landsat Thematic Mapper–derived image enhancements and correlated these with a range of fire history characteristics. We were interested in the following questions:

- Can Landsat TM data be used to extract meaningful landscape patterns from forested ecosystems?
- Can these patterns be connected to fire history?
- Which landscape metrics show the strongest link to fire history?
- Which vegetation indices or image enhancements were best able to extract meaningful landscape patterns?

Background
Fire does not have a uniform impact on the landscape. The complexity of fire effects has been documented by many researchers (Whelan, 1995; Pyne et al., 1996) and has been associated with variations in fire frequency and severity (Pyne et al., 1996). The spatial variability of fire effects is related to current variations in fuel amount and conditions. Fire history is thus also a significant feature of a forest landscape that conditions future fire patterns and severity.
Remote Sensing of Landscape Patterns

The spatially complex nature of fire makes it a good candidate for remote sensing research. Because satellite-based data are acquired over broad areas, the spatial pattern and arrangement of surface features can be easily quantified using a variety of landscape metrics and statistics. Landscape studies have used fractal dimension (Ricotta et al., 1998; Ricotta and Retzlaff, 2000), geographic windows (in contrast to geometric windows) (Dillworth et al., 1994), spatial autocorrelation measures (Chuvieco, 1999), and patch statistics (Chuvieco, 1999; Tran and Giles, 1999; Roy and Tomar, 2000) with varied success. Significant findings from these studies are discussed below.

Ricotta et al. (1998) used fractal dimension to quantify landscape structure preceding and following a fire in the Mediterranean basin. They hypothesized that landscape structure was high and that landscape spatial structure was resilient to fire. Due to the fire-tolerant characteristics and regrowth strategies of Mediterranean shrubs, they found that a burned area returned to its pre-fire spatial structure within a relatively short time period (Ricotta et al., 1998). A related study (Ricotta and Retzlaff, 2000) examined scale issues of fractal characteristics and wildfires.

An alternative method to analyzing landscape patterns was discussed by Dillworth et al. (1994). The authors compared spatial characteristics derived from traditional geometric windows (square) to those calculated using geographic windows (irregular shapes determined by land cover). The geographic window sizes vary for each pixel, based on the similarity of surrounding pixels. They found the geographic window technique to be superior for quantifying patch characteristics, because the size and shape of the window was adjusted to fit actual landscape patterns and not constrained by a square or rectangular shape (Dillworth et al., 1994).

Spatial autocorrelation measures the similarities between pixels that are separated by a specified lag distance. These statistics have been used to analyze landscape heterogeneity. A high degree of spatial autocorrelation is caused by clustering of similar pixel values in space, or landscape homogeneity. Chuvieco (1999) used this technique and others to evaluate landscape patterns preceding and following a large fire in Spain. The results showed that spatial autocorrelation increased following the fire, because most vegetation was removed (Chuvieco, 1999).

Defining a landscape in terms of patches is a commonly used technique in ecological research (Allen 1994). Tran and Giles (1998) studied the effects of deforestation on a host of landscape pattern metrics, including patch statistics. They found that mean patch size, mean patch density, and interpatch distance were linked to deforestation. Chuvieco (1999) found that a stand-replacing fire reduced the number of landscape patches.

Despite significant findings from much of this research, Benson and MacKenzie (1995) cite problems with some of these metrics. They found that average patch size, average patch perimeter, and fractal dimension increased when pixel size increased in their study. These results imply that spatial patterns can be affected significantly by the sensor spatial resolution. Frohna (1998) presents a thorough investigation of problems associated with fractal dimension, particularly with raster data. Ricotta and Retzlaff (2000) also cite a need for techniques to quantify spatial structure, while addressing scale issues. Additionally, some landscape metrics require nominal scale data, which necessitates subjective class definition and labeling (Chuvieco, 1999).

Spectral Enhancements

The image enhancements that we chose to calculate landscape metrics were the Kauth-Thomas Transform (KT), the Normalized Difference Vegetation Index (NDVI), and the Intensity, Hue, and Saturation (HIS) components of the KT. Each of these image enhancements is described below.

