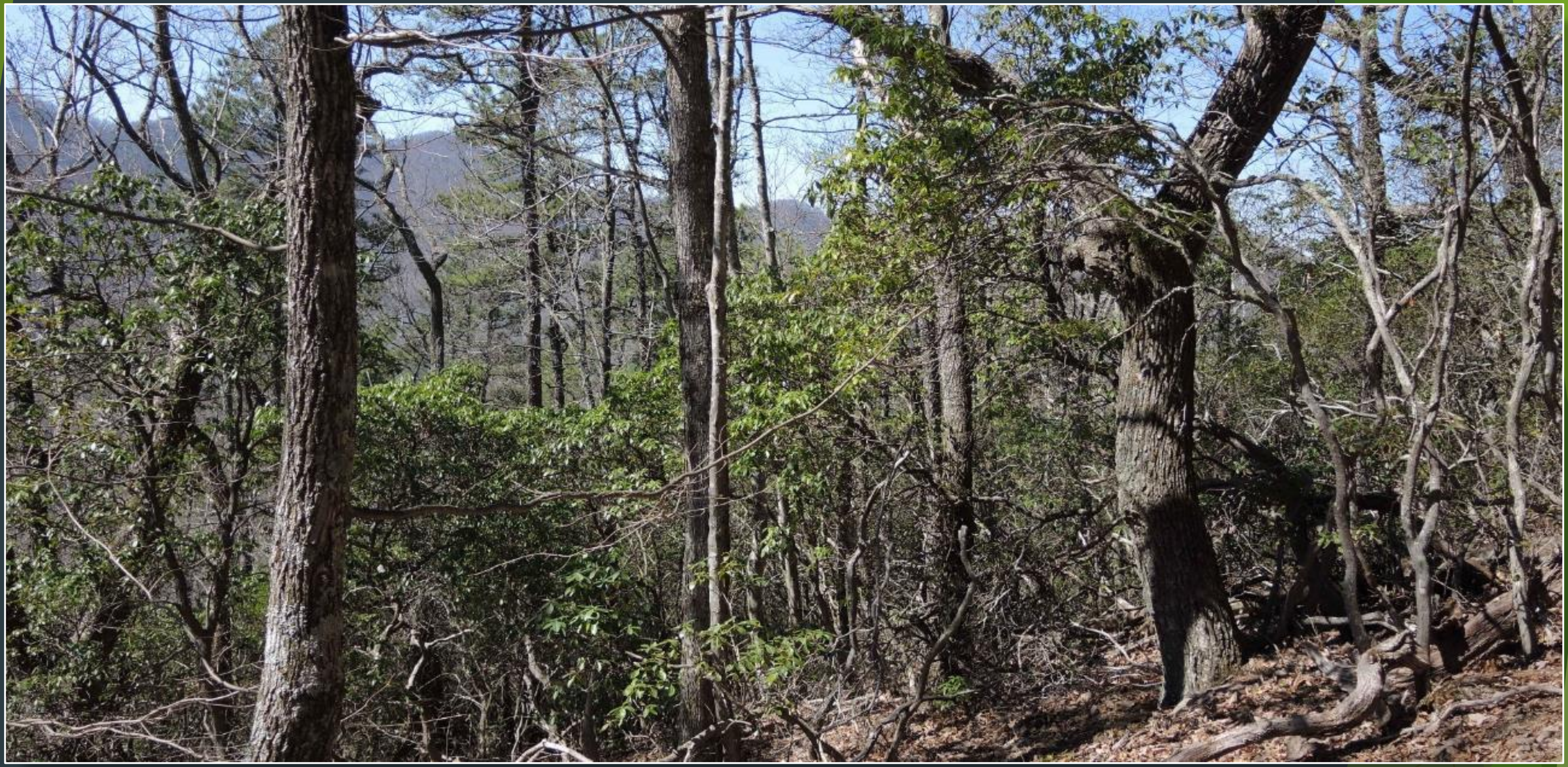
Forest structural complexity of the Southern Appalachians revealed by above ground LiDAR classification



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US-IALE Annual Meeting
Asheville, NC April 3-7, 2016

Outline

(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 mi^2)

(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 <u>species</u> (composition) and coarse seral status (height/age).

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

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

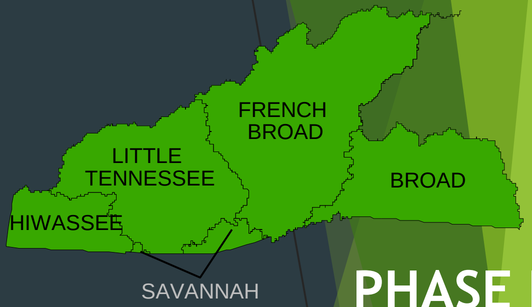
- Our collaborative project strives to make data-intensive LiDAR more <u>accessible</u> for forest and habitat managers.

