

Discriminating disturbance from natural variation with LiDAR in semi-arid forests in the southwestern USA

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Abstract. Discriminating amongst spatial configurations and climax size of trees in forests along varying physical gradients from time since last disturbance is a significant component of applied forest management. Understanding what has led to the existing vegetation's structure has important implications for monitoring succession and eco-hydrological interactions within the critical zone: the near-surface environment where rock, soil, air, and biota interact and regulate ecosystem services. This research demonstrates the utilities of local indicators of spatial association (LISA) to (1) quantify natural variation in forest structure as derived from aerial Light Detection and Range (LiDAR) across topographically complex landscapes at ecologically relevant scale, i.e., individual trees; (2) map previously recorded but poorly defined forest disturbances; and (3) link scalable topographic indices to observed tree size distributions. We first selected a priori undisturbed and disturbed stands scanned by aerial LiDAR that included: preservation, mechanical fuels treatment, and logging in two similar semi-arid forest ecosystems. Next, we compared two topographic indices: the topographic position index (TPI) and topographic wetness index (TWI) to climax tree height and two related LISAs: the Getis-Ord G_i^* and Anselin local Moran's I_i . G_i^* and I_i measure local spatial clustering, producing z-scores that represent the significance of each statistic. The tallest trees in each study area were found to be located on negative TPI and greater TWI values (valley bottom positions and higher wetness conditions, respectively). Stands of trees with positive z-scores (i.e., overstory trees with similarly tall neighbors) were most likely to be located in the a priori undisturbed areas. Disturbed locations, on the other hand, were defined by neighborhoods of negative z-scores (i.e., shorter trees with short neighbors). Future applications include locating and reconstructing historical disturbances and developing a consistent strategy for characterizing stands for forest inventory monitoring.

Key words: Anselin local Moran's I_i ; disturbance ecology; forest structure; Getis-Ord G_i^* ; LiDAR; local indicators of spatial association; topographic indices.

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INTRODUCTION

Foresters and ecologists have long been challenged by the inherent scaling limitation of field

techniques which limit their ability to relate plot level measurements to landscape scale processes. Although conventional forestry field protocols (i.e., Bechtold and Patterson 2005) provide

abundant locally detailed information about composition and structure, plot-based spatial averaging results in large uncertainty at landscape scale (Chave et al. 2004, Tomppo et al. 2008, Mascaro et al. 2011). Conversely, remote sensing provides information at landscape level extents, but typically sacrifices the spatial resolution and detailed measurement information of plot-based inventory. This difficulty in linking landscape patterns to plot scale measurements is part of what Levin (1992) called ‘the problem of pattern and scale.’ Prior to airborne laser scanning (ALS), also called Light Detection and Range (LiDAR), remote sensing technology could not precisely resolve the most fundamental unit of ecology: the individual. With LiDAR foresters can characterize individual trees from the plot to the landscape scale (Falkowski et al. 2006, 2009, van Leeuwen and Nieuwenhuis 2010, Kaartinen et al. 2012, Vauhkonen et al. 2012, Maltamo et al. 2014, Swetnam and Falk 2014). Today’s dilemma is not how to collect enough detailed information to characterize a population with statistical significance, but how to analyze large LiDAR data sets in ways that answer the most beneficial questions at landscape scale.

Foresters have used ‘site indices’ to predict tree growth and to estimate potential maximum tree height from environmental factors at the plot-scale for over a century (Woolsey 1911, Minor 1964, Clutter et al. 1983). Differences in growth rate and potential maximum tree size with age, i.e., the site index, in semi-arid forests are variable and emergent by elevation, slope and aspect (Whittaker and Niering 1975, Niering and Lowe 1984). For example, in the southwestern USA at low elevation excessive heat and dryness result in low productivity desert environments; as elevation increases average daily temperatures decrease and average annual precipitation increases in relation to adiabatic lapse rate until the mountainsides are capable of supporting woodland and forest species. Biomass in southwestern USA semi-arid forests peak in the so-called mixed-conifer forest type where the growing season is not limited by freezing air temperatures and precipitation is abundant. At higher elevations temperature continues to decrease resulting in a progressively shorter growing season. South-facing aspects (in the northern hemisphere) receive more direct solar radiation than do

north-facing aspects. As a consequence south aspects are hotter and drier, and often support more xeric and light-tolerant vegetation relative to north aspects at the same elevations. In later successional stages after vegetation has established and shaded the soil surface, local microclimate conditions can increase soil wetness which allow for more mesic species to establish (Breshears et al. 1998). In semi-arid ecosystems availability of soil water with increased soil depth is key to sustaining increases in plant metabolism and thus greater biomass over time. Maximum tree height is known to vary with topographic position even in temperate and tropical forests (McNab 1993, Detto et al. 2013). Topographic wetness also affects total soil moisture and pH, which in turn affects the species richness of vascular plants (Zinko et al. 2005, Sørensen et al. 2006, Kopecký and Čížková 2010, Moeslund et al. 2013). In the present study we explore the relationship of vegetation size and community complexity both by topographic position and wetness in relation to known disturbance histories.

Semi-arid forests are particularly vulnerable to episodic drought, insect outbreak, and wildfire disturbances that alter forest structure (Allen et al. 2002). Such threats will likely intensify as global warming progresses (Westerling et al. 2006, Williams et al. 2012, Stephens et al. 2013). Identifying and tracking the legacies of past disturbances are critical to managing semi-arid landscapes effectively (Allen et al. 1998, Swetnam et al. 1999). Across the late 19th and 20th century southwestern USA forests were significantly affected by wildfire suppression and anthropogenic land use practices, particularly logging and livestock grazing (Touchan et al. 1996, Swetnam et al. 1999, Allen et al. 2002). As a result, many southwestern forests’ tree size distributions and age structure are today considered to be outside their ‘historic range of natural variation’ (Morgan et al. 1994). With incomplete historical records of disturbance, analyses of current forest condition and disturbance legacies cannot be placed into a developmental continuum useful for forest managers. For example, a contemporary mixed-conifer stand could represent a climax state, a post-disturbance sere, or be the result of fire exclusion which led to a shift in dominance from pine-oak to more shade tolerant species (O’Con-

nor et al. 2014a).

An important step in characterizing land use history along a developmental continuum is to differentiate whether existing vegetation represents the climax state or is an early- or mid-successional stage following an unrecorded disturbance (Black et al. 1998, Foster et al. 1998, 2003). Land-use and disturbance histories are not particularly well documented in the southwestern USA prior to the 1900s (Bahre 1991, Turner 2003). Often only paper maps and reports survive, with an unknown number of records having been lost or discarded. Even if records of an event (either human or natural) exist, it is unlikely that they include information with precision sufficient to allow for geo-referencing. Further complications involve historical records that do not separate planned management actions from actual outcomes. Historical records of fires or logging contracts typically represent only the perimeter with little additional quantitative information (Johnson and Wittwer 2008, Farris et al. 2010). These problems complicate the reconstruction of past disturbances and their lasting legacies on existing vegetation.

In cases where spatial information about historical disturbance is lacking, evidence can be obtained from tree rings. These include: tree establishment dates (Brown and Wu 2005, Speer 2010), ring width variations caused by insect outbreaks (Lynch 2012), and fire scars (Margolis and Balmat 2009, Farris et al. 2010, Falk et al. 2011, Swetnam et al. 2011). Proxies such as fire-scar and tree-ring reconstructions can delimit where and when fires occurred, but they are difficult and expensive to acquire and are applicable only within a sampled area. More spatially explicit and practically easier to generate techniques are needed to help foresters and ecologists understand the existing community complexity of their forest landscapes.

The goal of this research is to demonstrate the utility of local spatial statistics, called local indicators of spatial association (LISA; Anselin 1995), to discriminate variation and pattern at an individual tree scale. In the present study we use ALS-derived individual tree inventories (Swetnam and Falk 2014, Swetnam et al. 2014) to calculate the LISAs and delineate variation as it relates to spatial pattern. We further consider whether LISA relate to local-scale topographic

variations and to recorded disturbances. Our objectives were to: (1) quantify variation in forest structure derived from ALS at an ecologically relevant scale, i.e., the individual tree; (2) map previously recorded but poorly defined disturbance locations; and (3) link variation in individual size and community composition to scalable indices of topographic wetness and topographic position.

MATERIALS AND METHODS

A large body of literature has shown trees in semi-arid forests tend to cluster in space by size (Sánchez Meador et al. 2009, Larson and Churchill 2012). To examine these patterns of clustering we considered how climax tree size distributions arise in relation to topographic variation and whether these can be detected by LISAs. We also examined whether recorded disturbances were readily apparent by comparing LISAs to where historical maps indicated logging contracts were awarded and along boundaries such as fence lines. We compared two related LISA statistics: Anselin local Moran's I (Anselin 1995), and the Getis-Ord G_i^* statistic (Getis and Franklin 1987, Getis and Ord 1992, 1996, Ord and Getis 1995, 2001, O'Sullivan and Unwin 2010). We chose to use LISA over other statistical measures of forest structure such as mean canopy height (Detto et al. 2013), canopy cover, or lacunarity (Plotnick et al. 1996, Frazer et al. 2005) because we were interested in defining variation of local neighborhoods at the scale of individual trees.

