

Structural diversity indices based on airborne LiDAR as ecological indicators for managing highly dynamic landscapes



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ABSTRACT

An objective, quantifiable index of structural biodiversity that could be rapidly obtained with reduced or no field effort is essential for the use of structure as universal ecological indicator for ecosystem management. Active remote sensing provides a rapid assessment tool to potentially guide land managers in highly dynamic and spatially complex landscapes. These landscapes are often dependent on frequent disturbance regimes and characterized by high endemism.

We propose a modified Shannon–Wiener Index and modified Evenness Index as stand structural complexity indices for surrogates of ecosystem health. These structural indices are validated at Tall Timbers Research Station the site of one of the longest running fire ecology studies in southeastern U.S. This site is dominated by highly dynamic pine-grassland woodlands maintained with frequent fire. Once the dominant ecosystem in the Southeast, this woodland complex has been cleared for agriculture or converted to other cover types, and depends on a frequent (1- to 3-year fire return interval) low- to moderate-intensity fire regime to prevent succession to mixed hardwood forests and maintain understory species diversity. Structural evaluation of the impact of multiple disturbance regimes included height profiles and derived metrics for five different fire interval treatments; 1-year, 2-year, 3-year, mixed fire frequency (a combination of 2- and 4-year fire returns), and fire exclusion. The 3-dimensional spatial arrangement of structural elements was used to assess hardwood encroachment and changes in structural complexity. In agreement with other research, 3-year fire return interval was considered to be the best fire interval treatment for maintaining the pine-grassland woodlands, because canopy cover and vertical diversity indices were shown to be statistically higher in fire excluded and less frequently burned plots than in 1- and 2-year fire interval treatments. We developed a LiDAR-derived structural diversity index, LHD, and propose that an ecosystem-specific threshold target for management intervention can be developed, based on significant shifts in structure and composition using this new index.

Structural diversity indices can be valuable surrogates of ecosystem biodiversity, and ecosystem-specific target values can be developed as objective quantifiable goals for conservation and ecosystem integrity, particularly in remote areas.

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1. Introduction

Stand structural changes in forested or woodland systems often reflect biodiversity changes (Smith et al., 2008) and provide insight

into ecosystem function (Spies, 1998). Conventionally compositional biodiversity measures have been the “go-to” approach in developing a proxy for ecosystem functionality sustainability (e.g. SAFE model, Andriantatsaholainaina et al., 2004) and ecosystem service models (e.g.: INVEST, Tallis et al., 2011). Compositional biodiversity indices are powerful indicators of ecosystem health, but cost and time-prohibitive, particularly at coarse spatial scales and in remote and poorly studied areas. However, structural biodiversity indicators might well provide more comprehensive and repeatable surrogate measures given time and budget constraints. Field-derived structural measures target stand stage

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classification with canopy cover as the most widely used indicator (Smith et al., 2008) due to its cost-effectiveness and determinant effect on other structural measures. However, field-derived measures quickly increase in cost and decrease in effectiveness given the need for landscape-wide management strategies (i.e. prioritization for conservation or active silvicultural management).

A surrogate measure of biodiversity in a forested setting using structural components needs to include an easy to implement unbiased indicator of structural complexity or spatial arrangement. Indices of structural complexity have been proposed (McElhinny et al., 2006) that combined 13 core attributes, some requiring extensive field sampling (e.g. number of hollow-bearing trees, life-form richness, litter dry weight). Other diversity indices, such as the Shannon Diversity Index (SHDI) (Shannon et al., 1949) often used in community ecology as a measure of species composition biodiversity, have been applied to landscape ecology. Initially, SHDI was adapted to provide a measure of patch type diversity (McGarigal and Marks, 1995; Hietala-Koivu et al., 2004; Zhang et al., 2008), synthesizing complex spatiotemporal patterns of landscape diversity. In more recent years, a modified SHDI has integrated vertical structure, thus providing a three dimensional index of basal area-weighted tree heights (Staudhammer and LeMay, 2001; Frazer et al., 2005). Limitations of the development and validation of structural diversity indices include the enormous effort required in acquisition of foliage height density data (cover at fine height intervals), the difficulty in converting the data to spatial scales relevant to ecological modeling, and the often long delay in providing feedback to silvicultural managers of highly dynamic landscapes (i.e. where intervention is required every 2–3 years).

Airborne LiDAR has rapidly become a powerful technology in forestry and natural resource management, particularly with the ability to measure 3-D structure at broad spatial scales (Lefsky et al., 2002a; Newton et al., 2009). This active remote sensing technique has demonstrated the ability to characterize forest stands and approximate forest inventory data with canopy height (Lovell et al., 2003; Clark et al., 2004; Coops et al., 2007), basal area, above-ground biomass (Drake et al., 2002a, 2002b; Lefsky et al., 2002b), and leaf area (Roberts et al., 2003; Lefsky et al., 2005). In addition, one of the most promising ecological applications of small footprint LiDAR is the direct acquisition of vertical foliage distribution, which provides detailed information of the forest subcanopy elements. Canopy height profiles derived from high resolution LiDAR have a variety of ecological applications which include characterizing successional stages of forest stands (Harding et al., 2001), predicting species richness (Goetz et al., 2007; Hinsley et al., 2009; Müller et al., 2009) and assessing habitat features for both wildlife assemblages and species (Goetz et al., 2010; Seavy et al., 2009).

LiDAR (Light Detection And Ranging) datasets provide a means to evaluate three-dimensional forest structure (Zimble et al., 2003) with a much reduced effort and cost than ground based measurements. Field constraints such as accessibility, lack of objective and efficient measurement techniques, and high personnel and equipment costs have quickly made use of LiDAR remote sensing more attractive to land managers and conservation ecologists. As a result of such popularity, reduced acquisition costs, and greater density of data returns, this technology should be key in the development of a structural diversity indicator for biodiversity modeling and ecosystem health.

The importance of developing a remotely derived structural indicator of biodiversity and ecosystem health lies in the necessity of quickly assessing, monitoring, and adapting management strategies for sustainability. This is most critical in ecosystems that are highly dynamic and depend on frequent disturbance and thus require continual management. Often, these are systems that have the highest biodiversity and are at most risk from modifications of natural disturbance regimes [e.g., cerrado, longleaf pine

(*Pinus palustris*), ponderosa pine (*P. ponderosa*), tallgrass prairie]. We propose an approach that uses key structural measures and the structural diversity index, LiDAR-derived Height Diversity Index (LHDI), as a surrogate for ecosystem integrity and as a benchmark trigger for on-the-ground management. It is so designated for distinctiveness from compositional or landscape metrics. Once established, these ecosystem-specific triggers or targets may be universally applied and function as early detection indicators of deteriorating conditions and the need for rapid intervention. Furthermore, a structural diversity index can be a relevant input to enhance several ecosystems services models, especially those developed on a spatial platform, such as the INVEST (Tallis et al., 2011) biodiversity, carbon storage & sequestration, and managed timber production models.