The six non-thermal bands of Landsat Thematic Mapper (TM) data are transformed into three new components by applying the appropriate KT coefficients to a transform (sensor specific). Examination of the coefficients reveals which characteristics are emphasized. For example, the first component (KT-Brightness, or KT-B) has positive coefficients for all six bands, with the highest value for band 3, or red (0.55177) (Crist and Cicone, 1984). The resulting KT-B image shows areas of bare soil and rock as bright, while vegetated areas are dark. Recent fire scars are usually visible as bright patches in a KT-B image, if a significant fraction of vegetation has been removed.

In contrast, the second component (KT-Greenness, or KT-G) has negative coefficients for the visible bands, with the heaviest weighting in band 4, or the near-infrared (0.85468) (Crist and Cicone, 1984). The KT-G image is nearly the opposite of the KT-B image, with bright areas corresponding to live, green biomass and bare areas appearing dark. A severely burned area will appear dark in a KT-G image, shortly following the fire.

The third KT component has been the focus of much controversy, although it is still widely referred to as KT-Wetness (KT-W). The coefficients for KT-W contrast TM bands 1 (blue), 2 (green), 3 (red), and 4 (near-infrared) with band 5 (mid-infrared). The heavy weighting in the mid-infrared is where the “wetness” label originates (these wavelengths are sensitive to moisture content), although this KT component is also responsive to shadowing (Colin and Spies, 1992). KT-W has been extremely useful in fire-related remote sensing due to its sensitivity to fuel moisture and other forest conditions (Collins and Woodcock, 1996) and structure (Colin and Spies, 1992).

Some advantages of using KT to study post-fire forested landscapes are illustrated by Patterson and Yool (1998), who compared KT to principal components analysis (PCA) for mapping fire severity. They achieved higher accuracy in a supervised classification using KT rather than PCA. They concluded that KT was superior for post-fire applications, because the coefficients are sensor-based and therefore independent of scene-based variations. Because the precise location of fire perimeters is generally not known, any post-fire image analysis includes both burned and unburned areas. When using a sensor-based transform such as PCA, the greatest contrast is likely to occur between the burned and unburned portions of the scene, rather than differentiating fire severity levels within a burned area (Patterson and Yool, 1998).

The NDVI is a ratio vegetation index that accentuates the difference between near-infrared and red reflectances over a wide range of interest. This is based on the fact that high NDVI values correspond to healthy, green vegetation. Studies in many different environments have found relationships between NDVI and canopy cover (Laszlo, 1993), canopy size (Hall et al., 1995), and primary production (Tucker and Sellers, 1986). NDVI has also been used extensively to evaluate fire-related forest conditions (Marchetti et al., 1995; White et al., 1996), including spatial characteristics preceding and following fire (Chuvieco, 1999). Because NDVI is a ratio index, it offers the advantage of minimizing topographic effects.

Data and Methods

Study Area

Our research was conducted in the Rincon Mountains, located just east of Tucson, Arizona. Most of the mountain range is contained within the Rincon Mountain District of Saguaro National Park (Figure 1). The Rincon Mountains represent one of the Arizona Sky Islands, so named because they are literally islands of forest ascending above and surrounded by the Sonoran Desert. Located at a transition between desert types, the
vegetation communities found in the Sky Islands are unique and diverse, including desert scrub, oak woodland, pine-oak gallery, pine forest, and mixed conifer forest. The Rincon Mountains range from approximately 900 to 2800 meters in elevation. The present study is concentrated at elevations greater than 2000 meters, where vegetation is restricted to fire-prone oak, pine, or mixed conifer. Precipitation in the region is bimodal, dominated in winter by frontal storms and in summer by monsoon thunderstorms that bring brief heavy rains. Average annual precipitation varies greatly with elevation and is as high as 760 mm on the mountain peaks.

Field-based fire research has been extensive in the Rincon Mountains, and we are not aware of other forest fire research utilizing remotely sensed data in this area. The abundance of field data makes the Rincon Mountains an ideal location to investigate new techniques for studying fire with remote sensing. Additionally, insight gained here may be applicable to other arid environments throughout the world, where a better understanding of fire is of great importance.