Study areas

Our exemplar sites are (1) the Monument Canyon Research Natural Area (RNA) in the Jemez Mountains, New Mexico, which has never been logged and did not incur catastrophic disturbances over the entire 20th century, and (2) the Pinaleno Mountains, Arizona, which was opportunistically logged in the mid-20th century (Fig. 1).

The Jemez Mountains are located west of Santa Fe, New Mexico at 35.8° N, 106.5° W (Fig. 1). Their most dominant feature is a collapsed volcanic caldera with a rim approximately 19 km wide. Monument Canyon RNA is located on the south rim of the caldera on the Santa Fe National Forest (N.F.) at 35.8° N, 106.6° W (Fig. 1)

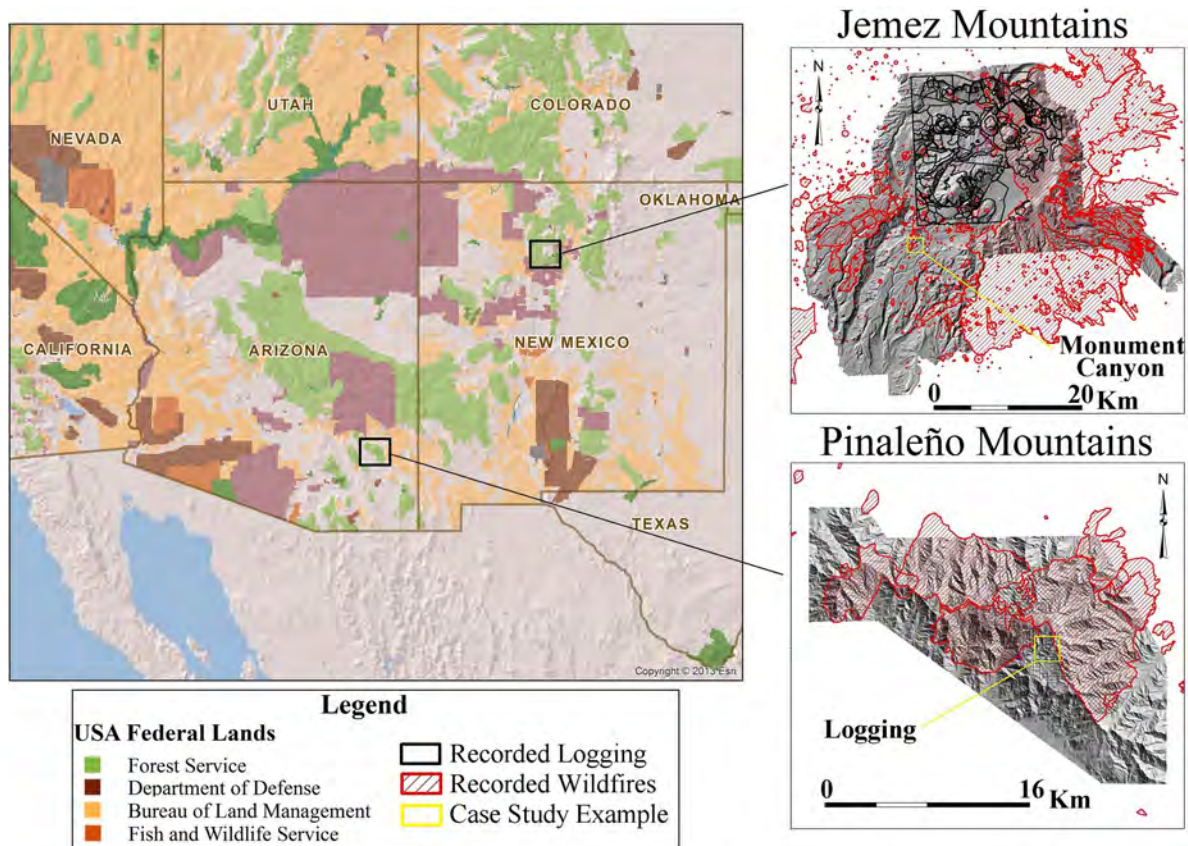


Fig. 1. Pinaleño and Jemez Mountain ALS flight areas (right panels) in the southwestern USA. Recent recorded disturbance histories are highlighted by the colored polygons: black (logging), red (recent wildfires), and yellow (example areas in figures). Logging history data are from USFS (2013) and Balmat and Kupfer 2004. Fire history perimeters are from USFS (2013).

and is comprised of two mesas: Cat Mesa and San Juan Mesa, bisected by a central canyon and several tributary canyons draining to the southwest. Elevations vary between 2,460 and 2,550 m above mean sea level (amsl) (Figs. 2 and 3).

The Pinaleño Mountains are located southwest of Safford, Arizona at 32.7° N, 109.9° W, on the Coronado N.F. (Fig. 1) and reach 3,267 m amsl. The Pinaleños are the tallest of the Sky Island Archipelago mountains, characterized by a complex of steeply sided canyons with relatively gentle uplands above 2,700 m amsl (Fig. 1) (Whittaker and Niering 1975).

The Jemez and Pinaleños share many tree species (Whittaker and Niering 1975, Muldavin et al. 2006). Several species of *Pinus* coexist above 2,130 m amsl including ponderosa pine (*Pinus ponderosa*) and Southwestern white pine (*P.*

stroboformis) along with Gambel's oak (*Quercus gambelii*). North aspects tend to be dominated by Douglas-fir (*Pseudotsuga menziesii*), and white fir (*Abies concolor*). Engelmann spruce (*P. engelmannii*), and subalpine fir (*A. lasiocarpa* in the Jemez and *A. lasiocarpa* subsp. *arizonica* in the Pinaleños) coexist at the highest elevations (Whittaker and Niering 1975, Niering and Lowe 1984, Muldavin et al. 2006). Post-fire seral communities of quaking aspen (*Populus tremuloides*) are present throughout the upper elevations of both study areas (Whittaker and Niering 1975, Muldavin et al. 2006).

Records of disturbance

Both sites have well characterized land use histories (Falk et al. 2007, Jones 2009, Swetnam et al. 2009). The disturbance regimes are similar to

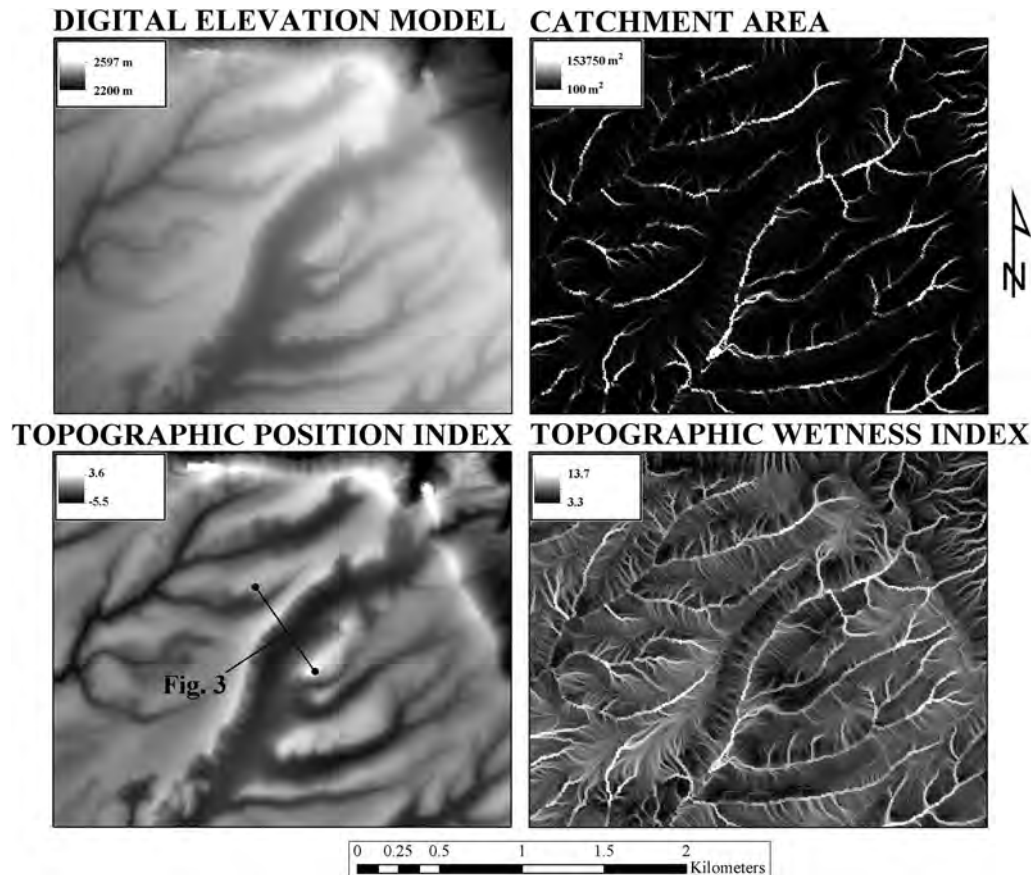


Fig. 2. Monument Canyon RNA 10 m Digital Elevation Model (DEM) (upper left), Catchment Area (upper right), Topographic Position Index (TPI) (lower left), and Topographic Wetness Index (TWI) (lower right).

other semi-arid forests across the southwestern USA and northern Mexico (Foster et al. 1998, Allen et al. 1998, 2002, Swetnam et al. 2009, Farris et al. 2010). Fire history reconstructions for the Pinaleno (Grissino-Mayer et al. 1994, O'Connor et al. 2014a) and Jemez (Touchan et al. 1996, Falk 2004, Falk et al. 2007, Dewar 2011) indicate frequent (3–10 year return interval) fire regimes with primarily low- and mixed-severity effects in pine and dry mixed-conifer forest types. There is also evidence of some high-severity wind- and topography-driven crown fires burning smaller areas in these ranges over longer intervals at higher elevations (Margolis et al. 2007, 2011, Margolis and Balmat 2009, O'Connor et al. 2014a). Other less frequent events (relative to surface fires) include semi- to multi-decadal drought (Swetnam and Betancourt 2010, Williams et al. 2012), and insect outbreaks (Swetnam and Lynch 1993, Negrón et al. 2008, Lynch 2009,

O'Connor et al. 2014b).