This work validates the application of practical, repeatable, and objective structural metrics, including a LiDAR derived structural complexity index on a highly dynamic, disturbance driven landscape. The study site selected, Tall Timbers Research Station, is representative of the highly dynamic pine woodland and savanna ecosystems in the southeastern U.S., an open pine-dominated system with high understory biodiversity. The role of fire in shaping the composition and understory species richness of these communities is well established in the literature (Walker and Peet, 1983; Mehlman, 1992; Waldrop et al., 1992; Glitzenstein et al., 2003, 2008). Our study further benefits from a long-term study design (>50 yrs), consistent implementation, and detailed compositional studies of species richness as indicator of biodiversity (Hermann, 1995; Beckage and Stout, 2000; Glitzenstein et al., 2012). Because fire exclusion has clear consequences in ecosystem shifts – from open pine woodlands or savanna to dense hardwood dominated forests with reduced species richness (Masters et al., 1995; Glitzenstein et al., 2008) – the need to establish an early indicator of ecosystem health and biodiversity shifts is critical. We propose that remotely derived structural indices allow a universal method to be applied in developing ecosystem-specific targets for management or intervention.

The objective of this study was to evaluate the use of airborne LiDAR in the development of practical, repeatable, and objective structural metrics, as surrogates for structural complexity and biodiversity in a landscape with frequent disturbances. This study also proposes an ecosystem-specific structural diversity index as an early indicator of the need for intervention that is validated herein for pine-savannas. We hypothesize that LiDAR derived indices will provide an equivalent threshold for management intervention as more time consuming and thus costly traditional field measurements.

2. Materials and methods

2.1. Study area

This study took place at Tall Timbers Research Station (TTRS), located just north of Tallahassee, Florida, and covering 1600 hectares within the Red Hills region of north Florida (Fig. 1) (~long. 30°39' N, lat 84°13' W). The upland pine ecosystems at TTRS are old-field derived from a agriculture dominated landscape, and currently dominated by a mixed canopy of loblolly pine (*P. taeda*), shortleaf (*P. echinata*) and longleaf (Hermann, 1995; Masters et al., 2005). The groundcover at the study site is dominated by many legumes and sunflower family members and interspersed with grasses (broomsedge bluestem, *Andropogon virginianus*, primarily), but lacking the wiregrass (*Aristida beyrichiana*) typical of native longleaf pine savanna ecosystems (Hermann, 1995).

The TTRS actively manages its secondary upland pine forest using low intensity transition season (February–April) prescription

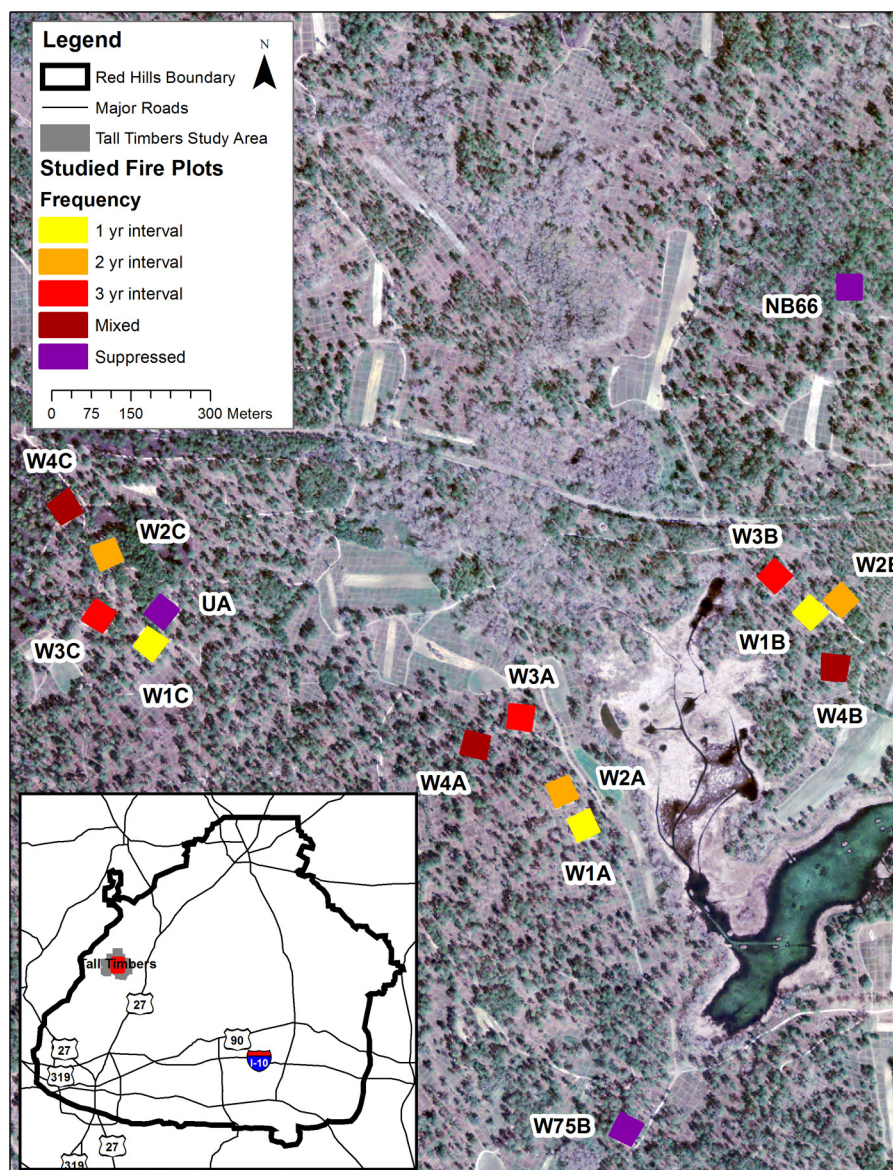


Fig. 1. Location map of the Stoddard Fire Plots within Tall Timbers Research Station (TTRS), a research plantation within the Red Hills Region.

fire with a return interval of ~ 2 years for ecosystem maintenance. Fire is applied in a small-scale heterogeneous pattern. This frequency approximates the natural fire regime for lower coastal plain ecosystems (Huffman, 2006).

2.2. Stoddard Fire Plot description

The Stoddard Fire Plot study began in 1960 and is one of the longest running fire frequency experiments in existence. Originally the study consisted of 84–45 by 45 m experimental units with replicated fire frequencies ranging from no burns and 1 to 75 year intervals and a series of summer burn treatments. Units were located throughout the central upland area of TTRS (Tall Timbers Research Station 1962) (Table 1). All plots were burned in 1959 and thereafter at the designated fire interval. The original study design was altered in 2000 dropping intervals longer than 3-years and retaining 2 unburned units. The original 4-year fire interval was reinstated in 2007 but had been burned 5 times between 2000 and 2007 with some hardwood removal (Glitzenstein et al., 2012). We include this treatment designated as the mixed fire return interval

in this study. Additionally an unburned control was incorporated to balance the experimental design from another long-term study on Tall Timbers – NB66. The NB66 unit has been excluded from fire since winter 1967. Thus the current experimental design is a randomized complete block design with five treatments on each of three blocks; A, B, and C. The designations W1, W2, W3, and W4 correspond to the 1-, 2-, 3-, and mixed fire return interval treatments respectively (Table 1). All the treated plots were burned using generally low intensity fire (<100 – 2200 kWm) during the transitional season (between dormant and growing season or February–April) at their dedicated fire rotation for over 50 consecutive years (Glitzenstein et al., 2012). Field measurements made on the Stoddard Fire Plots from 2004 onward were used as validation for LiDAR-derived metrics. Canopy cover and woody density data were collected for all Stoddard Fire Plots. Units were sampled for canopy cover in April, August, October, and December 2004, all months of 2005, January–March 2006, and April 2010. For the canopy cover assessment, 8 permanent plots within each fire plot were established. These permanent plots were located at 10 m intervals on two randomly located parallel lines

Table 1

Stoddard Fire Plots description: treatment type, dimensions, soil type, fire and land use history (extracted from 1930s Imagery). *Plots out of rotation from 1999 to 2007 at 2-year cycles (mixed management plots).