**TM Data**

We selected an 11 May 1996 Landsat TM scene (Scene ID: LT03034009613210) from the Arizona Regional Image Archive (ARIA) (http://aria.arizona.edu) for this project. This scene was chosen for a number of reasons: Late spring is an appropriate season to study forest conditions, because both winter and summer grasses are not at peak greenness (too early for summer rain, too late for winter). If the grasses were green, their strong near-infrared signal could overwhelm reflectance of oak and pine canopies. The late spring image was also entirely cloud-free. This May scene corresponded well with available fire history records: the scene was recent enough to include most fires, but old enough to allow future expansion to a multi-temporal study.

**Fire Atlas**

Using a digital version of the fire atlas, we chose several sets of overlapping fire polygons (areas that had burned repeatedly) and delineated new polygons within the intersection area. The new plots were not chosen randomly, because we wanted to sample a range of fire histories, while simultaneously avoiding exposed rock and deep shadows. Nine fire plots were chosen in three fire history categories: once burned (single fire), twice burned (two fires), and multiple burns (three or more fires). We selected three plots that had burned only once during the study period. These were labeled as 1.1, 1.2, 1.3 for once-burned plots. The plots with two fires were named 2.1, 2.2, 2.3, and the multiple-fire plots were called 3.1 for a plot that burned three times, and 5.1 and 6.1 for plots having had five and six fires, respectively (Table 1). The first number corresponds to the number of fires within the study period, and the second distinguishes between plots with the same number of fires.

**DMEs**

DEM s were used to create shaded relief maps for use in georeferencing. DEMs locationally conform to the National Map Accuracy Standards, and are thus useful to use as reference images for georectification of image data. By creating shaded relief maps matching the solar illumination conditions of the TM scene, we are able to georectify image data using the DEM and image. This shaded relief georectification technique is particularly useful in areas with rough terrain, because shadows and sunlit slopes, ridges, and peaks can be used to locate GCPs. The selected GCPs can be used to create a polynomial transformation and convert the image data to match real-world coordinates.

**Topographic Positions**

Topographic positions for the nine fire plots were quite variable due to the rugged terrain in the study area. This raised concern over the validity of directly comparing spectral and spatial patterns between the plots. To address this issue, we selected nine analog control plots (one for each fire plot) on an adjacent peak that had not burned during the study period. Each control plot was selected to match the size and topography of a fire plot. Control plot selection was not random, because we attempted to avoid features such as image shadows and large rock exposures, while keeping the control plots within the same elevation ranges as the fire plots. To match topography, we viewed the slope and aspect images while drawing polygons for the control plots. Because this was a subjective process, we also compared average slope and aspect histograms for each fire and control plot pair, after selecting the

<table>
<thead>
<tr>
<th>Plot</th>
<th>Area (m²)</th>
<th>Mean Elevation (meters)</th>
<th>Mean Slope (°)</th>
<th>Aspect</th>
<th>Vegetation</th>
<th>Fire History</th>
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<tr>
<td>1.1</td>
<td>468874.5</td>
<td>2111.7</td>
<td>12.18</td>
<td>SE</td>
<td>oak</td>
<td>1994</td>
</tr>
<tr>
<td>1.2</td>
<td>334647.6</td>
<td>2114.4</td>
<td>14.20</td>
<td>W-SW</td>
<td>pine/oak</td>
<td>1989</td>
</tr>
<tr>
<td>1.3</td>
<td>271291.5</td>
<td>2065.7</td>
<td>7.23</td>
<td>S</td>
<td>pine</td>
<td>1994</td>
</tr>
<tr>
<td>2.1</td>
<td>103886.7</td>
<td>2108.1</td>
<td>10.38</td>
<td>E</td>
<td>oak</td>
<td>1994, 1994</td>
</tr>
<tr>
<td>2.2</td>
<td>55579.9</td>
<td>2208.5</td>
<td>12.86</td>
<td>S-SW</td>
<td>pine/oak</td>
<td>1943, 1994</td>
</tr>
<tr>
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<td>465263.5</td>
<td>2255.2</td>
<td>16.30</td>
<td>NW</td>
<td>pine/oak</td>
<td>1972, 1989</td>
</tr>
<tr>
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<td>968071.5</td>
<td>2152.9</td>
<td>9.00</td>
<td>S-SE</td>
<td>pine</td>
<td>1943, 1954, 1994</td>
</tr>
<tr>
<td>5.1</td>
<td>117544.0</td>
<td>2158.1</td>
<td>11.71</td>
<td>E</td>
<td>pine/oak</td>
<td>1943, 1950, 1958, 1972, 1993</td>
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</tbody>
</table>
control plots. This helped to ensure that the topographic patterns were similar between each fire plot and its corresponding control plot. Average aspect was not a useful way to summarize the plot topography, because circular scaling problems occur. 0° and 360° are nearly the same aspect (due north), yet a plot with equal quantities of each value results in an average of 180° (due south). We used the control plots to compare patterns between burned and unburned plots with similar topography. The control plots were also used to normalize statistics for the fire plots.