Monument Canyon RNA was preserved from all logging and wildfire since its establishment in 1935 (Falk et al. 2007). It is one of only a few stands of ponderosa pine that have not been logged in the southwestern USA. Overstory trees in Monument Canyon exceed 300 years in age (Falk et al. 2007). Part of Monument Canyon recently underwent a mastication thinning treatment in which trees <20 cm DBH were removed along the San Juan Mesa. Sites with >30° slope were not thinned. Prior to thinning Monument Canyon was considered one of the worst examples of *P. ponderosa* 'dog-hair thicket' in the western USA (Allen et al. 2002, Falk 2004). Historically the whole RNA burned either at once or episodically oscillated between the two mesas across years with a mean fire interval of <4 years (Falk et al. 2007, Swetnam et al. 2011).

The Pinalenos logging campaign was prevalent

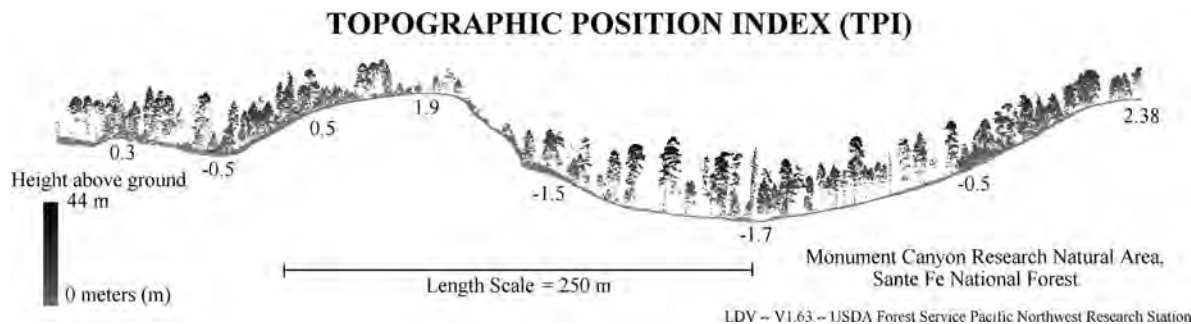


Fig. 3. ALS point cloud transect across the Monument Canyon RNA. Numbered values represent the TPI using a length scale of 250 m with inverse distance weighting. TWI values for the mesa tops are strongly positive and for valley bottoms strongly negative. Tree canopies are clearly visible in this ALS point cloud image; note the correlation of the height of the tallest trees to the valley bottoms, cf. shorter trees on mesa tops.

in the pine and mixed-conifer vegetation types during the late 19th and early 20th century (Sanderson and Koprowski 2009). Logged areas have recovered to the point they are no longer easily discernible by aerial orthophotography or satellite based indices of vegetation such as Normalized Difference Vegetation Index (NDVI). Trees in the Pinalenos can be very long lived, with individuals exceeding 600 years in age (O'Connor et al. 2014a). O'Connor (2013) digitized 1960s orthophotographs and delineated polygons for then planned logging areas, records of the actual logging locations do not exist. Modern GIS activity layers are comprehensive for both study areas for the 1970–2012 period (USFS 2013, Coronado N.F., and Santa Fe N.F.).

Airborne laser scanning and individual tree isolations

In June of 2010 discrete return ALS were flown over the Santa Fe N.F. and Valles Caldera National Preserve, by the National Center for Airborne Laser Mapping (NCALM) as part of the National Science Foundation's Critical Zone Observatory Program. In late June and early July 2012 the southwestern portion of the Santa Fe N.F. was flown by Watershed Sciences (Portland, OR) as part of the Southwest Jemez Collaborative Forest Landscape Restoration Program (Table 1). Both flights overlapped the Monument Canyon RNA (Table 1, Fig. 1).

In 2008 the Pinalenos were flown with ALS by Watershed Sciences (Portland, OR) as part of the Pinaleno Ecosystem Restoration Project (Mitchell et al. 2012) (Table 1, Fig. 4).

ALS data for both study areas were processed in FUSION/LDV (McGaughey 2012). A variable area local maxima (VLM) algorithm (Swetnam and Falk 2014) articulated individual trees from 0.333 m pixel canopy height models (Persson et al. 2002, Falkowski et al. 2006) in MATLAB 2012b (Mathworks 2012) (Figs. 5–7). The precision and accuracy of the VLM technique are reported in detail by Swetnam and Falk (2014) and Swetnam et al. (2014), who found that the VLM had $\pm 8\%$ error for overstory trees, with most commission errors due to multiple-leader canopy trees, and omission errors due to trees being located directly beneath a taller overstory tree.

Local indicators of spatial association (LISA)

Global spatial autocorrelations developed from weighted matrices assume homogeneity of the region of interest yielding a single statistic for a study area or population, and implicitly assume no variation across space (Moran 1950). In nature this condition is rarely satisfied, suggesting the need for statistics that vary over space (Legendre 1993). When data are heterogeneous, local spatial autocorrelation varies over space at the scale of the data (Anselin 1995, O'Sullivan and Unwin 2010). A global statistic is thus likely to be significantly different from autocorrelation measured at the local scale (O'Sullivan and Unwin 2010). In general, almost any standard statistic can be decomposed from a global to local statistic (Cressie 1993, O'Sullivan and Unwin 2010). Local statistics require a search radius or a number of near neighbors from which to draw a statistical distribution; and these groups of individuals

Table 1. ALS flight parameters for the two study areas as reported by the vendors and produced in USFS FUSION (McGaughey 2012) 'Catalog' Quality Control and Quality Assessment module. Density of the data is reported in pulses per square meter (ppsm).

Parameter	Pinaleño	Jemez	
		Valles Caldera National Preserve	Southwest Jemez
Vendor	Watershed Sciences	NCALM	Watershed Sciences
Acquisition dates			
Leaf off		January 2010	
Leaf on	September 2008	June 2010	June, July 2012
Scanner	Leica ALS50 Phase 2	Optech Gemini	Leica ALS60
Pulse rate	70–90 kHz	100 kHz	105.9 kHz
Scan rate	52.2 Hz	<100 Hz	<100 Hz
Returns per pulse	1–4, Intensity	1–4, Intensity	1–4, Intensity
Scan angle	±15°	±25°	±13°
Vert/Horiz. accuracy	3.2 cm/1.0 m	7.0 cm/1.0 m	2.8 cm/1.0 m
Flight level	800–1,300 m	~1,000 m	650–1,100 m
Mean return spacing	7.36 ppsm	January: 8.86 ppsm June: 5.91 ppsm	13.35 ppsm
μ bare ground spacing	0.98 ppsm	1.11 ppsm	2.58 ppsm
Acquisition area	34,608 Ha	January: 29,400 Ha June: 75,600 Ha	52,588 Ha
Total point returns	2,892,925,979	January: 2,541,885,987 June: 7,754,915,628	7,020,498,000
Projection	UTM Zone 12	UTM Zone 13	UTM Zone 13
Coordinate Reference System	WGS84, NAD83	WGS84, NAD83	WGS84, NAD83

Note: For Pinaleño and Jemez, the units were in meters, the flight line overlap was +50% side lap, and the classifications were: default = 1, ground = 2, withheld = 11.

(e.g., trees) are what form the clusters of like-valued neighbors.

Statistical tests of pattern analysis typically begin with a null hypothesis of complete spatial randomness: Rejection requires the existence of a dispersed or a clustered distribution based on a z -score (the standard deviation [SD] about the mean) where the p -value of statistical significance is typically set at 0.05 or 0.01 (a 95% or 99% confidence interval [CI]). Positive z -scores indicate clustering of large values and negative z -scores indicate clustering of small values (e.g., a z -score of 2.58 indicates at the 99% CI a tree with tall neighbors, and -2.58 indicates a tree with short neighbors). Statistics that evaluate the existence of clusters in spatial arrangements are indicators of spatial association and include Moran's I (Moran 1950) and the Getis-Ord global G statistic (Getis and Ord 1992) (see Appendix A for equations).