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:



PHASE III

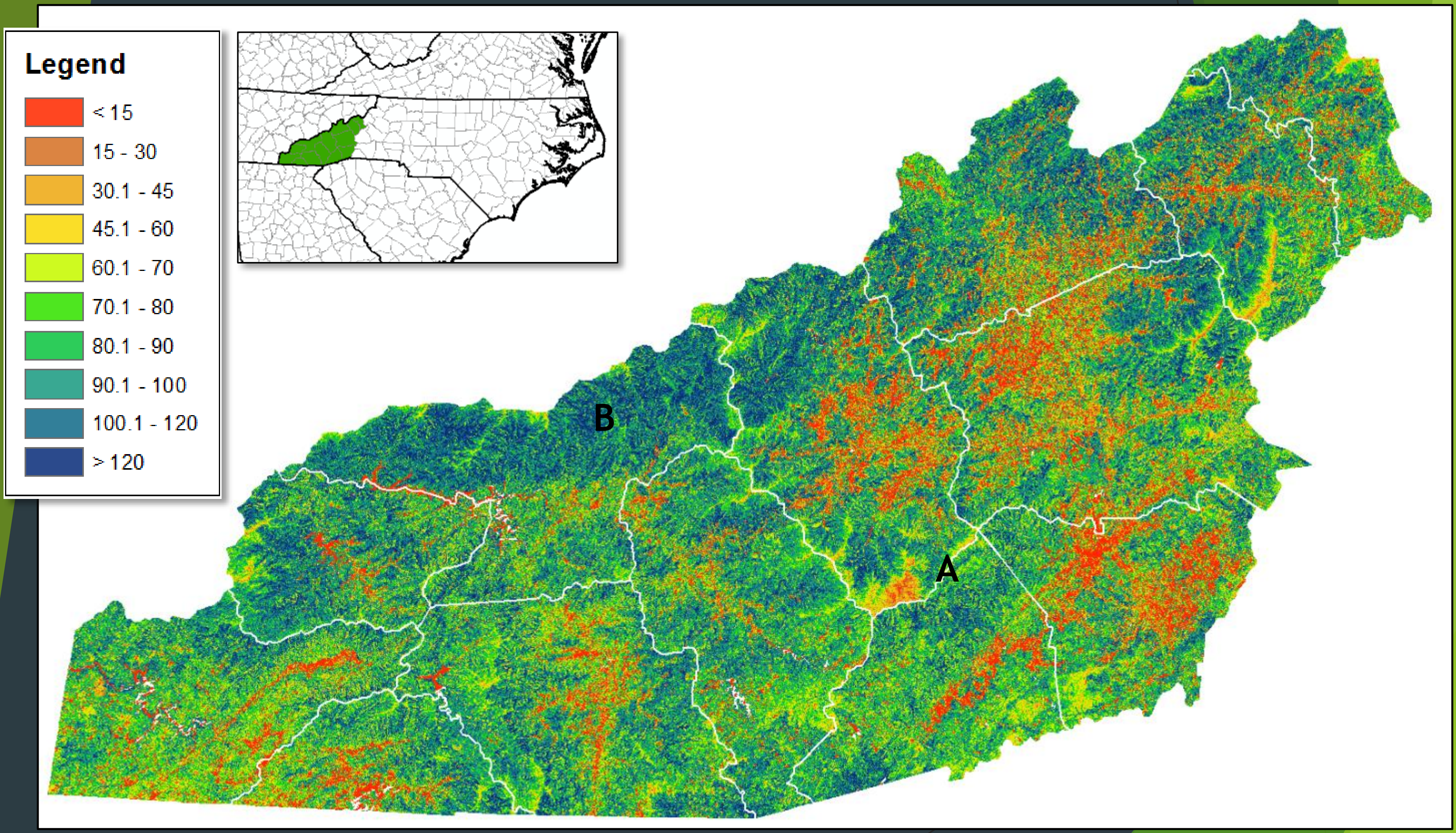
(1) Point height calculated from high res DEM
(2) Extreme values removed
(3) Density calculated across 5 ft. height bands
(4) Density recalculated as % of above ground points in each band
(5) Non-hierarchical K-means clustering used to reiteratively identify 10, 20, 40, 75 and 200 unique structural types

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.