Plot Name	Fire Treatment	Acres	Soil Type	Burn Date (prior 2002 LiDAR)	Burn Date (prior 2008 LiDAR)	Out of Rotation	Forested Natural (%)	Forested Dense (%)	Total Forested (%)	Roads (%)	Cleared (%)
W1A	1 year	0.50	Faceville 8-12	22/03/2001	23/03/2008	No	43.75	0	43.75	0	56.25
W1B	1 year	0.51	Orangeburg 2-5	23/03/2001	23/03/2008	No	27.46	32.44	59.89	4.41	35.7
W1C	1 year	0.52	Faceville 5-8	22/03/2001	23/03/2008	No	0	51.98	51.98	0	48.02
W2A	2 year	0.50	Faceville 5-8	22/03/2001	05/04/2007	No	86.67	0	86.67	0	13.33
W2B	2 year	0.51	Orangeburg 2-5	23/03/2001	05/04/2007	No	0	46.52	46.52	41.52	11.96
W2C	2 year	0.52	Faceville 5-8	22/03/2001	05/04/2007	No	11.97	0	11.97	0	88.03
W3A	3 year	0.51	Fuquay 0-5	27/03/2001	29/03/2007	No	46.02	0	46.02	0	53.98
W3B	3 year	0.50	Orangeburg 8-12	23/03/2001	29/03/2007	No	63.05	0	63.05	11.47	25.48
W3C	3 year	0.51	Pelham 5-8	22/03/2001	05/04/2007	No	0	67.24	67.24	0	32.76
W4A	mixed ^a	0.51	Faceville 5-8	22/03/2000	29/03/2007	1999-2007	0	67.69	67.69	0	32.31
W4B	mixed ^a	0.54	Orangeburg 2-5	21/03/2000	05/04/2007	1999-2007	8.21	37.28	45.49	0	54.51
W4C	mixed ^a	0.56	Faceville 5-8	23/03/2000	05/04/2007	1999-2007	71.34	0	71.34	21.73	6.93
NB66	Unburned	0.51	Orangeburg 8-12	None	None	No	0	24.62	24.62	35.23	40.15
UA	Suppressed	0.52	Faceville 5-8	None	None	No	61.42	0	61.42	27.77	10.81
W75B	Suppressed	0.53	Faceville 2-5	None	None	No	77.8	0	77.8	22.2	0

perpendicular to the northernmost fire plot boundary. To avoid bias caused by influences from adjacent treatment units, no sampling took place within 10-m of any edge. Overstory canopy cover was determined using a 9-point grid in a sighting tube with vertical and horizontal levels (Johansson, 1985). Canopy cover was determined at each plot center and the four cardinal points at 2-m and 4-m from each permanent plot location.

2.3. LiDAR remote sensing

A small footprint multiple return LiDAR dataset flown in March 2008 was obtained from the Tallahassee-Leon County Geographic Information Systems Department. This mass point dataset was acquired by a LiDAR survey with a flying height of 1800 m, 15° field-of-view and a pulse rate of 40 kHz using a Leica ALS50 Geosystem for detailed floodplain mapping. This system allows up to four returns to be collected per pulse (1st, 2nd, 3rd, and last). The points corresponding to the ground surface were identified using a trend surface filtering algorithm. The mean and minimum point spacing of the LiDAR dataset are 1.55 and 1.19 m, respectively, the horizontal accuracy was 0.52 m root mean square error (RMSE), and vertical accuracy was 0.10 m RMSE.

Point cloud data were obtained in the LAS 2.0 format which included both the class (ground versus non-ground) and multiple return numbers. The point cloud data were converted to multipoint files (all, ground points only, and canopy points only), and subsequently all first return heights were interpolated in the ArcGIS 9.x 3D Analyst environment to a Digital Surface Model (DSM) (Zimble et al., 2003). After the construction of the Digital Elevation Model (DEM) using ground returns, the Digital Canopy Height Model (DCHM) model was extracted from the difference between the DSM and the DEM. All IDW interpolations performed were second power interpolations with a variable search of up to 12 neighbors and a 1 m grid output size (instead of a much smaller 0.2 m grid used by Zimble et al., 2003). Data was post processed using the ArcGIS Spatial Analyst Point to Raster tool to fill most, if not all, empty cells, with nearby interpolated values. The DEM heights were assigned to all point cloud data, allowing the computation of height above ground for every data point.

An ESRI ArcGIS geodatabase was created to manage and streamline all the spatial data layers relating to each individual unit. Field data for each unit was collected using a sub-meter GPS, and a 5 m buffer was applied to the collected plots' boundaries for extraction of the LiDAR point cloud data. This buffer provided greater certainty that none of the field data collection was outside of the analyzed LiDAR data and reduced measurement of any edge effect. The database included the high accuracy Stoddard Fire Plot locations, buffered plot locations, and the extracted LiDAR point cloud data.

2.4. Analyses

We extracted structural variables of interest for 2008 LiDAR data using database queries and histograms. The variables of interest included canopy cover, canopy height (maximum, minimum, mean, and standard deviation), height diversity and height evenness indices (LHDI and LHEI, respectively). We extracted canopy height and cover indices using methodology similar to that described by Lim et al. (2003) for discrete return LiDAR. For canopy heights each entire Stoddard Fire Plot was used to obtain the highest canopy point. Maximum mean height corresponded to the highest mean height value for all of the individual raster cells within the entire plot, and mean canopy height used an average of all canopy returns over 2 m, and is expected to underestimate average field tree heights (Lim et al., 2003). Canopy cover closure was measured by redefining canopy returns as only the ones over 2 m and dividing the total number of these returns in each plot by all

discrete returns in the same plot. The proportion of canopy returns is a standard canopy cover index (Lim et al., 2003), which, for this study, has been modified to exclude the herbaceous and lower shrub layers.

In order to examine the Stoddard plot three-dimensional structure, histograms of the proportion of LiDAR returns per 1 m height interval were constructed. Additionally, structural diversity indices, the LHDI and corresponding LHEI were calculated as structural complexity surrogates, using a finer scale interval of 0.5 m intervals. The LHDI was a modification of the Shannon–Weiner diversity index (H'), which is typically denoted by $H = -\sum[(p_i) * \ln(p_i)]$, where p_i is the proportion of total sample represented by species i . For the structural index LHDI, the species is replaced by the 0.5 m height interval, and p_i is the proportion of total LiDAR returns that fall within a specific height category. The LHEI is a modification of Pielou's evenness index, which expresses the Shannon–Weiner Diversity Index relative to the maximum value it could be. The LHEI was calculated by dividing the LHDI by the natural log of the maximum height classes represented in any of the plots (72).