General Approach
The general approach used in this study was to analyze spatial patterns for forested areas having different fire histories over a 54-year period (1943 to 1996). Study plots were chosen to include a range of fire frequencies (one to six fires during the time period) and fire-free intervals (54 years to less than one year). Unburned control plots (no fires between 1943 and 1996—history prior to 1943 is unknown) with similar vegetation and topography were selected from an adjacent mountain peak to pair with each study plot. We used these analog control plots to make comparisons between burned and unburned forest stands and to allow some “normalization” of the data.

To quantify the spatial patterns in the data, we calculated landscape metrics (see Table 2) for each study plot (fire) and control plot (no fire). We used Rank Correlation Analysis to assess the significance of relationships between fire history and landscape patterns. Details of the image processing and analysis are discussed below.

Preparation of TM Data
TM data were corrected for atmospheric effects using methods described by Chavez (1996) and were registered geospatially to corresponding USGS DEMs using a second-order transformation (RMSE < 1 pixel). The resulting georectified reflectance image was used to calculate the KT Transform and NDVI (Figure 2). To expand the analysis, we also converted the false-color composite of Brightness, Greenness, and Wetness from the KT into Intensity (KT-I), Hue (KT-H), and Saturation (KT-S). In a recent study in the Mediterranean, Koutsiis et al. (2000) were successful in mapping fire scars using a similar technique.

Data Analysis
The steps above resulted in seven spectral variables: KT-B, KT-G, KT-W, NDVI, KT-I, KT-H, and KT-S. The next step was to characterize the spatial patterns of those seven images with respect to fire history. The spatial measures we used require data that are thematic so that the landscape can be divided into distinct patches. If the image enhancements were left as continuous floating point data, each pixel would end up as a separate patch and no new information would be revealed. To solve this problem, we masked the image enhancements to 2000 meters above and rescaled each image into the range 0 to 10, using the minimum (excluding zero) and maximum values in a linear conversion. Our technique for data reduction differs from that of Chuvieco (1999), who used histogram equalization to reduce continuous data into a thematic map.

Figure 2. Grayscale versions of each image enhancement with fire plot locations shown. (a) KT-Brightness, (b) KT-Greenness, (c) KT-Intensiy, (d) NDVI, (e) KT-Hue, and (g) KT-Saturation. Plot labels shown in (a).
(1999) study required data reduction for roughly 250,000 pixels, while our study area only contained about 64,000 pixels after the elevation masking. We felt that a simple linear reduction would best preserve the trends in the data, particularly because we were examining smaller sites within the image subset. Reducing the data value range simplified the image enhancements, but many single pixels were left within most study plots. We used a 3 by 3 majority filter to avoid having the study results overwhelmed by noise from single pixel “patches.” It is worth noting that Chuvieco (1999) found that spatial pattern trends remained fairly constant, irrespective of class reduction. He calculated statistics for several different class numbers to avoid bias, but found that the number of patches was reduced by a fire, whether the data were reduced to three classes or twelve (Chuvieco, 1999).