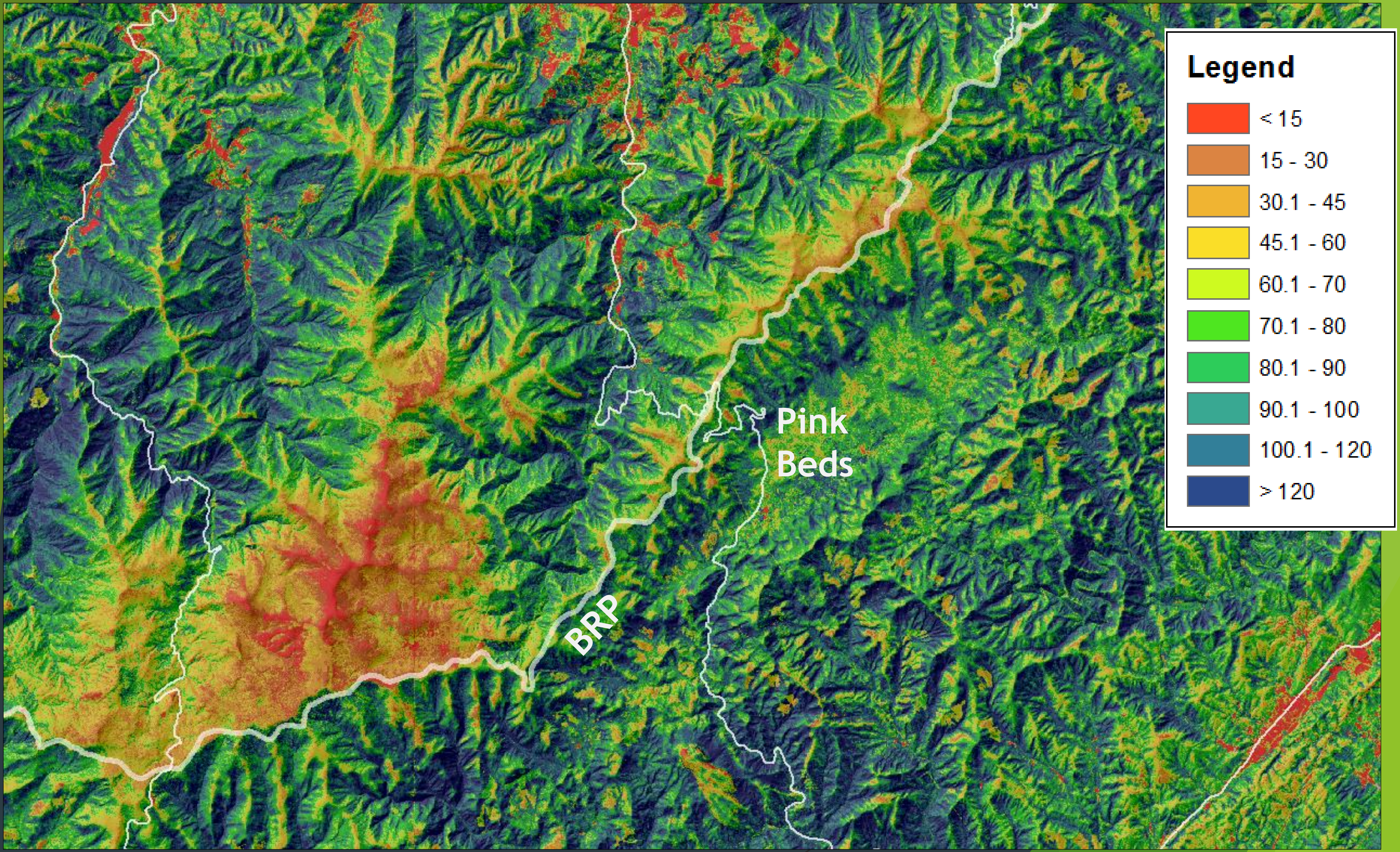
Maximum vegetation height from LiDAR

Across a 13-county area of western NC



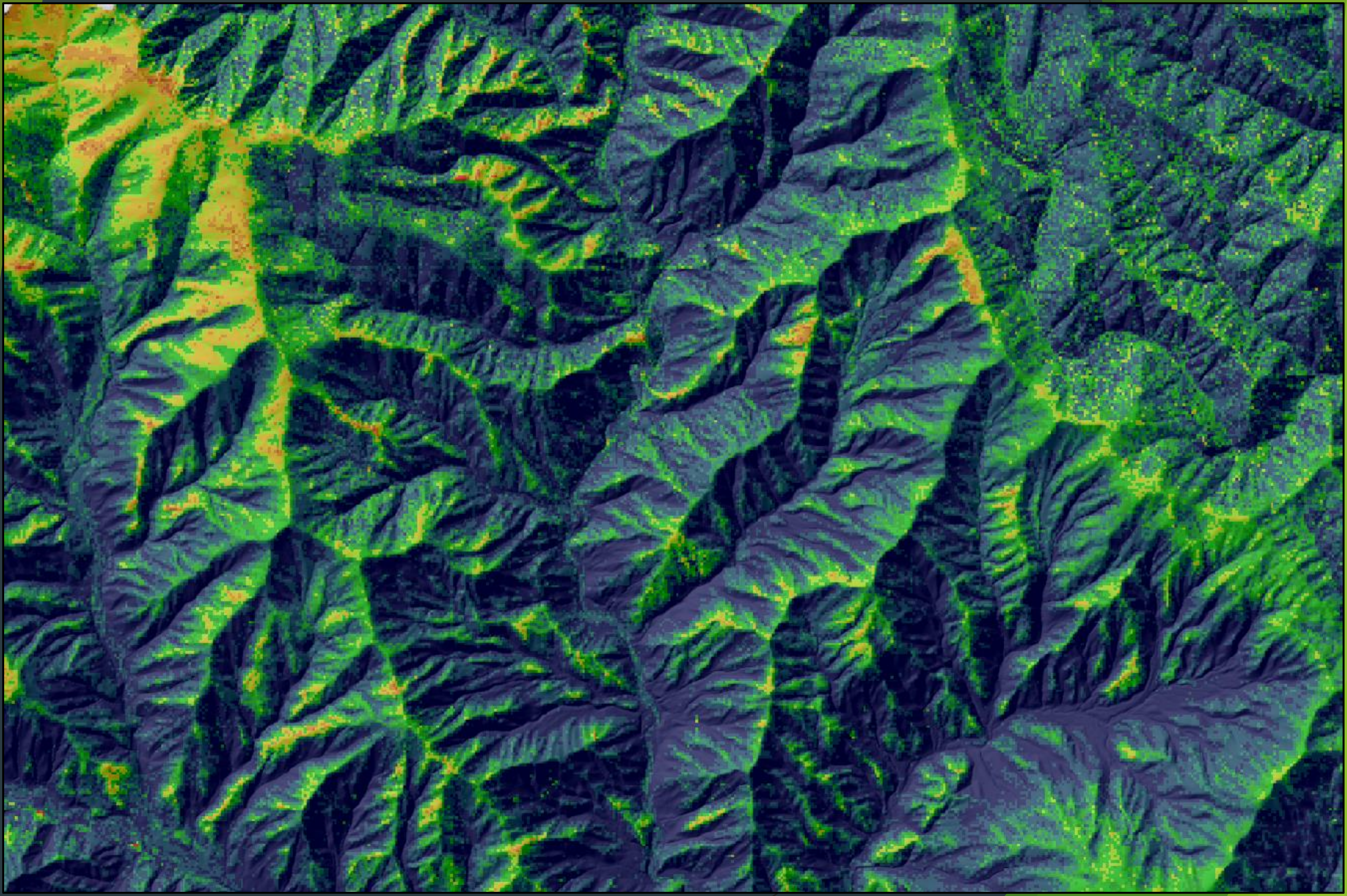
Maximum vegetation height from LiDAR