For our study, Moran's I represents a summation of matrix cross products of z -scores of neighbor trees and the reference tree for all sample points, and thus can be illustrated by LISA where Anselin's local Moran's I (Anselin 1995) is calculated for statistical associations of each i, j pair at multiple spatial scales (Anselin

1995, Zhang and Zhang 2007) (Appendix A). Similarly, Ord and Getis (1995) produced a LISA statistic of G , called G_i^* (Appendix A), to compare local concentrations of high to low z -scores in an attribute where each is the center of a three-dimensional kernel. We applied these LISA statistics to the ALS derived individual tree inventory based on tree height and neighbor distance.

For the Getis-Ord G_i^* we set inverse Euclidean distance as the weight of the default neighborhood with a search threshold to the maximum observed tree height (49 m) with the 'Hot-Spot Analysis' Tool in ArcGIS 10.1 Toolbox (Mitchell 2005, ESRI 2012). Test z -scores are significant at the 90% CI for $z = \pm 1.644$, at the 95% CI $z = \pm 1.959$, and at the 99% CI $z = \pm 2.575$. To calculate Anselin local Moran's I_i we used the 'Cluster and Outlier Analysis' Tool in ArcGIS 10.1 Toolbox (Mitchell 2005, ESRI 2012). The I_i equation was also weighted by the height of trees using the inverse distance method with a maximum distance of 49 m. Maximum neighborhood area was based on the assumption that radial roots extend maximally out to the length of the tree's height (Woolsey 1911).

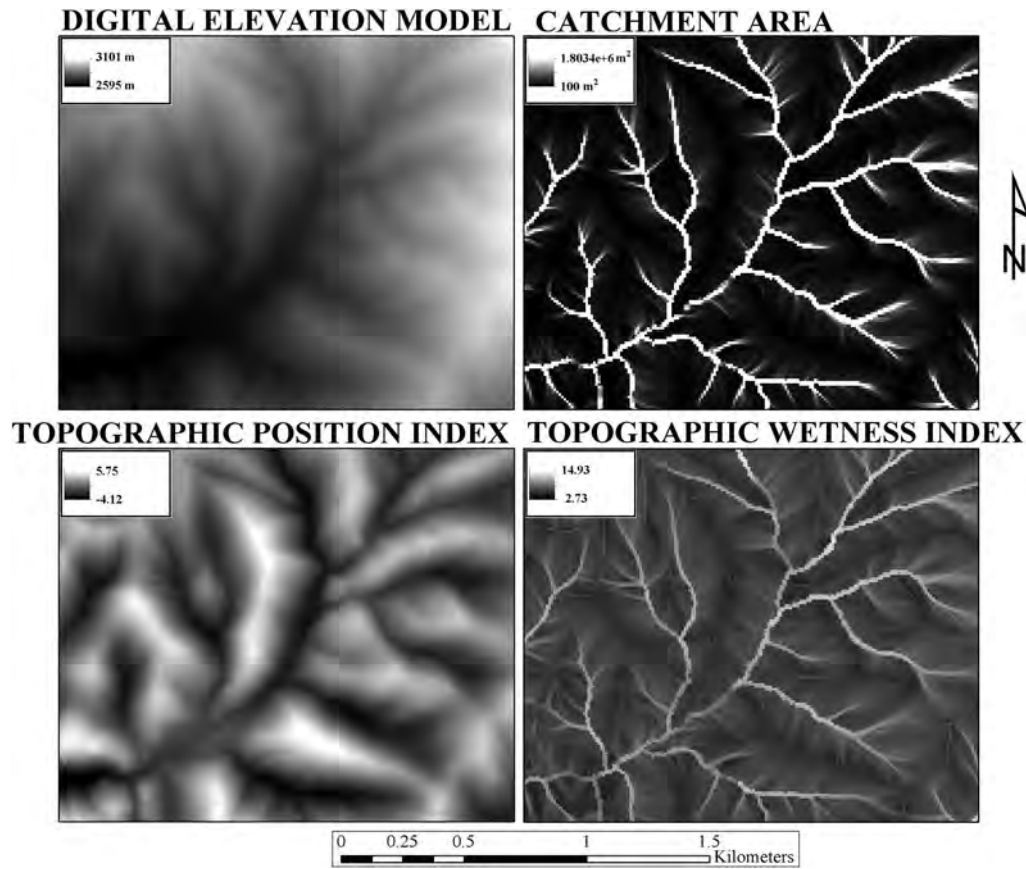


Fig. 4. Pinaleno Mountains 10 m Digital Elevation Model (DEM) (upper left), catchment area (upper right), TPI (lower left), and TWI (lower right).

Topographic indices

We also explored whether the topographic wetness index (TWI, Beven and Kirkby 1979, Quinn et al. 1991) and topographic position index (TPI, Guisan et al. 1999, Weiss 2001, Wilson et al. 2007) correlate with maximum tree size and the two LISA statistics. The TPI is calculated as:

$$\text{TPI}(r_{\text{scale}}) = \text{Elevation} - \mu_{\text{focal}}(\text{Elevation}, \alpha, r_{\text{inner}}, r_{\text{outer}}) + 0.5 \quad (1)$$

where r_{scale} is the size of the moving window, Elevation is the value of the cell above mean sea level, μ_{focal} is the average of all elevations within the window, α is the annulus, r_{inner} is the radius of the inner circle, and r_{outer} is the radius of the outer circle (Weiss 2001). We calculated TPI in Quantum GIS 2.2 (QGIS 2013) with the GDAL-

DEM tool set to the inverse distance weighting method (Wilson et al. 2007, GDAL 2013). Because we were interested in ecologically relevant scales including differences in soil depth and soil moisture, we set the r_{scale} distance to 250 m, which corresponded to the average length scale of ridge-to-valley topography of the two featured landscapes (Figs. 2–4). Index values relate to topographic position (i.e., ridge, slope, valley-bottom, etc.) with the most negative values in valley-bottoms and most positive values on ridge tops (Figs. 2–4).

The TWI for estimating soil moisture was first demonstrated in the “TOPMODEL” (Beven and Kirkby, 1979) and is defined as

$$\text{TWI} = \ln\left(\frac{a}{\tan\beta}\right) \quad (2)$$

where a is the local upslope area draining

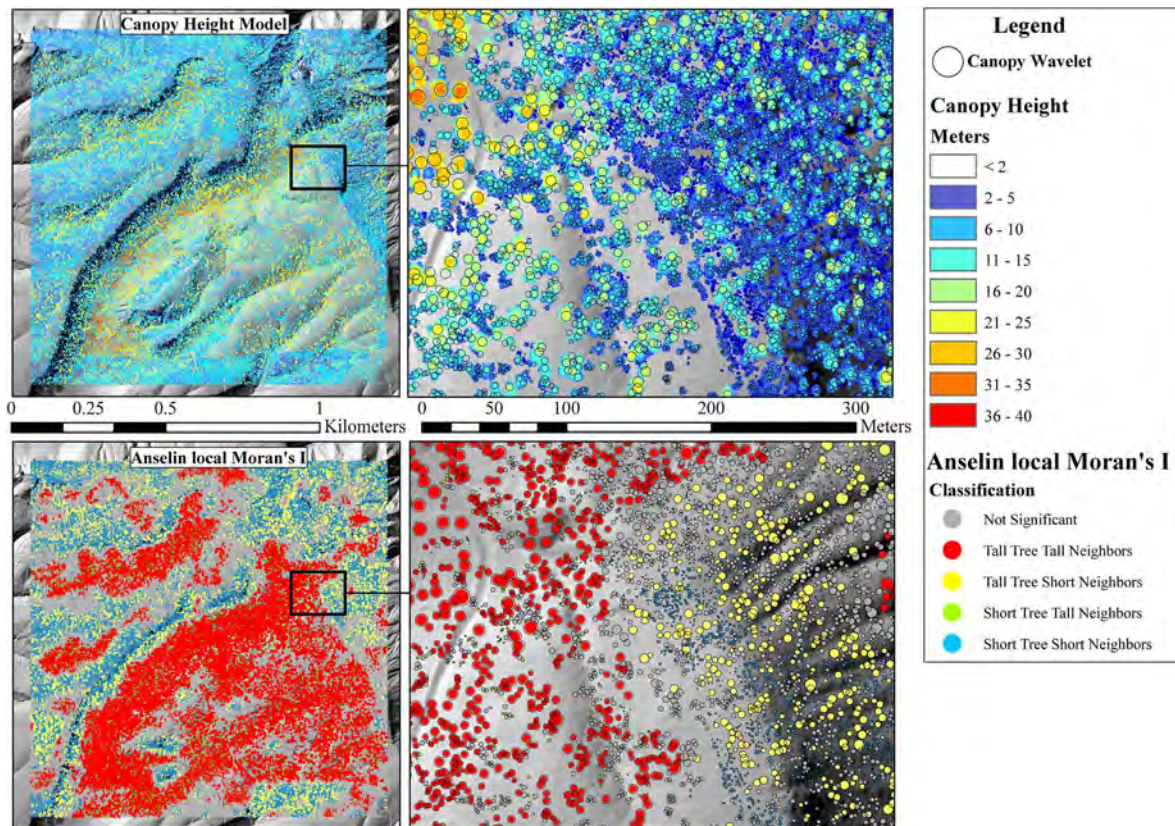


Fig. 5. Canopy height model for Monument Canyon RNA study area with VLM local maxima (top two panels). Tree heights are colored blue to red (in meters); black boundary circles are based on a wavelet fit to each colored blob and represents estimated canopy diameter. Anselin local Moran's I_i (bottom two panels) is derived from the local maxima and weighted by tree height. Tall trees with tall neighbors are colored red, short trees with short neighbors are colored blue.

