Forest structural complexity of the Southern Appalachians revealed by above ground LiDAR classification

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(1) **The applied research need:** To better characterize patterns and processes of vegetation structure

(2) **The opportunistic dataset:** mid-2000s North Carolina LiDAR (13 counties of Western NC; roughly 14.5 Million 60 foot grid cells (~1,800 mi²)

(3) **Products considered:**
   - Maximum vegetation height
   - A full above-ground structural typology or classification

(4) **Some thoughts on application**
The applied research need

- Existing approaches to mapping vegetation across large regions are largely based on dominant, commercial or charismatic species (composition) and coarse seral status (height/age).

- Complex vertical and spatial structure has long eluded us, despite its importance for understanding successional dynamics, hazards and habitat diversity.

- Quantitative raster-based mapping (with plot-based sampling networks) hold the most promise for monitoring the behavior of dynamic systems consistently.

- Our collaborative project strives to make data-intensive LiDAR more accessible for forest and habitat managers.
NC Airborne LiDAR dataset and processing

Phase III data collected for flood hazard mapping (Feb-Apr, Dec 2003)
Use of above ground aspects (veg.), an after thought

**Max canopy height** at 60’ grid resolution was calculated from a LiDAR-based DEM from same effort

**Typology of vertical structures:**

1. Point height calculated from high res DEM
2. Extreme values removed
3. Density calculated across 5 ft. height bands
4. Density recalculated as % of above ground points in each band
5. Non-hierarchical K-means clustering used to reiteratively identify 10, 20, 40, 75 and 200 unique structural types

The processing was conducted using a supercomputer at Oak Ridge NL

Subsequent landscape analysis was conducted using a 250,000 random point sample of various rasters for jurisdictional, land use history, vegetation compositional and topographic gradient analysis.
Maximum vegetation height from LiDAR
Across a 13-county area of western NC
Maximum vegetation height from LiDAR
For Shining Rock Wilderness and Pink Beds Area
Maximum vegetation height from LiDAR
For Bradley Fork (upstream of Smokemont) GSMNP
Compositional Vegetation types
Bradley Fork (upstream of Smokemont) GSMNP
Disturbance history
Bradley Fork (upstream of Smokemont) GSMNP
Distributions of maximum height by jurisdiction
Using a NLCD filter for natural types

- Blue Ridge Parkway
- Great Smoky Mtns. NP
- Non-Protected/Non-Public
- Pisgah Natl. Forest

N= BRP: 802; GSMNP: 19,839; Non: 120,514; Pisgah NF: 21,991 (Sum: 163,146)
Distributions of max. height by elevation
For all Western NC lands using a NLCD filter for natural types

N=210,248 randomly sampled 20x20m LiDAR grid cells
Distributions of max. height by moisture index
For all Western NC lands using a NLCD filter for natural types

N=210,248 randomly sampled 20x20m LiDAR grid cells
Distributions of maximum height for selected xeric Landfire existing vegetation types

Minimum of 5-foot height class

Relative frequency (percent of veg type)

N = Serpentine woodland: 1,558; Pine forest-woodland: 4,945; Oak forest: 81,786
Distributions of maximum height
For selected mesic Landfire existing vegetation types

Relative frequency (percent of veg type)

Minimum of 5-foot height class

N= Spruce-fir forests: 2,904; Cove forests: 77,956; Northern Hardwood: 11,802
Mean height of stands of different origin years

Pisgah and Nantahala NFs, NC

- Moist: 12,182 ft
- Dry: 44,324 ft

Total = 56,506 ft

Graph showing height (ft) over origin years.

- Moist: $y = -0.335x^2 + 3.3907x + 81.353$, $R^2 = 0.9087$
- Dry: $y = -0.337x^2 + 3.3523x + 91.658$, $R^2 = 0.884$
The Structural Typology
LiDAR relative density profiles for clusters

Enlargement

200 Clusters

5-foot height band’s percent of profile
The Structural Typology

Relative proportion of LiDAR returns in Upper (bands 11-33), mid (6-10) and lower (1-5) fixed height bands for the Greater Shining Rock Wilderness Area, Pisgah NF and Blue Ridge Parkway
The Structural Typology
Tri-polar (R-G-B) colors on three height zones
The Structural Typology
Shannon’s Diversity of 33 relative height densities of 200 LiDAR cluster groups for the Greater Shining Rock - Pink Beds Area
The Structural Typology
Shining Rock Wilderness-Pink Beds, Pisgah
The Structural Typology
Detectability of key understory attributes Pink Beds, Pisgah NF
Maximum canopy height
Mount Mitchell and Pisgah NF
The Structural Typology
Mount Mitchell and Pisgah NF
Concluding thoughts on applied use
Type-averaging reduces the precision of key measures, like height, while conveying more information in a comprehensible package.
Concluding thoughts on applied use
Raster v. polygon approaches to veg mapping—complementality

- Compositional Typology
- Structural Typology
Concluding thoughts on applied use

Clustering (and field observations) suggests that there are limited basic structural types.
Concluding thoughts on applied use

Clustering (and field observations) suggests that there are limited basic structural types.

While clustering generates this whole matrix of possibilities, local canopy ht. is most precise, suggesting a complementary use of both datasets may be most useful.
Conclusions

(1) LiDAR based canopy height and full-profile cluster-based maps provide different, but complimentary forest structure information.

(2) Elevation and moisture are dominate controls on natural vegetation structure across the Southern Appalachians.

(3) Beyond topographic controls, structure varies with disturbance history, often showing legacies of many decades.

(4) Species composition may affect maximum height (apart from topography), but composition clearly affects understory density (e.g., Rhododendron). Structure can thus inform composition and vice versa.