For Shining Rock Wilderness and Pink Beds Area



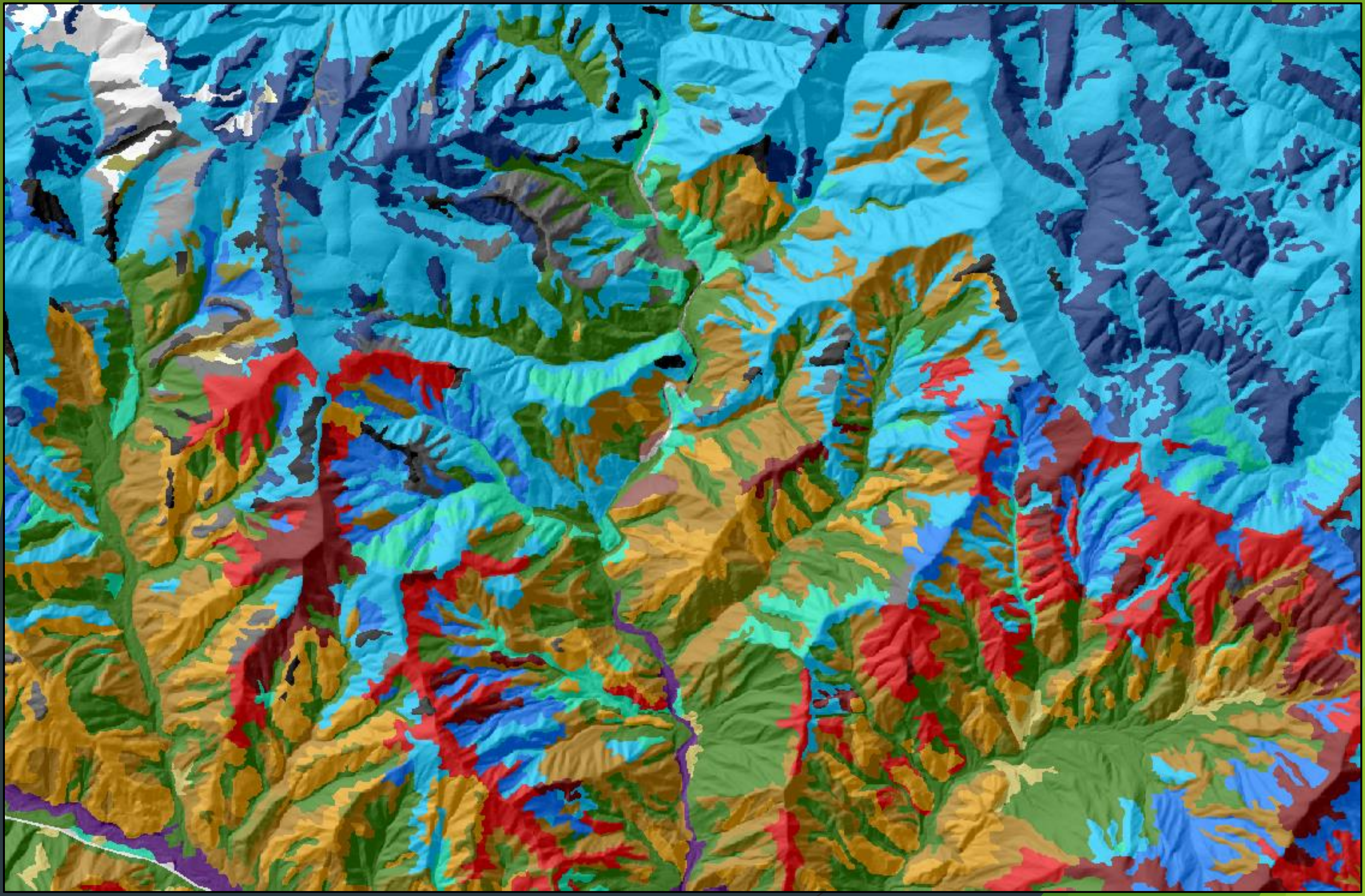
Maximum vegetation height from LiDAR

For Bradley Fork (upstream of Smokemont) GSMNP