Simplified versions of each image were converted into polygon layers, and landscape metrics were calculated using the Patch Analyst Extension in ArcView. As a normalization measure, we computed plot ratios (we will refer to as statn, e.g., MPSh) for each plot pair (statn = stat fire plot/stat control plot). Because the fire plots were located in variable terrain (disparate slope and aspect) and mixed vegetation (some plots were oak, some pine, some mixed), we felt this normalization was warranted. The resulting normalized plot ratios were used in final correlation analyses.

Results and Discussion

Plot-Specific Spectral Variations

In addition to studying the patch patterns of fire, we thought it was instructive to also examine the basic statistics for each plot used in the study. Characteristics of spectral data have been the focus of much remote sensing research, so we felt that it would be complementary to include that aspect in this paper. Paired t-tests were used to compare means for each fire and control plot. Because the control plots had been without fire for more than 54 years, we hypothesized that each fire plot mean would be significantly different from its corresponding control plot mean. Bar charts comparing means for fire and control plots are shown in Figure 3 and discussed in this section.

Figure 3. Bar charts showing means for each of the seven image enhancements. Paired means that are not significantly different (p > 0.05) are marked with *.
Immediately following a fire that has removed a significant amount of vegetation, we would expect KT-W, KT-G, and NDVI to be lower (reduction in moisture content of leaves or complete removal of green biomass) for the burned area. For a lower severity or less recent fire, it is not as clear what pattern is expected. The discussion below is limited to NDVI comparison between different fire plots due to topographic differences. We discuss all image enhancements for fire/control plot comparisons. All mean comparisons were significantly different \((p < 0.05)\) unless otherwise noted.

**Single-Fire Plots**

Single-fire plots (1.1, 1.2, 1.3) exhibited differences that can be explained by fire history. The plot burned in the 1994 Rincon Fire (1.1) had lower mean NDVI than did the other two single-fire plots (1943 fire, 1989 fire). The 1994 single-fire plot (1.1) had not previously burned for a minimum of 52 years (no fires since before 1943), so fuels would have continued to accumulate over that time period. The site's largely southeast aspect makes it drier than more northern exposures, but permits higher site productivity than southwest facing slopes. This combination of factors could allow for considerable fuel accumulation with sufficient desiccation for a high severity fire. Visual assessment of a color infrared digital orthophoto quarter quad (DOQQ) from June 1996 confirms that the plot was severely burned in the 1994 Rincon Fire (Plate 1).

A single fire plot that stands out was burned in 1943 only (plot 1.3). This long fire-free interval (54 years) makes the stand conditions of this plot potentially similar to the unburned control plots. If the 1943 Manning Camp Fire was low intensity, there are likely to be older trees in this plot. However, if that fire had been severe, trees on this plot would largely be younger. Comparison of means for the 1943 single-fire plot (1.3) and its control plot shows that they were not significantly different for KT-W, NDVI, or KT-S. The extended time without fire would have allowed for significant growth in the understory and considerable fuel accumulation. As a result, the conditions of the forest in this plot are quite different from those found in the 1994 single-fire plot (1.1). Descriptive statistics confirm the distinction, with plot 1.3 having higher mean NDVI than the more recently burned plot 1.1.

**Twice-Burned Plots**

Although fire severity information is unknown for most fires in this study, we expected the twice-burned plots to exhibit some resemblances. All three plots had one recent fire (1989 or 1994) and one older fire (1943, 1954, 1972), so there is potential for plot similarities. We thought that the plot that burned in 1972 and 1989 (2.3) would be distinct from the others, because the older fire was more recent. This corresponds to a fire-free interval of at least 30 years prior to the 1972 fire, because the fire-free period preceding 1943 is unknown. This plot also had a shorter interval between fires (17 years). The actual pattern that we observed was different than what we had expected: Plots 2.1 (1954, 1994 fires) and 2.3 (1972, 1989 fires) had more similarities, with the third plot (2.2 = 1943, 1994 fires) being more distinct. Plot 2.2 had lower mean NDVI than the other twice-burned plots. This trend suggests that plot 2.2 (1943, 1994 fires) was severely burned in the 1994 Rincon Fire. This plot is located upslope and adjacent to the 1994 single fire plot (1.1), which we concluded had been severely burned in the 1994 Rincon Fire. Like its single-fire neighbor, the twice-burned plot (2.2) has a largely south-facing slope, but the slight increase in elevation might allow for higher site productivity. Combined with a 51-year fire-free period, the plot was susceptible to a severe fire under the right weather conditions (low humidity, high winds). To confirm this theory, we examined a color infrared DOQQ from June 1996. The photo clearly shows a significant portion of the vegetation cover has been removed (Plate 1). Plot 2.1 (1954, 1994 fires) has a similar fire history, with a 40-year fire-free period prior to the 1994 Rincon Fire, but damage was less severe and widespread on that plot (Plate 1).