Data from a LiDAR dataset collected in 2002 (similar specs and point spacing as the 2008 dataset) were also analyzed to produce the same diversity indices (LHDI and LHEI) and used as an independent dataset to test out consistency in the results.

The impact of the frequency of fire and location of the plots on the different LiDAR extracted structural variables of interest were examined by using several One-Way ANOVAS. The dependent variables examined were canopy cover, mean and maximum canopy heights, LHDI and LHEI. The independent variables were the fire return interval (1-, 2-, 3-year fire frequency and exclusion) and the location (i.e. block number, A, B, and C). The mixed fire return units were included in only selected statistical analyses, because these were out of rotation between 1999 and 2007. The dependent variables that were significant among treatment groups using ANOVAS, were further tested using the Fisher Least Significant Difference (LSD) test.

We evaluated historical land-use by photography from the 1930s to determine if prior land-use biased treatment results. The areas of open canopy, dense forest, cleared land, roads, and clearings were digitized for all units. The relationship between significant structural variables and the historical land use variable alteration ratio (a ratio of the total percentage of cleared land to total forested percentage) was explored by linear regression and analyses of variance. No significant linear correlations between past land use and structural metrics were encountered ($r^2 < 0.01$), (data not shown) eliminating this factor from further analyses. Additionally, soil type was also investigated as a potential predictor for structural metrics. Likewise it was not a significant factor in explaining differences in canopy cover and structural diversity among fire return treatments.

Principal Components Analysis (PCA) was used to display structural differences among the treatments (Ter Braak and Smilauer, 2002). The PCA analysis was performed in Statistica 10 using default options and selecting the most commonly used structural metrics and diversity indices (Canopy Cover, Mean and Max Heights, LHDI and LHEI) to ordinate all treatment plots (including the mixed fire return interval and excluded plots). Eigenvalues of the correlation matrix and ordination of the treatments across the first and second loading factors were plotted.

3. Results

3.1. Plot metrics: canopy cover and heights

LiDAR derived canopy cover percentages (CC_{Li}) were different according to fire treatments (Table 2). Canopy cover increases with

Table 2

Mean and SD of derived structural canopy information from the LiDAR dataset: canopy cover, mean and maximum canopy heights, Height Diversity Index (LHDI), Height Evenness Index (LHEI). Different letters mean significant differences between fire treatments for $N = 3$ and $P < 0.05$ using Fisher's LSD test.

Treatment type	Canopy cover (%)		Mean height (m)		Maximum height (m)		LHDI		LHEI	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1-Year	39.89a	4.54	16.98	5.07	32.09	2.91	2.21a	0.24	0.54a	0.04
2-Year	48.32a	5.63	15.16	4.75	29.43	1.56	2.48a	0.24	0.63b	0.05
3-Year	53.1b	8.07	16.97	1.74	29.86	2.17	2.97b	0.39	0.71c	0.07
Unburned	68.04c	4.74	18.32	0.86	32.75	2.47	3.35c	0.25	0.81d	0.05

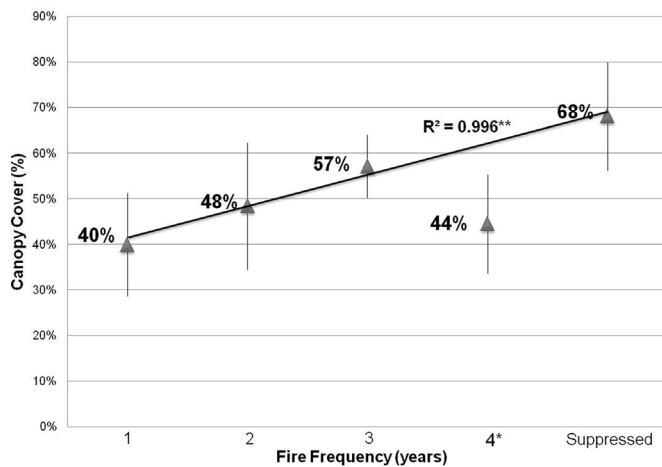


Fig. 2. Means and Confidence Intervals of LiDAR-derived Canopy Cover among Treatment and Control Units. * Plots have been out of rotation from 1999 to 2007 at 2-year cycles. **Trendline and corresponding R^2 ($R^2 = 0.996$) do not include mixed fire return units.

an extension in the fire return interval: LiDAR-derived cover had a mean of 40% for one year fire return interval, 48% for 2-year return plots, 57% for 3-year plots, and finally 68% for fire excluded units (Fig. 2). The only apparent exception to this pattern is the canopy cover of the mixed fire return units (see Section 2.2) with means of 44%, similar to the 2-year fire return canopy cover means.

Overall treatment induced canopy cover differences were consistent between field and LiDAR-derived canopy cover ($r^2 = 0.82$, Fig. 3).

Further analysis of the canopy cover variable determined that no significant differences were present between the 1- and 2-year fire return intervals (Table 2). Canopy cover means were significantly different between 1- or 2-year interval units and 3-year intervals or control units. The mixed interval units, had lower canopy cover than both 3-year fire interval and control treatments ($P = 0.040$ and $P < 0.001$, respectively), but no differences to either the 1-year or 2-year intervals. Additionally, we observed a difference between canopy cover of the control and 3-year fire interval treatments.

Mean canopy height values for all units ranged between 9.75 m and 22.12 m. We detected no differences among treatment groups: mean group heights varied only between 15.2 and 17 m for 1-, 2-, and 3-year fire interval treatments (Table 2). The only treatments with higher mean canopy heights were the unburned plots, with a mean height of 18 m.

Maximum canopy height values for all units ranged between 27.7 m and 35.58 m. Similar to the mean canopy heights, no significant difference in canopy maximum heights was found among treatment types: maximum heights were lowest in the 2- year fire interval treatment (29 m), similar for all other treatment and control units (31–33 m) (Table 2). The fire treatment did not seem to have an impact in the maximum canopy height of the Stoddard plots, with fire excluded control units having essentially identical average heights (32.75 m) to the 1-year fire interval treatment (32.09 m).

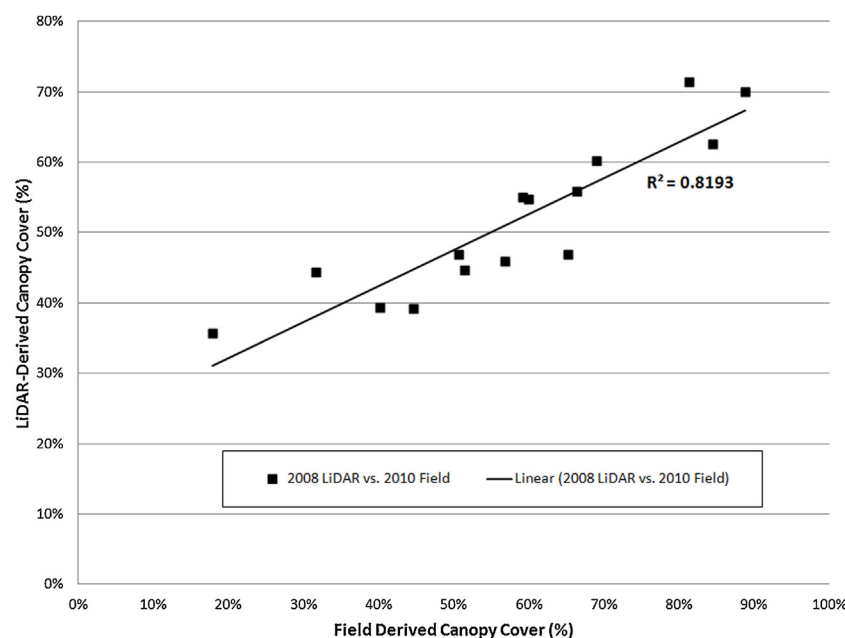


Fig. 3. Correlation Results between Field and LiDAR Canopy Cover Data (2008 LiDAR versus 2010 Field measurements). Trendline indicates a statistically significant correlation with an $R^2 = 0.819$.