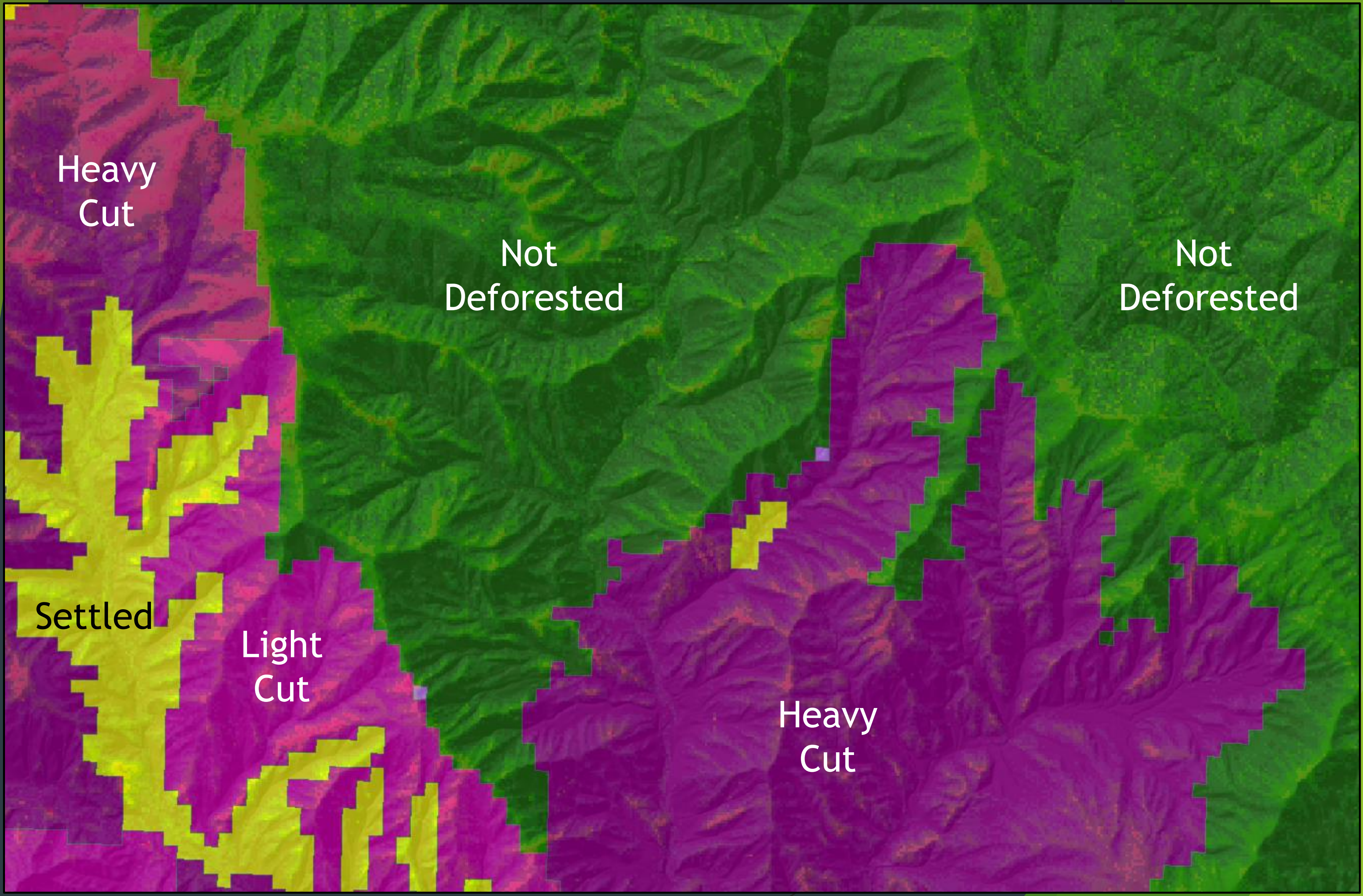


Compositional Vegetation types

Bradley Fork (upstream of Smokemont) GSMNP

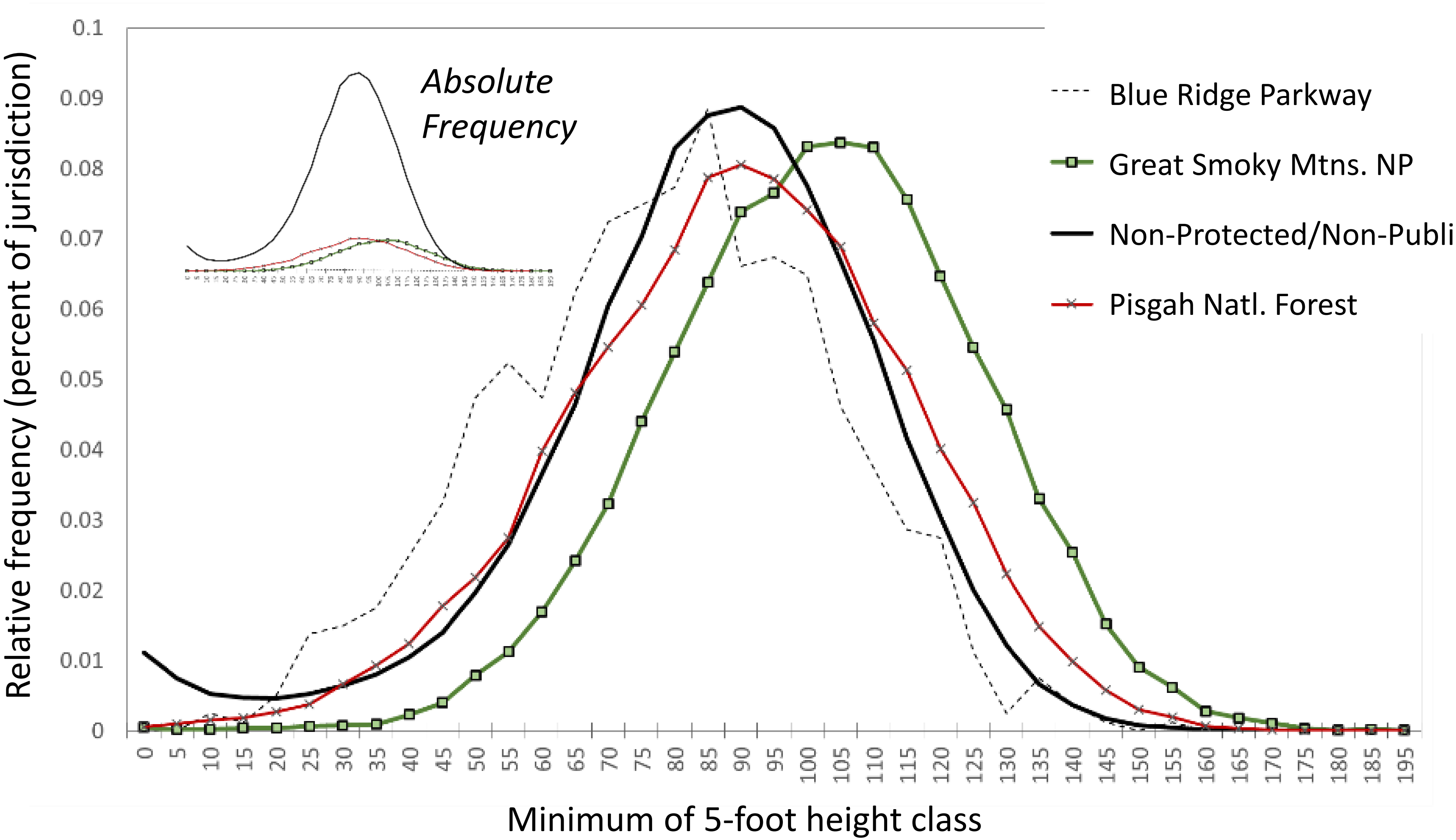


Disturbance history