through a digital elevation model (DEM) pixel or contour length unit and $\tan\beta$ is the tangent of the local slope β . All TWI calculations were performed in Quantum GIS 2.2 (QGIS 2013) with the extension for System for Automated Geoscientific Analysis (SAGA, v. 2.0.8). Kopecký and Čížková (2010) tested 11 variations of TWI flow routing algorithms versus soil moisture and vegetation species diversity, they recommend a multi-flow routing algorithm (Quinn et al. 1991, 1995) for characterizing variation in vegetation. A multi-flow routing algorithm using the deterministic infinity (D^∞ ; Tarboton 1997) method was executed in the SAGA 'Catchment Area (Recursive)' and 'Topographic Wetness Index' module (Böhner and Selige 2006). A convergence value equal to 1.1 was used. All DEMs were 10 m resolution (Figs. 2 and 4), which helped account

for the lateral redistribution of water to the roots around each point located tree.

RESULTS

Individual tree isolations from the airborne LiDAR

For the Monument Canyon RNA (289 ha), the variable area local maxima algorithm identified 199,219 trees from the 0.333 pixel canopy height models. In the Pinaleños (166 ha, ALS Tile ID: F8405), the variable area local maxima algorithm identified 116,006 trees from the 0.333 pixel canopy height models. Tree heights range from a minimum 2-m cut-off to 49.3 m.

LISA of tree and stand level characteristics

Both LISA statistics discriminated various

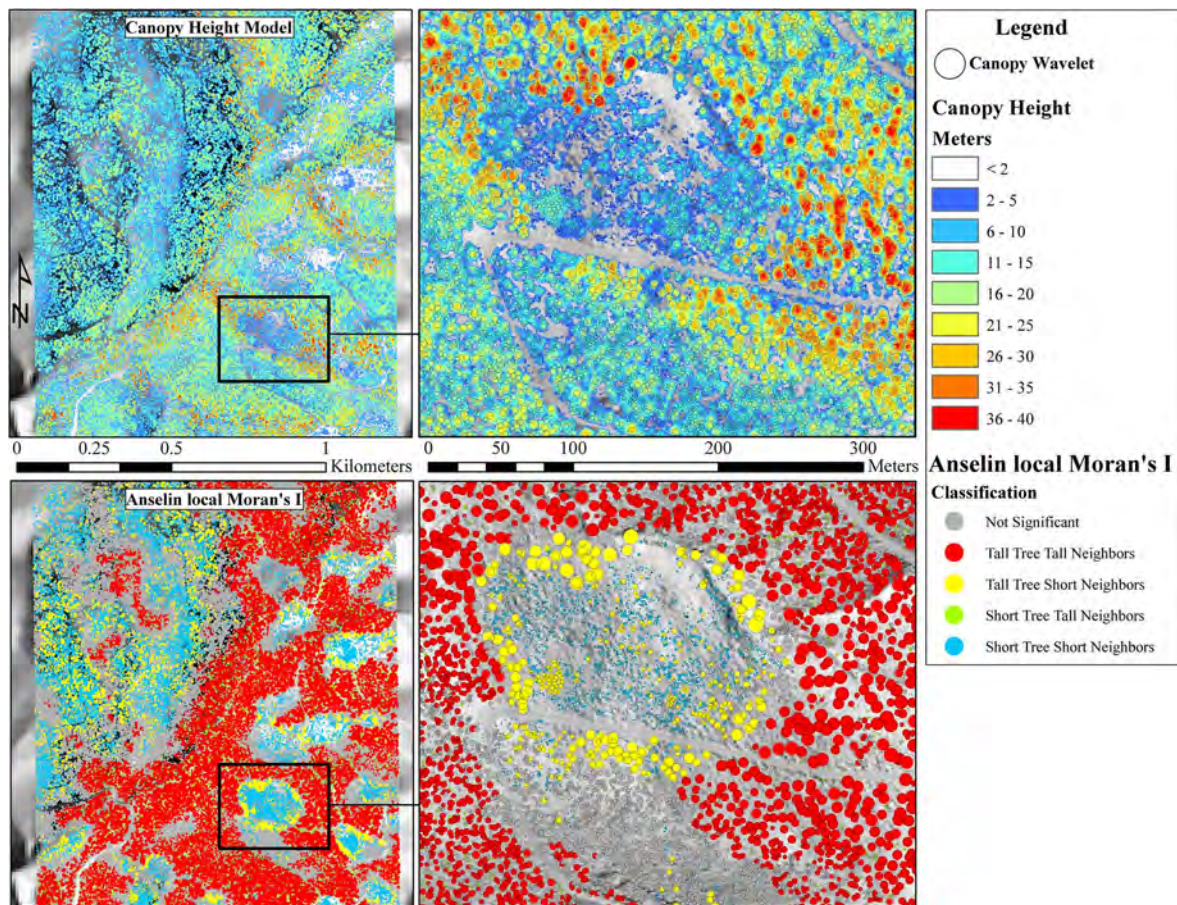


Fig. 6. Same as Fig. 5 but for the Pinaleño Mountains study area.

structural differences and found strong evidence of clustering throughout Monument Canyon and the Pinaleño (Figs. 5–7). The negatively valued z -scores tended to characterize clustering within the disturbed areas (e.g., within logged and thinned treatments). Recently established standing cohorts had either negative Anselin local Moran's I_i z -scores (colored blue) or non-significant z -scores (gray), most evident in the Pinaleño logging deck where an aspect reversal takes place (Fig. 6).

For Getis-Ord G_i^* trees with short neighbors had significantly negative z -scores ($z < -2.58$, $p < 0.01$) and trees with tall neighbors had significantly positive scores ($z > 2.58$, $p < 0.01$) (Table 2). Trees with z -scores between -2.58 and -1.65 and between 1.65 and 2.58 were also significantly positive at the 90–95% CI. Z -scores were non-significant ($-1.65 < z < 1.65$) in

neighborhoods with a wide variation in heights, suggesting those trees were randomly distributed. For example, within the Pinaleño logging deck the average z -score changed rapidly from negative (green) to positive (red), with a brief non-significant transition (yellow) between the short and tall trees (Fig. 7, right panel). For the Anselin local Moran's I_i z -scores the results are proportionately equivalent (Figs. 5 and 6), with negative z values for small neighbor trees and positive z values for tall neighbor trees (Table 2). The added cross-product score of Anselin local Moran's I_i , whether the object tree is also tall or short, resulted in a different set of classification values. The additional information further revealed more complex variations within the clusters of trees (Figs. 5 and 6, Table 2).