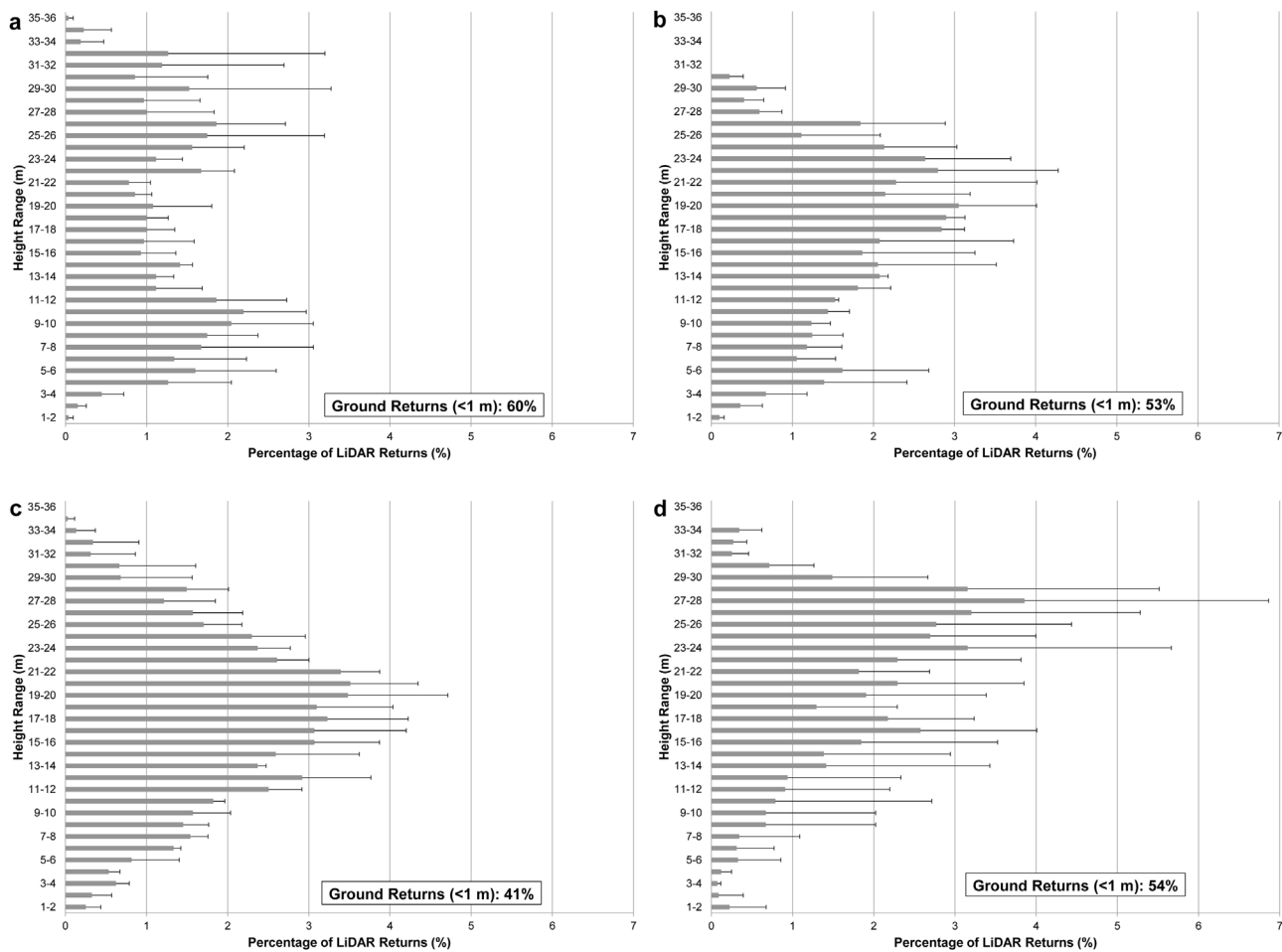


Fig. 4. Mean Height Distribution of LiDAR Returns for differently treated Fire Plots: (a) 1-year, (b) 2-year, (c) 3-year and (d) mixed fire return interval. Standard deviation across plot replicates of the same treatment (A, B, and C) represented as error bars. The 0–1 m height category (which includes ground returns) was removed from these height distribution plots to allow visualization of the remaining height categories. Mean ground return percentages are provided in text form in each of the plots.

3.2. Structural complexity and diversity measures

The percentage of LiDAR returns across heights was dramatically different among treatments (Figs. 4–6). The amount of ground

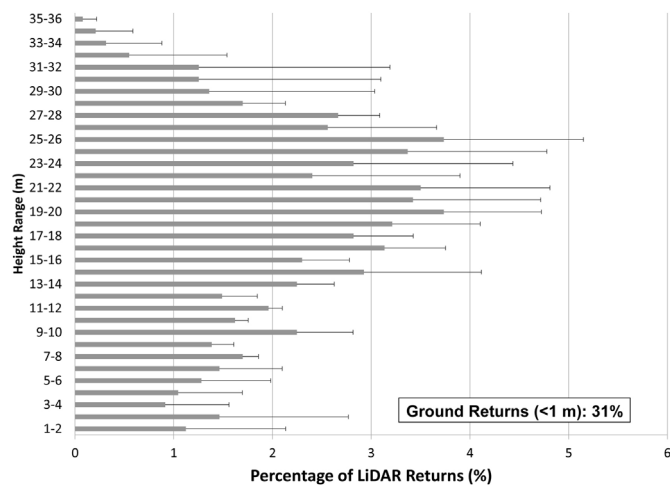


Fig. 5. Mean LiDAR-derived Height Distribution of Control (Fire excluded) Fire Plots. The 0–1 m height category (which includes ground returns) was removed from this height distribution plot to allow visualization of the remaining height categories. Mean ground return percentage is provided in text form within the plot.

returns (<1 m) was the most variable of all height categories, indicating the canopy cover differences among treatments (Fig. 6). Frequently burned units had over 50% of the returns categorized as ground returns (60% for 1-year interval units and 53% for 2-year interval units), while less frequently burned units (3-year fire interval) and control units had 41 and 31% of ground returns, respectively.

Overall, in more frequently burned plots, the proportion of LiDAR returns was reduced in lower height categories (<3 m), and this proportion increased with a decrease in fire frequency. In 1-year fire interval plots, shrub level vegetation was absent or strongly reduced (<0.2% of LiDAR returns), and the bulk of LiDAR returns concentrated at the midstory canopy level, between 5 and 12 m in height (Fig. 4a). In the 2-year fire interval units, the shrub layer was still reduced, but more visible than in the 1-year interval treatments, and vegetation was typically less clustered at one height interval, and occurred from mid to higher canopy heights, between 17 and 20 m in height (Fig. 4b). With a decrease in fire frequency, the 3-year interval units present a structural distribution resembling a normalized curve, with no visible gaps in either lower or higher height categories (Fig. 4c).