**Multiple-Fire Plots**

Multiple-burn plots had burned three times (3.1), five times (5.1), and six times (6.1) between 1943 and 1996. The most frequently burned plots (5.1, 6.1) had experienced the same fire history, excluding a 1956 fire, which only burned one of them (6.1). Due to the similarities of those two plots (including slope, aspect, elevation, and vegetation), we expected to find spectral similarities. Results revealed that mean NDVI for the frequently burned plots (5.1 and 6.1) was not significantly different \((p > 0.05)\). When compared to the other multiple-fire plot (3.1), these plots have lower mean NDVI. The difference implies that the frequently burned plots have higher canopy cover and more green biomass than did the other multiple-burn plot. Visual comparison of the plots confirms that this is the case (Plate 1). The length of the fire-free period preceding the 1994 Rincon Fire is also linked to mean NDVI. Plots burned in the 1994 Rincon Fire that had been without fire more than 50 years preceding the fire have the lowest mean NDVI, while plot 6.1 has the highest mean NDVI. The fact that forest cover appears to be high on the frequently burned plots also suggests that the numerous fires occurring between 1943 and 1996 were surface (low intensity) fires in those plots. Had either plot experienced a crown fire during that time, it is unlikely that forest cover would be at its current level. The relatively frequent, low intensity fires prevented fuels from accumulating to levels that favor high severity crown fires. These observations illustrate the detrimental impacts that long periods of fire suppression can have on these forests.

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Plate 1. Color Infrared Digital Orthophoto from June, 1996 showing fire plot locations (yellow) and partial perimeter of 1994 Rincon Fire (magenta).
Control Plots

The relationships between fire plots and their corresponding control plots varied with fire history, but in most cases means for fire and control plot pairs were significantly different (Figure 3). For example, all control plots had higher mean KT-C than did their fire plots ($p < 0.05$), excluding the two frequently burned plots (5.1 and 6.1). These fire plots usually had opposite tendencies than the other fire plots. In most cases, control plots had higher means than their fire plots, but the frequently burned plots had higher means. KT-S had the opposite pattern, with most fire plots having higher means than their control plots. In this case, the frequently burned plots had lower or equal means.

All of the results in this section have confirmed that fire plots 5.1 and 6.1 exhibit spectral similarities to each other and spectral differences from the other fire plots. These two plots have fire histories that more closely resemble pre-settlement fire regimes than any of the study plots and trends in their spectral patterns have consistently distinguished them from the other plots. Plots 1.5 and 2.2 are also distinct, exhibiting spectral characteristics that suggest higher severity than other plots burned in the 1994 Rincon Fire.

Correlation Analyses of Spectral and Landscape Statistics with Fire History

To assess relationships between forest patterns and fire history, we compared landscape metrics calculated from the image enhancements to several fire history characteristics (Table 3). Due to our small sample size and ordinal nature of some fire history data, we used Spearman’s Rank Correlation Analysis to quantify relationships (results shown in Table 4). The following discussion begins with an overview of correlations using the spectral means (non-spatial). Then, we consider which landscape metrics (abbreviations are shown in Table 2) had significant relationships ($p < 0.05$) with fire history. We complete the section with a discussion of which image enhancements best extracted relevant landscape patterns.