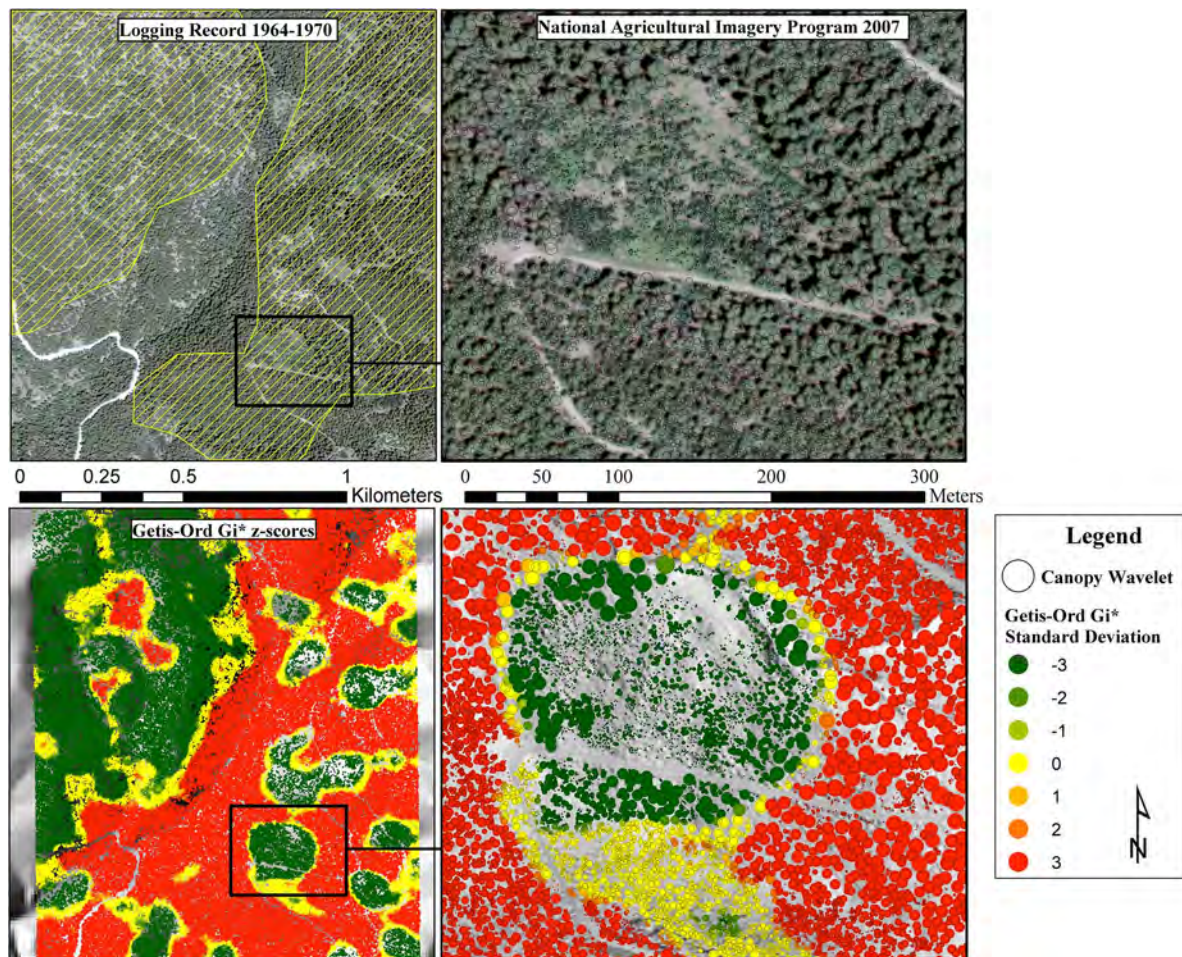


Fig. 7. Orthophotograph (NAIP 2007) for Pinaleño sample area with historical logging records originally hand drawn on a 1960s orthophoto, later converted into a polyline (top left panel). A closer inspection of a patch-cut in the NAIP image with VLM local maxima represented (top right panel). Getis-Ord G_i^* (bottom panels) spatial statistics of the same area: negative values (green) represents clusters of small trees, positive values (red) represent clusters of tall trees. The west slope (left side) was clear cut, while the east slope (right side) was patch cut.

LISA patterns of logging and disturbance legacies

Both LISA statistics distinguished a variety of coherent patterns that aligned readily with known disturbance histories: timber contracts, fenced boundaries, recent fuels reduction treatments, historical fire perimeters; and changes in topography: aspect reversals, valley/canyon bottoms vs. ridge/mesa tops (Figs. 2–7).

Most of Monument Canyon's central drainage and the San Juan Mesa (southeast corner) are dominated by old-growth ponderosa pine (Falk et al. 2007); these stands are clearly defined by positive Anselin local Moran's I_i z-scores (Fig. 6,

red disks). Variations are defined by (1) the fence line along the southern boundary and (2) excluded areas from a recent fuels treatment operation. On San Juan Mesa (southeast corner of Fig. 5) south of the boundary fence there are mainly tall trees with short neighbors (yellow and green) that represent unthinned areas, while north of the fence tall trees with tall neighbors (red) dominate.

In the Pinaleños stand patterns are likely the result of logging within the known logging contract boundaries, e.g., clear cutting on the west side of the drainage, and patch cutting on the east side of the drainage (Figs. 6 and 7).

Table 2. Average z-scores and the comparative types of stand conditions for both Getis-Ord G_i^* (column 1) and Anselin local Moran's I_i (columns two and three). In the far right column the first letter identifies the i th target tree, the second letter is the type of neighborhood it is surrounded by, e.g., H-L is a tall tree with short neighbors, L-L is a short tree with short neighbors, NS is not significant (the neighborhood trees are heterogeneous in structure), etc.

Stand condition	z-scores						
	G_i^*	I_i			I_i neighborhood groups		
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
Pinaleño							
1950s cut	-6.2	3.5	0.3	-2.5	L-L	NS	H-L
Old-growth adjacent patch cut	8.5	-3.3	1.2	8.2	L-H	NS	H-H
N-facing 1960s logged patch cut	-11.2	30.5			L-L		
S-facing 1960s logged patch cut	-0.7	0.4			NS		
High-severity fire	-14.2	-3.9	-1.3	6.3	H-L	NS	L-H
Monument Canyon							
Even-aged young PIPO	-3.2	6.6			L-L		
Even-aged mature PIPO	5.5	11.5			H-H		
Primeval mature (+300 years)	4.3	-0.5	15.3		NS	H-H	
Open-structure mature (120 stems/ac)	2.1	-5.2	0.0	6.6	L-H	NS	H-H
Closed-structure mid (800 stems/ac)	-1.5	2.8	1.5		L-L	NS	

Currently, forest structure within the logged area varies from unharvested old-growth mixed-conifer along the main riparian drainage (Big Creek) to recent reproduction in the logged areas. These differences are apparent in the ALS data, but are not evident in the 2007 National Agricultural Imagery Program (NAIP) orthophotography (Fig. 7).

Logged areas in the Pinaleños are in close proximity to skidding roads (Figs. 6 and 7). Within the clear cut sections, Anselin local Moran's I_i reveals older 'seed-trees' amongst the young trees (Fig. 6, left side of the catchment). This is an important difference versus the Getis-Ord G_i^* (Fig. 7) which does not discriminate amongst the individuals because G_i^* does not look at the cross products of the neighbor trees.

Maximum tree size and LISA vs. topographic indices

TPI and TWI were calculated with the same set of parameters using 10 m DEM models for both the Monument Canyon RNA (Figs. 2 and 3) and the Pinaleños (Fig. 4). The TPI for each site ranged from -5.5 to 3.6 (Figs. 2 and 4). Most of the trees in this analysis were located on TPI between -3 and 3.5. The TWI surface with D_∞ reported a range of values from 3.5 to 14.5, with most values for trees between 4 and 14 (Figs. 2 and 4).

Tree height increases asymptotically with

increasing wetness index over part of the range of TWI (≥ 4 to approximately ≤ 7), above these values maximum tree height remains constant (Fig. 8, right panel). The tallest trees are in the valley/canyon bottoms (~ 49 m height), and the shortest are on ridge tops (~ 20 m height), with a nearly linear decrease in height as TPI increases in value from $TPI \geq -1.8$ to $TPI \leq 3$ (e.g., Fig. 8, left panel). In the Monument Canyon RNA old-growth stands are continuous across canyon bottoms up to the mesa tops, and are of similar ages (Falk et al. 2007) (Fig. 5). These stands end abruptly along the southern border fence, corroborating records that old growth trees south of the fence were logged in the 20th century.

Stands of the tallest neighbors, given by the largest positive z-scores, versus TPI and TWI in Monument Canyon RNA (Fig. 9, black line) and the Pinaleños (Fig. 10, black line) skewed toward lower topographic positions (more negative TPI) and wetter sites ($TWI > 6$) than the population average (gray line).

DISCUSSION

Our results clearly demonstrate topographic position and wetness correlate to a majority of the variation in the climax tree height/size distribution. The tallest trees on the lowest topographic position and highest wetness indices was inversely correlated to the shorter trees on

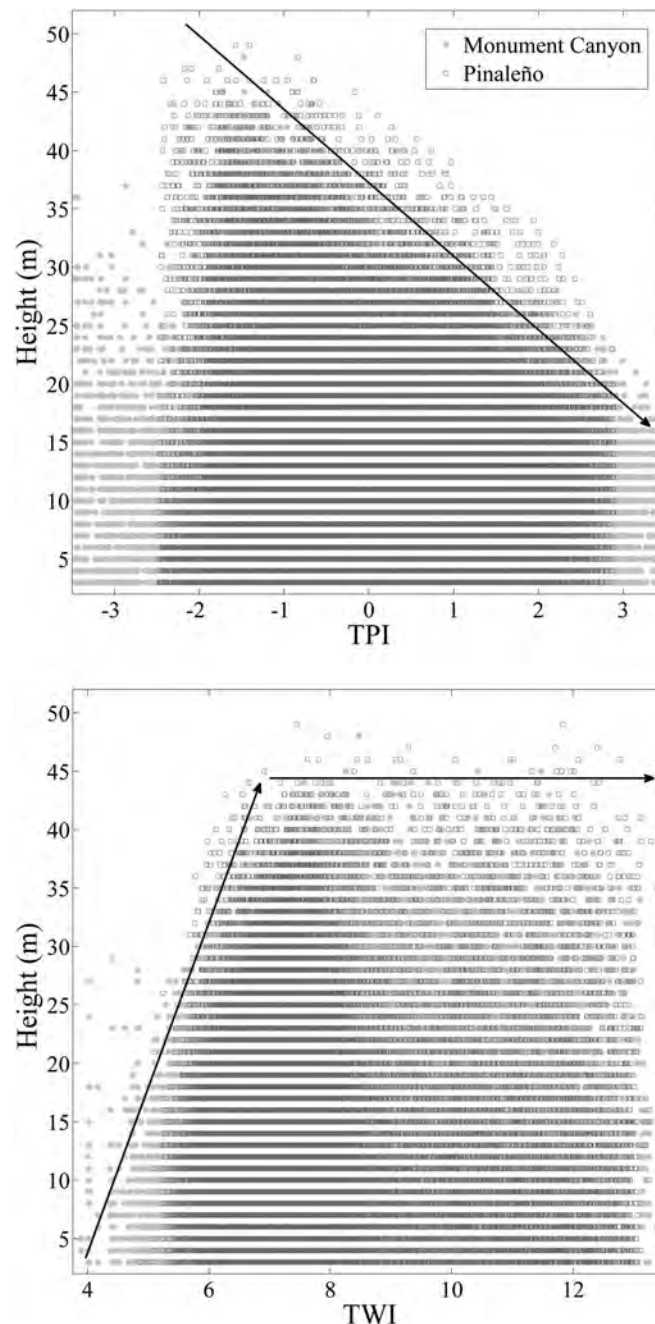


Fig. 8. TPI vs. tree height (top panel) and TWI vs. tree height (bottom panel). As TPI increases tree height decreases; the tallest trees (49.3 m) are in negative TPI sites (canyon bottoms), trees on the most positive TPI sites (ridges) are less than half the maximum height. Tree height increases as TWI increases from 4 to ~ 7 , and is then asymptotic.