One exception to the previously described pattern of increasing numbers of shrub-level returns was found on the mixed fire interval treatment. These units present a structure heavily weighted toward higher canopy with most vegetation found between 22 and 28 m in height (Fig. 4d). The number of returns in the shrub layer (<5 m) was almost non-existent, and less than 5% of LiDAR returns were

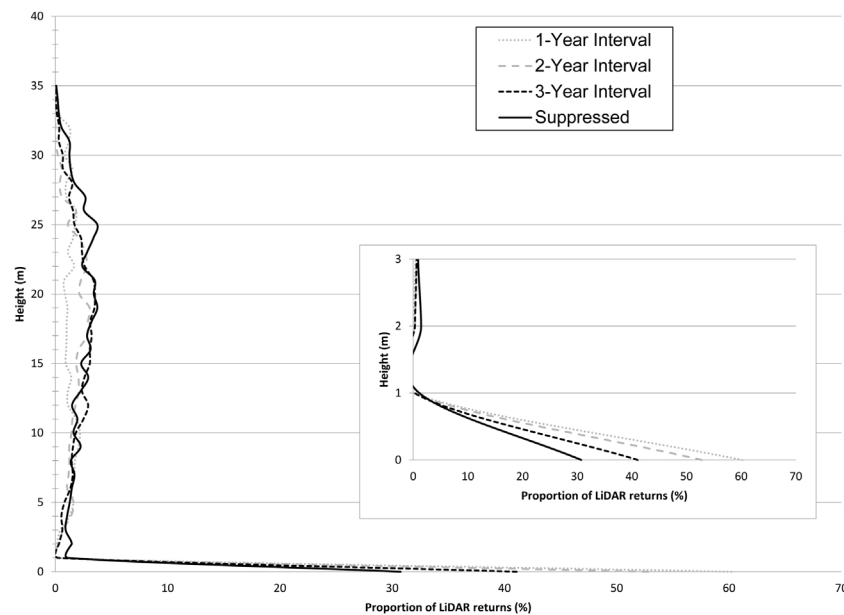


Fig. 6. Comparison of complete LiDAR-derived height profiles for 1-, 2-, 3-year fire return interval and fire suppressed plots. The mean proportion of LiDAR returns (x-axis) is provided across measured height (y-axis) for the three treatments. Inset provides a detailed comparison of ground return (0–1 m) distributions among treatments, one of the most significant differences in the overall height profiles.

present in height categories below 12 m. In the control units, the distribution of LiDAR returns was more even and with a higher percentage of returns across the entire height profile (Fig. 5), which indicates the presence of dense vegetation across all height categories. In these plots, the hardwood component dominates the canopy, illustrating a shift over time of canopy constituents from open pine woodlands to a mesic hardwood-pine forest with dense canopy cover.

Structural diversity, as indexed by LHDI and LHEI, was also highly variable across all treatments. As the LiDAR returns become more evenly distributed across all height categories both indices indicate higher values. An increase in both the LHDI and LHEI was visible with a decrease in fire frequency (Fig. 7) and corresponded to an increase in field collected woody biomass ($r^2 = 0.723$ for the available 8 Fire Plots). The Stoddard Fire Plots have LHDI means of 2.21, 2.48, and 2.97 for 1-, 2-, and 3-year fire intervals, respectively, while control plots had a LHDI mean of 3.35. A very similar pattern was visible for the Evenness measure, with LHEI means of 0.54, 0.63, 0.71, and 0.81 for 1-, 2-, 3-year interval treatments, and control treatments, respectively. The mixed fire interval treatment exhibited values for both indices similar to 1- and 2-year fire interval units: LHDI means of 2.30 and LHEI means of 0.57.

Statistical comparison of structural indices means (or medians, when the data did not meet parametric assumptions) across treatment and control units indicated that the visually apparent patterns (Fig. 7) were biologically significant. Both diversity indices, the LHDI and LHEI, were statistically higher in lower frequency than in control plots with P -values <0.001 and <0.0001 , respectively.

Further Post Hoc Analyses of the LHDI variable showed no differences between the 1- and 2-year fire interval treatments (Table 2). The LHDI means were different between the 1-year and 3-year interval treatments, and also between 1- or 2-year treatments and control units. We found LHEI was highly correlated with LHDI (0.94), and post hoc results very similar. In addition to differences in means among treatment and controls described for the LHDI, the 1- and 2-year interval treatments were also different.

Both indices (LHDI and LHEI) were also found to be highly correlated to the LiDAR-derived canopy cover (0.94 and 0.99,

Table 3

Factor coordinates and associated eigenvalues of the LiDAR-derived structural variables used in the Principal Components Analysis (PCA).

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Canopy cover	−0.9684	0.2182	0.0086	0.1084	0.0530
Man height	−0.4934	−0.6859	−0.5349	0.0004	0.0020
Maximum height	−0.5470	−0.5722	0.6111	−0.0001	−0.0039
LHDI	−0.9493	0.2229	−0.0248	−0.2203	0.0003
LHEI	−0.9623	0.2374	−0.0572	0.1081	−0.0525

respectively), and similar post hoc results were encountered for the canopy cover variable, as described in Section 3.1.

3.3. Early indicators of ecosystem changes

Using exclusively structural components (Table 3), the sampled units appear distributed across Factor 1 in a gradient representative of fire frequency (Fig. 8). Here a threshold of change is clearly visible. About 67% of the variance in all key structural variables was represented by Axis 1, which loaded on canopy cover, LHDI, and LHEI, while Axis 2 which loaded on height measures explained an additional 19% of the variance encountered among units. Control units were clearly grouped in the negative factor 1-axis values, with most of the annual plots located on the opposite side of the ordination graph. Three-year plots were clustered near the control plots, but closer to the central portion of the graph, while 2- and mixed fire interval treatment units appear interspersed near center.

Both the LHDI and LHEI of vegetation in forested units were strong loading components in the ordination of the sampled plots (Table 3). The LHDI follows the typical saturation curve, with a rapid increase in diversity from 1- (1.99–2.46) to 3-year (2.97–3.01) fire frequency treatments, but a much slower progression toward excluded plots (3.1–3.5) (Fig. 9a). The point of inflection is where the LHDI curve crosses the y-axis at 3. Using the 2002-derived LHDI values (all within 10% of the 2008 reported values), the same point of inflection would still be applicable. A similar saturation curve, albeit with a broader inflection point (50–60%) can be constructed