Bradley Fork (upstream of Smokemont) GSMNP



Distributions of maximum height by jurisdiction

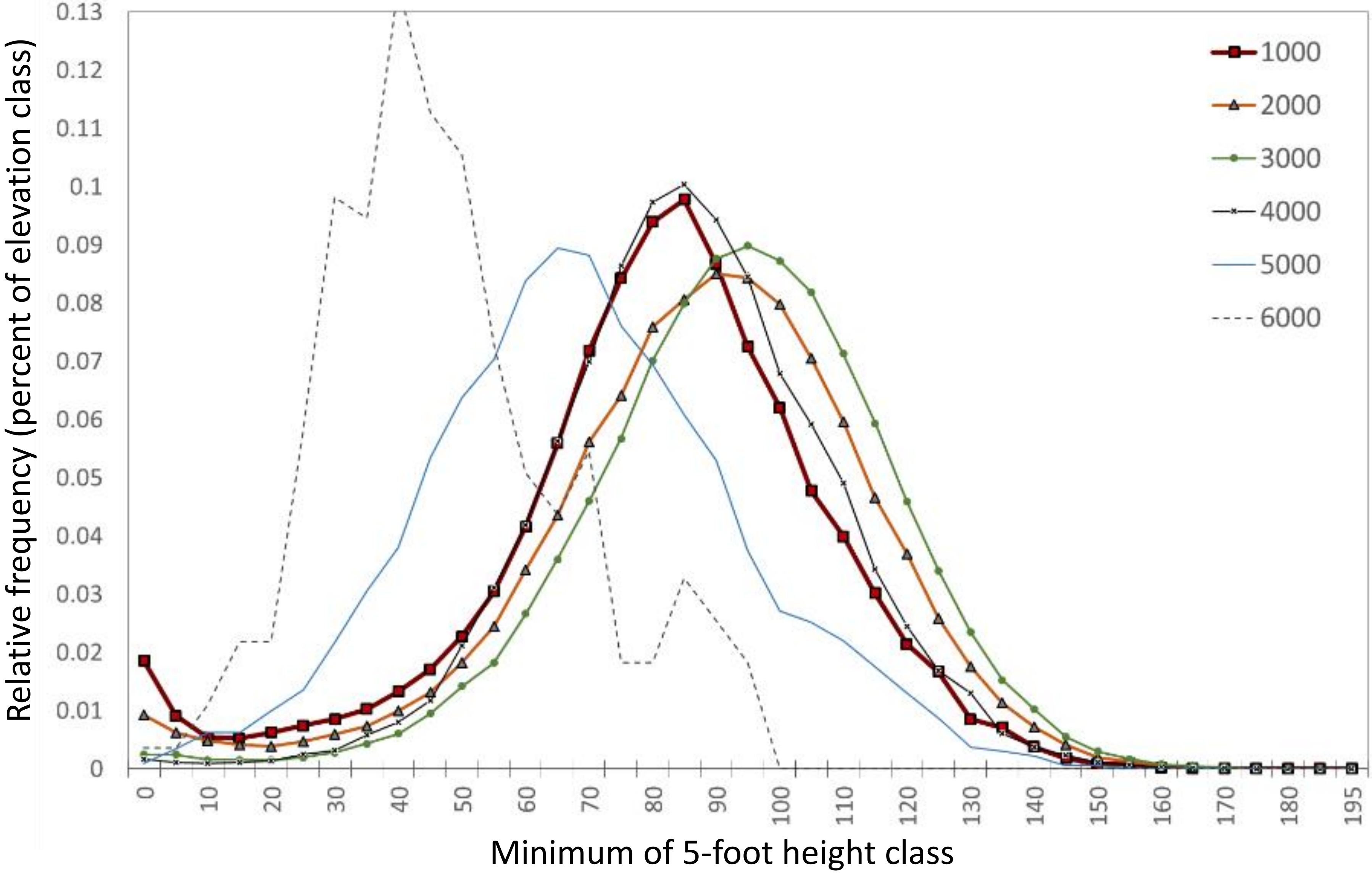
Using a NLCD filter for natural types



N= BRP: 802; GSMNP: 19,839; Non: 