the highest topographic positions and lowest wetness indices and varied by over 29 m in height, a 150% difference. We believe that this clustering of the largest trees is at least in part the

result of the redistribution of precipitation and soil depth characteristics that preferentially increase forest productivity. The trend of taller trees growing on lower slope positions is consistent

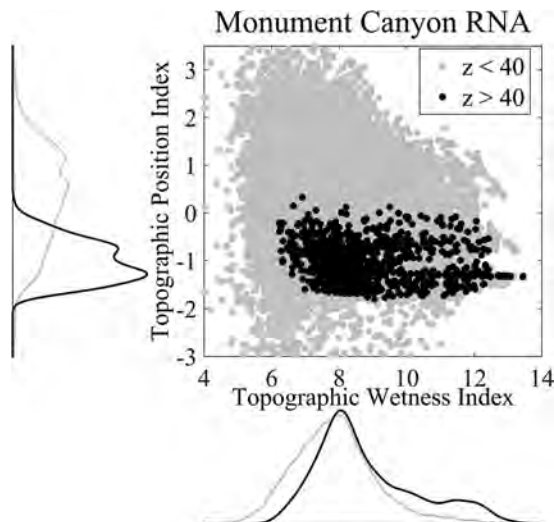


Fig. 9. Scatter plots and density distribution of z-scores for TWI vs TPI in Monument Canyon. The distribution of high z-scores, i.e., the tallest clusters of trees, suggests tall trees aggregate in more negative TPI values, i.e., the drainage basins between ridge tops. The distribution of z-scores by TWI closely resembles the sampling distribution of TWI suggesting autocorrelation in those data.

with other forest studies in temperate and tropical forests (McNab 1993, Detto et al. 2013) suggesting a globally common forest feature driven by productivity gradients.

Distinct variations in forest structure were also shown to be related to known disturbances and are clearly recognized by both LISA statistics. Logged areas were clearly defined versus a priori undisturbed sites. When topographic factors are accounted for, any departures from an expected climax state can be readily diagnosed. Our data are in agreement with Sánchez Meador et al. (2009), and Larson and Churchill (2012) having significant clustering in tree size across space. For Monument Canyon RNA, an essentially natural forest with a well-studied age distribution and fire regime (Falk et al. 2007, Swetnam et al. 2011), significantly positive LISA z-scores are found in both the canyon bottoms and on top of the mesas reflecting the nearly continuous distribution of old growth trees. In the Pinaleños, the most positive LISA z-scores are found in unharvested areas, as defined outside the recorded logging contract boundaries. Clusters of the tallest trees (z

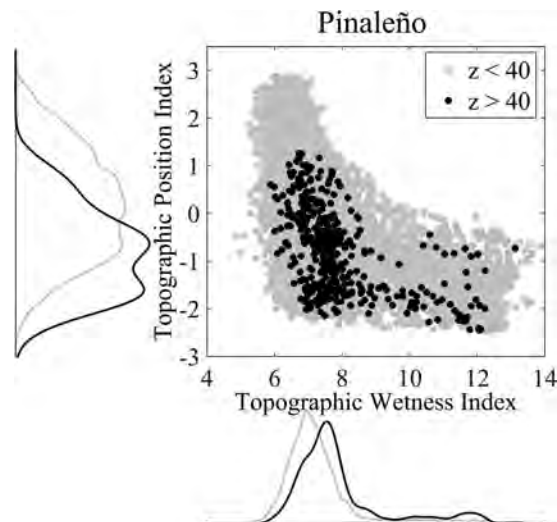


Fig. 10. Scatter plots and density distributions of z-scores for the Pinaleño; same scheme as Fig. 9.

> 40) were also associated with negative TPI values and larger TWI values at both sites (Figs. 8–10). The relationship of height and z-score with TPI and TWI appear to have minimum thresholds with respect to sites supporting taller trees (Figs. 8–10).

Disturbance legacies characterized by LISA

Disturbances have left a lasting legacy on the tree size distribution and clustering patterns of these southwestern forests. LISA statistics clearly defined differences in forest structure more than fifty years after the logging disturbance (Figs. 6 and 7). In the Pinaleños, two different types of logging (clear cut vs. patch cut) were expressed by similar LISA scores but with different patch sizes on either side of the catchment.

Both LISA statistics revealed variation in forest structure not readily apparent in the orthophotography (Figs. 6 and 7). Anselin local Moran's I_i provided additional information compared to the Getis-Ord G_i^* because Anselin local Moran's I_i incorporates matrix cross products of z-scores of neighbor trees and the reference tree. In this regard Anselin local Moran's I_i may be more informative than Getis-Ord G_i^* for characterizing different kinds of forest assemblages. For example, the z-score of a single large tree standing amongst a young cohort can be overwhelmed by the distribution of its short neighbors (and vice

versa) for the G_i^* . In stands with mixed age structure, such as in the Monument Canyon RNA where dense dog-hair thickets exist, Anselin local Moran's I_i was a key predictor for discerning where a tall tree is now surrounded by a new cohort (Fig. 5). Getis-Ord G_i^* clearly delineates where significant changes occur at the stand level, which may be more important when the objective is to delineate larger features, as in the logging perimeter (Fig. 7). In Appendix B we provide an extension to the Getis-Ord G_i^* technique, in which a Voronoi tessellation is used to create polygons of similar valued cohorts, equivalent to those used in USFS Common Stand Exams (<http://www.fs.fed.us/nrm/fsveg/>).

We tested these spatial relationships in two forest areas with known disturbance histories to evaluate fine scale variability in the ALS data. Cross validation to the known disturbance histories such as the logging record in the Pinaleños revealed other significant impacts not previously documented, mapped, or quantified explicitly. For both the Arizona and New Mexico examples of forest structure, Anselin local Moran's I_i and Getis-Ord G_i^* showed coherent differences consistent with both known land-use history (Figs. 6 and 7), and interestingly to topographic variation (Figs. 8–10). Areas logged with either clear cuts or selective patch cuts were also easily differentiated (Fig. 7). Further, Anselin local Moran's I_i and Getis-Ord G_i^* revealed variation not visible in the most recent orthophotography (Fig. 7). The presence of old logging roads which are most visible in the LiDAR bare earth model provided further confirmation logging was the disturbance agent in those locations.

Identifying structural changes in vegetation as a response to topographic variation versus disturbance is important for accurate reconstruction of the past disturbance regime. In Monument Canyon RNA, insignificant or negative z-scores were shown to relate to young stands along steep slopes and the mesa tops. Based on reconstructed evidence from tree rings (Falk et al. 2007, Swetnam et al. 2011) frequent low-severity fires historically spread across the entirety of Monument Canyon area until the late 19th century. It is plausible these fires were intensified by slope alignments as they spread up out of the canyon bottoms which led to the mortality of trees along those locations preventing larger trees

from establishing prior to fire exclusion. These regeneration trees, especially the dog-hair thickets, throughout Monument Canyon RNA are one of the consequences of *P. ponderosa* recruitment in the absence of episodic wildfire (Allen et al. 2002, Falk et al. 2007).

Conclusions and proposed applications

These examples illustrate how ALS data and LISA could be used in cases where disturbance history is less clearly documented, for example to distinguish residual old-growth forest from areas that are recovering from disturbance or some other unmeasured physical limitation. Given this potential, LISA statistics could be used to characterize forested stands with respect to:

1. Delineating existing stand boundaries, e.g., for common stand exams (see Appendix B for example);
2. Improving on historical maps where only a perimeter for a fire, insect disturbance, or timber management plan was recorded;
3. Quantifying site-indices based on scaled topographic indices, i.e., TPI and TWI, and using those to determine the level of departure from potential climax vegetation size;
4. Quantifying impacts of recent wildfires and insect outbreaks on stand structure versus those derived from other remote sensing products, e.g., NDVI mapping from satellite or aerial orthophotography, for which structure is only an implied variable; and
5. Comparing and contrasting forest-level responses to disturbance; e.g., using LISAs to evaluate the proportionality of mortality due to drought and/or an insect outbreak across different stands by topographic index variations.