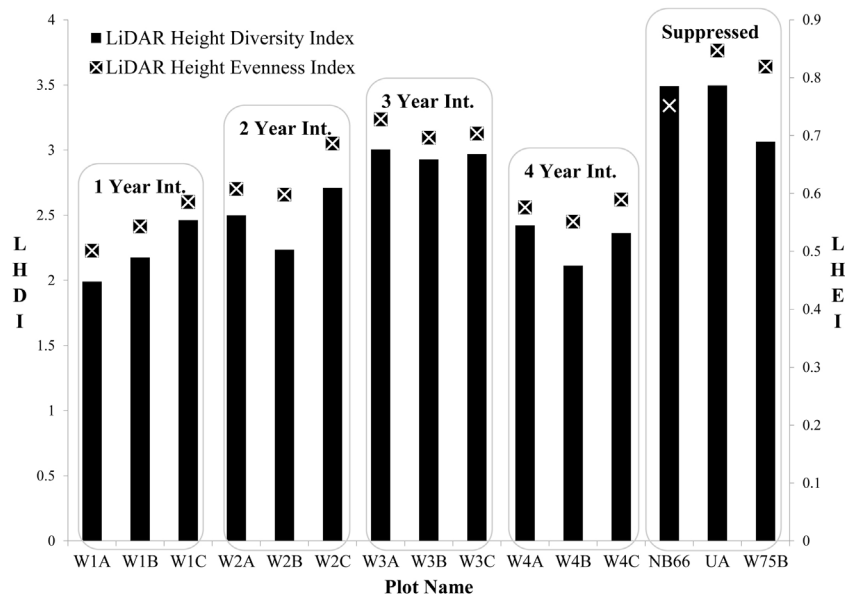


Fig. 7. LiDAR-derived Height Diversity Index (LHDI) (black bars) and Height Evenness Index (LHEI) (squares with white crosses) values among fire plots with multiple fire treatments and control plots. Individual fire plots are grouped by fire treatment.

with canopy cover, a variable found to be highly correlated with the diversity index in this particular study (Fig. 9b).

4. Discussion

The proposed structural indices, LHDI and LHEI, readily characterize the vegetation height profile of forested stands, providing land managers with consistent, quantifiable, and easy to implement tools they were lacking to meet ecosystem maintenance goals. Increases in the LHDI with disturbance interval follows a logarithmic relationship, similar to the saturation model proposed by Beckage and Stout (2000) and confirmed by Glitzenstein et al. (2012) using species richness datasets. Using this relationship, the height diversity index can be used as an ecological indicator of shifts in species richness, diversity and ecosystem function. In the case of highly dynamic disturbance driven ecosystems that require

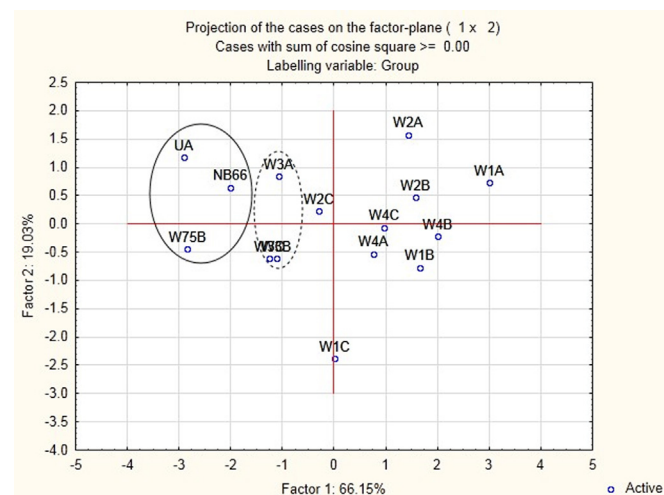
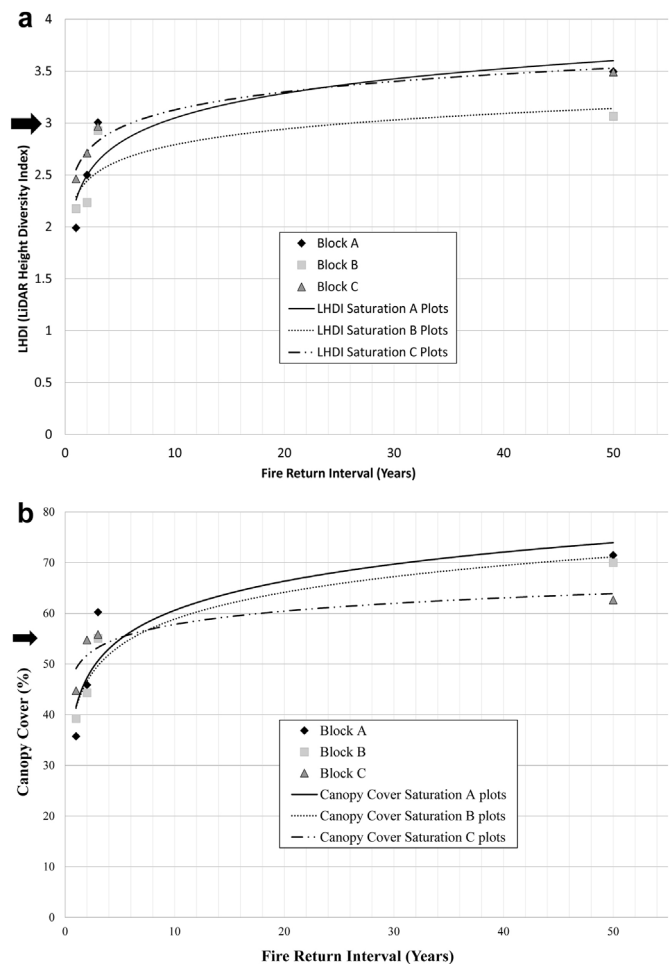


Fig. 8. PCA Results using LiDAR-derived structural information: Canopy Cover, Mean Height, Maximum Height, SHDI, and LHDI. Structural metrics allow grouping of fire suppressed plots and 3-year fire return interval plots. The more frequent interval treatments (1 and 2-year returns) are ordinated separately from the remainder of the fire plots.

Fig. 9. Saturation plots for both structural metrics found to be significantly different across treatments and can be used to provide management targets: (a) LiDAR Height Diversity Index (LHDI); (b) LiDAR-derived canopy cover. Arrows in either plot indicate suggested target for intervention.

active management, this same indicator can be used to establish intervention or management triggers or targets.

In this particular ecosystem, a similar saturation curve was also encountered using a simpler metric, canopy cover, due to its high correlation with the diversity index. Due to its simplicity in nature, particularly if extracted from LiDAR point cloud datasets, we propose that this metric could replace a more complex diversity index, as long as the strong correlation between both variables is confirmed. While canopy cover is easier to interpret for land managers, the variability associated with this variable was higher than the one associated with the structural LHDI index. The structural indices also include an important component of midstory variability which canopy cover does not, a critical component for ecosystem function in other ecosystems.

The methodology to develop both the simplified metrics and the structural diversity index can be adapted across spatial scales and to other ecosystems. This same measure could help fill-in some of the short-comings of forest management models, such as their inability to deal with heterogeneous stand structures (Mäkelä et al., 2012). Other models, such as ecosystem services models, could be refined with a measure of structural diversity, particularly for estimating biodiversity, carbon retention and timber harvesting at landscape scales. Even though other structural complexity indicators have been proposed (McElhinny et al., 2006), these require extensive labor-intensive field work, that would be cost and time-prohibitive, particularly for ecosystems that require frequent disturbance input. Even canopy cover field estimates are time-consuming, particularly if small changes in magnitude across stands are important to guide adaptive management. The use of fine-scale LiDAR has a clear advantage of allowing cost and time-effective detection of the often overlooked fine nuances of vegetation change at mid-structure levels of forests. Succession change at some level suggests tipping points or thresholds that need to be identified for land managers, because these imply marked functional and compositional changes in the ecosystem. The structural diversity indices developed in this study to capture these shifts in structural complexity can be used as early indicator of the need to intervene.