120,514; Pisgah NF: 21,991 (Sum: 163,146)

Distributions of max. height by elevation

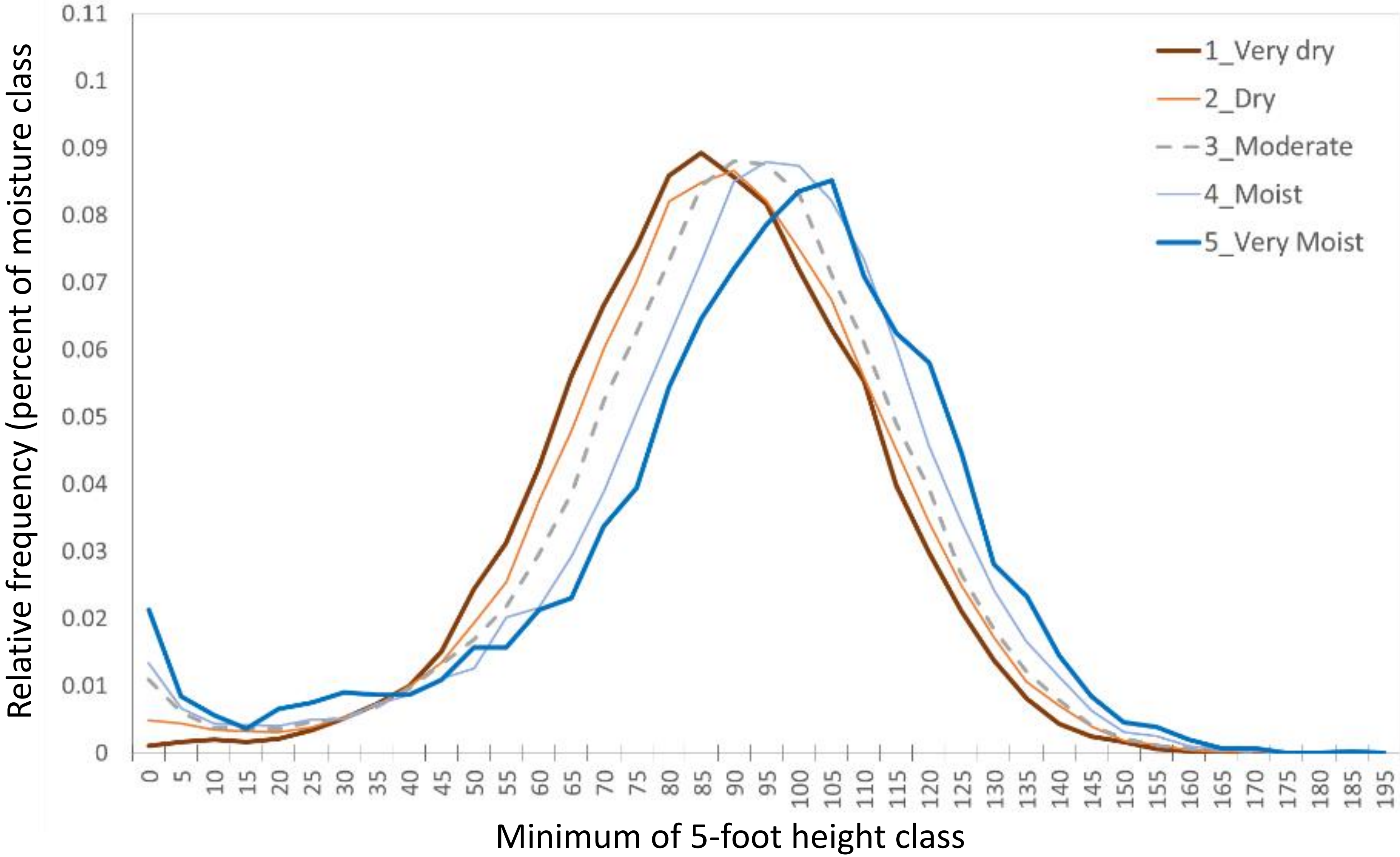
For all Western NC lands using a NLCD filter for natural types