Incorporating ALS data across landscapes and analyzing spatial properties of the resulting forest structure with LISA enables us to ask new questions about landscape patterns and processes. The forests in this study both have long histories of episodic disturbance, punctuated by logging and fire suppression. Where disturbance was known to have occurred LISAs showed skill at identifying spatial heterogeneity in the stand structure. These same methods can

be applied to other forests, where an evaluation of current conditions relative to their historical range of variability is needed. LISAs can therefore be used to quantify the structural legacies of a range of natural and human disturbances (fire exclusion, high-severity wildfire, or logging). The methods demonstrated here indicate the potential to characterize semi-arid forest structure in the Southwestern USA and potentially other semi-arid forests globally.

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SUPPLEMENTAL MATERIAL

APPENDIX A

LISA Equations

Getis-Ord G and G_i .—The Getis-Ord global G statistic (Getis and Ord 1992) is written as

$$G(d) = \frac{\sum_i \sum_j w_{ij}(d) x_i x_j}{\sum_{i=1}^n \sum_{j=1}^n x_i x_j} \text{ for all } i \neq j. \quad (\text{A.1})$$

The local statistic (Ord and Getis 1995, 2001, Getis and Ord 1996) is described by a location i , and thus the local G_i value is

$$G_i(d) = \frac{\sum_j w_{ij}(d) x_j}{\sum_{j=1}^n x_j} \text{ for all } i \neq j \quad (\text{A.2})$$

where $w_{ij}(d)$ are spatial weights from a weight matrix and x_j is the value at location j .

We employed the LISA version of the statistic, G_i^* , available in ESRI's ArcGIS 10.1 Toolbox (Mitchell 2005, ESRI 2012) the 'Hot-Spot Analysis' Tool

$$G_i^* = \frac{\sum_j w_{ij} x_j - \bar{X} \sum_{j=1}^n w_{ij}}{S \sqrt{n \left[\frac{\sum_{j=1}^n w_{ij}^2}{n-1} - \left(\frac{\sum_{j=1}^n w_{ij} \right)^2}{n^2} \right]}} \quad (\text{A.3})$$

where x_j is the value for feature j , w_{ij} is the spatial weight between the i and j , n is equal to the total number of features where

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n}$$

and the standard deviation

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2}.$$

G_i^* is a z-score where scores close to zero

indicate no apparent clustering within the sample.

Anselin's Morans I .—Moran's I (Moran 1950) is calculated as

$$I = \left[\frac{n}{\sum_{i=1}^n (y_i - \bar{y})^2} \right] \times \left[\frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \times (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \right] \quad (\text{A.4})$$

where i and j are the different areal units of the study, y is the value of a unit at each location; w_{ij} is a spatial weight term from the matrix which affects the covariance element by the spatial closeness. The Anselin local Moran's local I calculation conducted in ArcGIS (ESRI 2012) uses a local Moran's I_i

$$I_i = \frac{\overline{x_i - \bar{X}}}{S_i^2} \sum_{j=1, j \neq i}^n w_{ij} (x_j - \bar{X}) \quad (\text{A.5})$$

where x_i is an attribute of i , $\bar{X}$ is the mean of w_{ij} a spatial weight between i and j , where

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^n (x_j - \bar{X})^2}{n-1} - \bar{X}^2$$

and n is the number of features. The z-score is computed as

$$Z_{I_i} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad (\text{A.6})$$

where

$$E[I_i] = - \frac{\sum_{j=1, j \neq i}^n w_{ij}}{n-1}$$

and $V[I_i] = E[I_i^2] - E[I_i]^2$ (Mitchell 2005).

APPENDIX B

THIESSEN POLYGONS
FOR COMMON STAND DELINEATION

Commonly shared characteristics of trees allow them to be aggregated into ‘stands’ of like-valued individuals based on (1) species, (2) local topographic features, (3) soil type, or (4) some combination of parameters. We were interested in delineating the pattern of the existing forest structure to create similarly classified stands.

We generated Thiessen polygons (Brassel and Reif 1979; also called Voronoi polygons [Boots 1986]) in ArcGIS 10.1 (ESRI 2012) about the

individual points, which include the area of influence about a point relative to its neighbors. Thiessen polygons can be generated either before or after the Hot Spot Analysis (ESRI 2012), as the data are equivalently vector based (point or polygon).

We calculated the Getis-Ord G_i^* statistic to determine the break point in stand architecture and spatially connected the neighborhoods of Thiessen polygons. We merged the individual Thiessen polygons into a single polygon layer, which became the boundary of our common stand based on structural characteristics (Fig. B1).

In order to define common stand boundaries

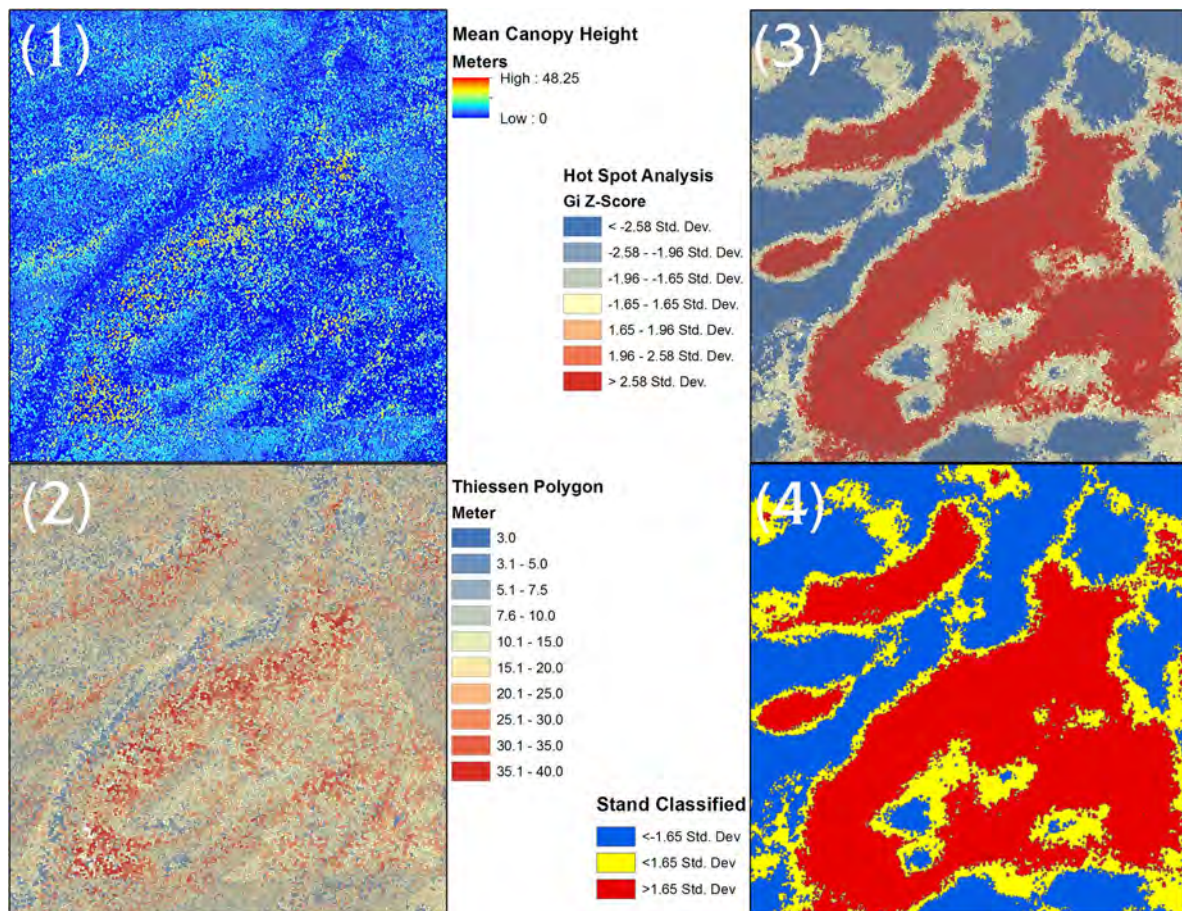


Fig. B1. The four panels from top left to bottom right are (1) canopy height model at 0.333 m^2 , (2) a Thiessen polygon weighted by height, (3) hot spot and cluster analysis Getis-Ord G_i^* of the Thiessen polygons, and (4) three break lines set at $z = < -1.65$, < 1.65 , and > 1.65 to define each stand. The break marks for a stand could be set along either the red or blue borders and be smoothed or simplified if desired.

we re-classified the continuous data using pre-defined sets of break-lines (e.g., manual, equal interval, quantile, standard deviation, etc., in ArcGIS 10.1 [ESRI 2012]). In our example here we used standard deviation. Once each break point was chosen we used the ‘Select Tool’ to create sets of polygons either greater than or less than the z-scores at a specified significance level. We chose to segment the example in Fig. B1 at the 95% level.

SUPPLEMENT

Data files used in the main text (*Ecological Archives*, <http://dx.doi.org/10.1890/ES14-00384.1.sm>).