Using normalized means (fire plot mean/control plot mean) as input to the correlation analysis, we obtained significant results for only two fire history variables: length of the most recent fire-free interval (last $ffi$) and average fire-free interval (avg $ffi$). The high number of significant correlations between last $ffi$ and the non-spatial statistics is likely due to the impact of the 1994 Rincon Fire. In the subjective comparisons of NDVI in the previous section, we noted an inverse relationship between mean NDVI and fire-free period preceding the Rincon Fire. Our observations were confirmed by the correlation results: an increase in last $ffi$ was linked to lower KT-G, KT-I, KT-H, and NDVI. In other words, plots that had been without fire over a long time period were more susceptible to vegetation removal (or reduction) in a subsequent fire. KT-G and NDVI are established indicators of green biomass, while the exact nature of KT-I and KT-H has not been established. Our results suggest that these new IHS enhancements may also be linked to related biophysical properties. Visual comparison between NDVI (Figure 24) and KT-I (Figure 25) shows remarkable similarities, as well.

Batch size variability ($PSGV_{\text{KT}}$) resulted in the greatest number of significant correlations (six) and the highest correlation coefficient ($-0.865$) for the landscape statistics. Mean patch size ($MPS_{\text{KT}}$) and patch per-unit area ($PPU_{\text{KT}}$) also performed well with four significant correlations each. Results indicate that most fire-free years (last30 and last50) and longer fire-free intervals (avg $ffi$) are linked to a lower number of patches ($PPU_{\text{KT}}$), larger patches ($MPS_{\text{KT}}$), and lower variability in patch size ($PSGV_{\text{KT}}$). These trends all point to frequent fires increasing landscape heterogeneity and fire exclusion leading to more homogeneous patterns. Fire ecologists have found that frequently burned forests often have a mosaic pattern due to variability in fire timing and severity across the landscape (Romme, 1982, Turner et al., 1994).

Patch shape complexity ($MPP_{\text{KT}}$) and landscape diversity ($SDI_{\text{KT}}$) were both negatively related to number of fire-free years. Length of most recent fire-free interval also related inversely to patch complexity. In the case of the most recent fire-free interval (last $ffi$), the 1994 Rincon Fire is likely driving the relationships that we observed. Six of the nine fire plots are included within that fire perimeter, and their conditions in 1996 (two years after the fire) are strongly linked to the fire-free interval immediately preceding the Rincon Fire. Correlations show that lower fire occurrence during the ten and thirty years preceding 1996 resulted in lower patch shape complexity. Results also indicate that less frequent fire between 1943 and 1996 leads to lower landscape diversity. If frequent fire tends to create heterogeneous landscapes, then we would expect patch complexity and landscape diversity to increase with fire occurrence.

Landscape evenness ($SDI_{\text{KT}}$) related inversely to time since the most recent fire (last $ffi$) and directly with last fire-free interval (last $ffi$) and average fire-free interval (avg $ffi$). This landscape metric indicates how evenly land-cover types are distributed over the landscape, without emphasizing richness as SDI does. We can interpret these relationships to mean that long fire-free periods result in more even landscapes. Our results agree with those of Romme (1982), who found that regimes of fire exclusion resulted in greater landscape evenness than did natural fire regimes. However, the relationship that we found between how recently a fire has occurred (last $ffi$) and landscape evenness was inverse, suggesting that evenness decreases with increasing time since fire. Once again, the 1994 Rincon Fire is likely influencing the relationship. The majority of fire plots (two-thirds) had burned only

<table>
<thead>
<tr>
<th>TABLE 3. DESCRIPTION OF FIRE HISTORY VARIABLES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>last10</td>
</tr>
<tr>
<td>last30</td>
</tr>
<tr>
<td>last50</td>
</tr>
<tr>
<td>last54</td>
</tr>
<tr>
<td>avg5</td>
</tr>
</tbody>
</table>

| TABLE 4. SIGNIFICANT ($p < 0.05$) RESULTS OF SPEARMAN’S RANK CORRELATION ANALYSIS. CORRELATIONS SIGNIFICANT AT 0.01 ARE SHOWN IN ITALICS. |