Beyond simple structural metrics, airborne LiDAR allows a better understanding of three-dimensional structural measurements (Lefsky et al., 2002a,b; Weishampel et al., 2007), such as height distribution and diversity among stands. An increase in shrub cover or dominance with a greater return interval in the fire regime is in agreement with other studies which measured a significant increase in number of hardwood stems with less frequent fire (Hermann, 1995). The distribution of LiDAR returns across height categories indicates an increase in structural complexity with lengthening of fire return intervals. The reduced number of saplings (which compose most of the woody encroachment on >1-year fire interval treatments) can be explained by a reduction in light availability after over 50 years of canopy closure in these now hardwood dominated environments and possibly increased root competition. This increase in structural complexity is an indicator of a functional system shift that dramatically reduces herbaceous richness and abundance and precipitates undue negative influence on other ecosystem components, such as the loss of pollinator resources and rare and endangered fauna (Glitzenstein et al., 2012).

The southeastern pine ecosystem used to test development of a structural diversity index and a management target, is one of the best studied. Pine woodlands are highly dynamic ecosystems, where structural characteristics are molded and shaped by fire requiring that managers use frequent prescribed fire for maintenance of ecosystem integrity (Glitzenstein et al., 2008).

Frequent fire return intervals are already being implemented for most of the managed upland pine forest. Why the need for a structural indicator of intervention? Using a simple and consistent fire regime, without understanding the ground conditions at

the time of intervention, might not yield the best results. Annual fires prevent shrub encroachment, both from hardwood and pine species in this secondary pine forest, and, consequently prevent pine recruitment that may eventually “degrade forest resources” (Hermann, 1995). Managing secondary old field upland pine forests with a combination of differential fire tolerant pine species is complex, and perhaps requires a variable fire frequency regime (Hermann, 1995). It is also possible to adapt fire regime to climate change or climate interannual variability. Knowing how and when to vary fire frequency requires use of a rapid, repeatable and consistent indicator. Obtaining adequate data in a field setting for canopy cover and height distribution is an extremely time consuming task, and often may be time and cost prohibitive, especially when trying to evaluate rapid changes through time. LiDAR derived data are objective, extremely fast, allowing appropriate feedback to be promptly incorporated in a responsive management strategy.

Structural metrics and indices allow a fire frequency gradient to be derived that mimics compositional biodiversity gradients for this same ecosystem (Glitzenstein et al., 2012). The most significant difference between compositional and structural ordination of variables was in the association of the mixed fire interval treatment with other treatments; using compositional data, the mixed interval treatments were similar to the 3-year fire interval treatments, but structural variables appear closer to the 2-year fire interval treatments. This could imply that the “memory effect” of shifting treatment type, even when briefly and temporarily, is stronger for compositional variables ones than for structural variables, a possible shortcoming of LiDAR. It also could simply be a result of the hardwood removal treatment that took place prior to shifting fire return intervals from 4 to 2-year fire returns.

Fire exclusion for a longer interval of time will dramatically alter the structure and composition of the upland pine forest (Vogl, 1973). Our findings of increased canopy cover with extension of fire return interval agrees with many previous studies that describe how repeated fires maintain an open overstory canopy in upland pine systems (Vogl, 1973; Masters et al., 2005; Listopad et al., 2011). In particular, moving from a 2-year fire interval to a 3-year or greater interval caused significant changes in canopy cover and diversity structural metrics. Masters et al. (2005) observed that recruitment of loblolly pine will not take place with a fire rotation of ≤ 3 years, while shortleaf pine will be able to survive and recruit with shorter interval burns. The three-year interval is apparently an “ecological threshold” for these upland pine systems (Masters et al., 2005; Masters and Robertson, 2007), with stands under 3-year fire frequencies being dominated by herbaceous understory, and stands at and over 3-year intervals dominated by woody vegetation, indicative of a clear shift in structural complexity, and, thus, changes in ecosystem function and diversity. This is further supported in these systems by increased songbird abundance with increased fire frequency. This is true particularly for pine-grassland obligate species that are strongly associated with changes in understory vegetation composition and structure (Cox and Widener, 2008). A land manager would have as objective goal in maintaining the LHDI under 3 (but greater than 2.5), in order to maintain a functional ecosystem with high biodiversity. The goal, using a simpler metric, canopy cover, would be to maintain canopy cover under 60%, but preferably above 45%.

Furthermore, on-site research of the application of the saturation model using species composition shifts across treatments (Glitzenstein et al., 2012), independently concluded the need for shorter fire return intervals (with highest diversity associated with 1- and 2-year treatments). This implies fire management at a 3-year interval – commonly thought as being within the “natural” fire regime for upland pine woodlands in the Southeast – will allow a progressive loss of compositional biodiversity with an increase

in hardwood presence at least on old-field derived lands. The rate at which this shift from an open pine-grassland to a more mesic hardwood-pine type forest would occur is probably linked to soil and fuel moisture (Masters and Robertson, 2007) and potentially other environmental variables.

The different fire treatments did not seem to influence the canopy height directly. Indirectly, the plots with much higher amount of shrub and canopy vegetation, such as the fire excluded plots, had slightly higher mean heights, as a result of more tree cover. The mean canopy height is not equivalent to the average tree field height. LiDAR-derived data includes some midstory canopy and shrub returns into account, and would, therefore, be more easily biased than field heights of the dominant and co-dominant tree matrix.

The modified Shannon Diversity Index, LHDI, has not been tested for consistency in other locations and across ecosystems. However, we did test the performance of the method of calculating the structural diversity index in the same Stoddard Plots using an independent LiDAR dataset, flown in February 2002 (with similar specs and point spacing, see Section 2.3). Even though the rainfall had been dramatically higher prior to the 2002 data collection, the diversity indices were mostly within 10% of the 2008 values, and the critical threshold of LHDI = 3 would still be applicable. Most three-year treatments would be prompted for intervention.

It is unfortunate that the longer fire frequency Stoddard plots were discontinued prior to the availability of LiDAR data. To better represent the saturation model using structural diversity data, it would have been important to have a variety of treatment types between 3-year and 50-year fire return interval, so the curve could be better defined. Perhaps additional datasets from similar upland pine forests can be added, even from other locations to enhance this model. Validation of the specific threshold established here for LHDI (<3) and canopy cover (~55%) should follow this study, and additional application of the structural index in another highly dynamic ecosystem would support a more universal application. Future testing should also focus on the correlation between structural indices and simpler metrics, such as canopy cover, and provide guidelines for selection of the most appropriate variable for land ecosystem-specific management.

The application of airborne LiDAR to develop a repeatable and objective metric such as canopy cover or a structural diversity index as an early indicator of management need and a surrogate for biodiversity assessments would help fill an important gap in biodiversity conservation. Even though these metrics can be produced for any forested ecosystem, it is perhaps most urgently needed for those with frequent disturbance regimes thus requiring intensive management. Guiding management decisions with a practical tool based on key scientific principles might allow LiDAR to bring land managers and scientists together and enhance their understanding of forest structure over large landscapes (Kao et al., 2005), becoming a key building block for ecosystem services modeling efforts.

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