<table>
<thead>
<tr>
<th>metric band</th>
<th>last10</th>
<th>last30</th>
<th>last50</th>
<th>last54</th>
<th>last $ffi$</th>
<th>avg $ffi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean $K_{\text{T-G}}$</td>
<td>0.821</td>
<td>0.878</td>
<td>0.785</td>
<td>0.790</td>
<td>0.743</td>
<td>0.734</td>
</tr>
<tr>
<td>$K_{\text{T-W}}$</td>
<td>0.771</td>
<td>0.690</td>
<td>0.771</td>
<td>0.690</td>
<td>0.681</td>
<td>0.681</td>
</tr>
<tr>
<td>$K_{\text{T-I}}$</td>
<td>0.681</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$K_{\text{T-H}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$NDVI_{\text{KT}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$PSCV_{\text{KT-B}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$PPU_{\text{KT}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$MPPQ_{\text{KT-N}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$SDI_{\text{KT}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$SDI_{\text{KT-H}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
<tr>
<td>$SDI_{\text{KT-S}}$</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
<td>0.725</td>
</tr>
</tbody>
</table>

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two years prior to image acquisition. If these plots had higher evenness than the other (less recently burned) fire plots, it would seem that evenness declines over time following fire. Although this is contrary to our other results and those of Romme (1982), it is possible that evenness decreases in the short-term following fire, but eventually increases in the long absence of fire. This particular metric is somewhat difficult to put into context with the other statistics, because a heterogeneous or homogeneous landscape could have high evenness provided that existing cover types are equally distributed (i.e., ten small patches of equal size versus two larger patches of equal size).

The image enhancements that extracted the patterns discussed above included all three Kt components (Brightness, Greenness, and Wetness). KT-B tends to be brighter than surrounding forest. Patch size variation (PSCVn) of this image enhancement appears to have a strong link to fire history, as well. KT-W (Figure 2c) has been well established in its utility for fire mapping (Patterson and Yool, 1998), so we expected the spatial patterns of that image enhancement to also be linked to fire history. Both KT-G and NDVI are indicators of canopy cover and green biomass, and spatial patterns derived from them are associated with fire history. Of the KT components we calculated from the KT transform, only the intensity component achieved significant results in the correlation analysis. Image intensity generally contains more spatial information than do other image components, so it was expected to be useful for this analysis. KT-I resembles the KT-B image, but with more fine-scale detail and topographic variations visible. Forested areas have greater contrast in the KT-I image, but pixel values follow the same trends as the KT-B image (bare areas have high values, vegetation appears darker). Our results suggest that KT-I is an improvement over KT-B for extracting forest spatial patterns.

Conclusions

The number of recent wildfires in the western United States underscores the need to reduce fuel loads in many areas and to determine which forests are at greatest risk for catastrophic fires. The research presented in this paper represents an important first step in using remote sensing techniques to understand forest-related spatial patterns. These vegetation patterns are worthy of study and analysis because they are affected by fire history and determine future fire behavior. Key findings of our study are summarized below.

The significance of fire frequency and fire exclusion was well illustrated by the results of our spectral comparisons. The most frequently burned plots (5.1 and 6.1) had higher mean spectral values than those of any other fire plots and more control plots for image enhancements linked to canopy cover and biomass mass. This confirms the beneficial effects of frequent fire in these ecosystems. Conversely, the plots that appeared most damaged by the 1994 Rincon Fire had long fire-free periods prior to that fire.

Rank correlation results showed the strong link between forest spatial patterns (as derived from satellite-based spectral enhancements) and fire history. Patch size (SPTs), patch size variability (PVTs), shape complexity (SChPs), and landscape evenness (lev) obtained significant results. For more of the fire history variables than did spectral data alone. This is significant and shows that forest spatial patterns can reveal a great deal of information about fire history. The spectral image enhancements that were most useful included KT-Brightness and KT-W, which have both been widely used in other forest research.

An issue that warrants investigation is monitoring spatial patterns for the same plots over time to determine the effects of post-fire regeneration. It would also be instructive to compare spatial patterns before and following fires of differing severity. Similar spatial analysis techniques have proven useful in Mediterranean ecosystems (Chuvieco, 1999), so application of these methods in other forest types may be valuable. Fire is a dynamic process and its temporal impacts on landscape patterns justify further study.

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References