N=210,248 randomly sampled 20x20m LiDAR grid cells

Distributions of max. height by moisture index

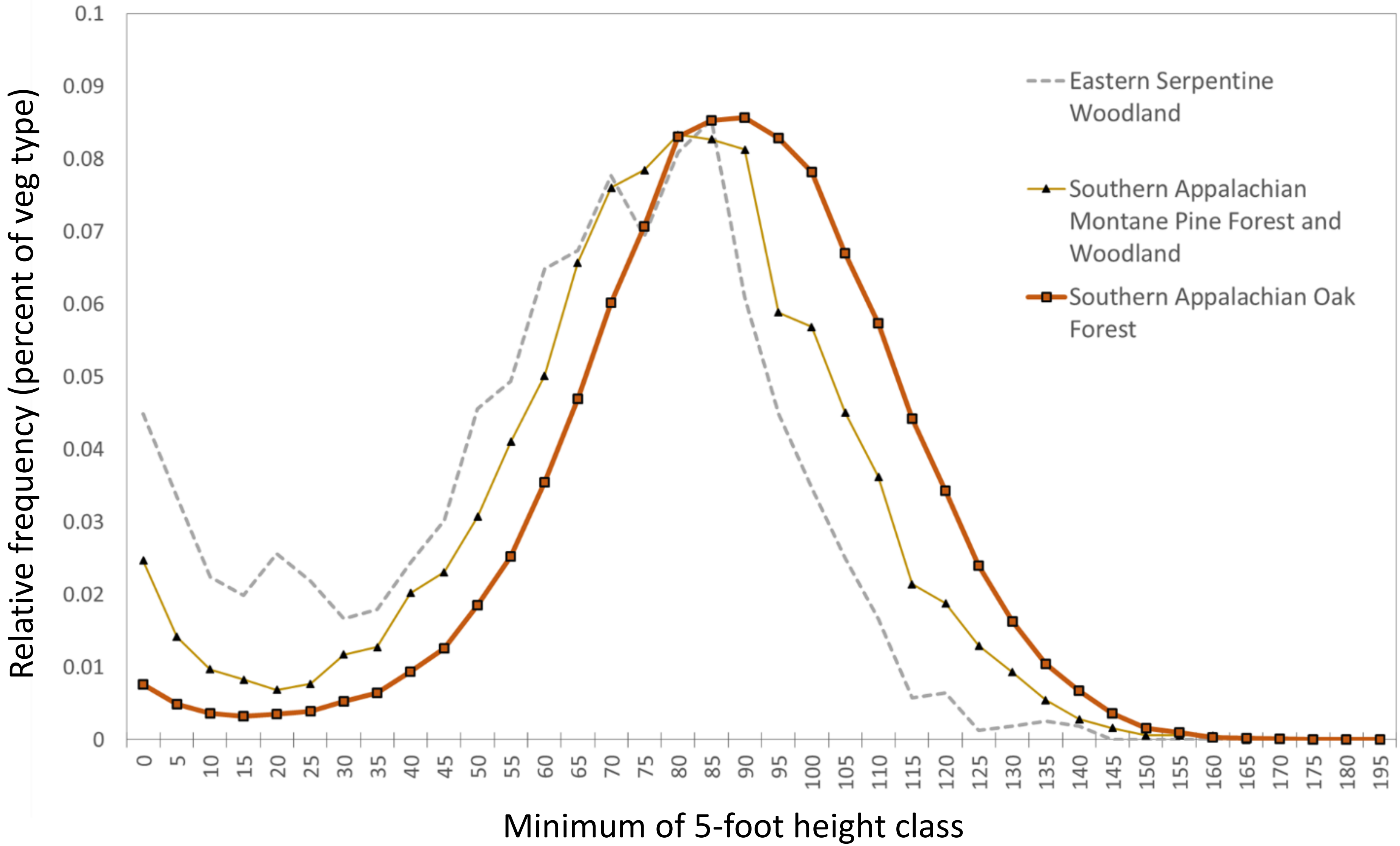
For all Western NC lands using a NLCD filter for natural types



N=210,248 randomly sampled 20x20m LiDAR grid cells

Distributions of maximum height

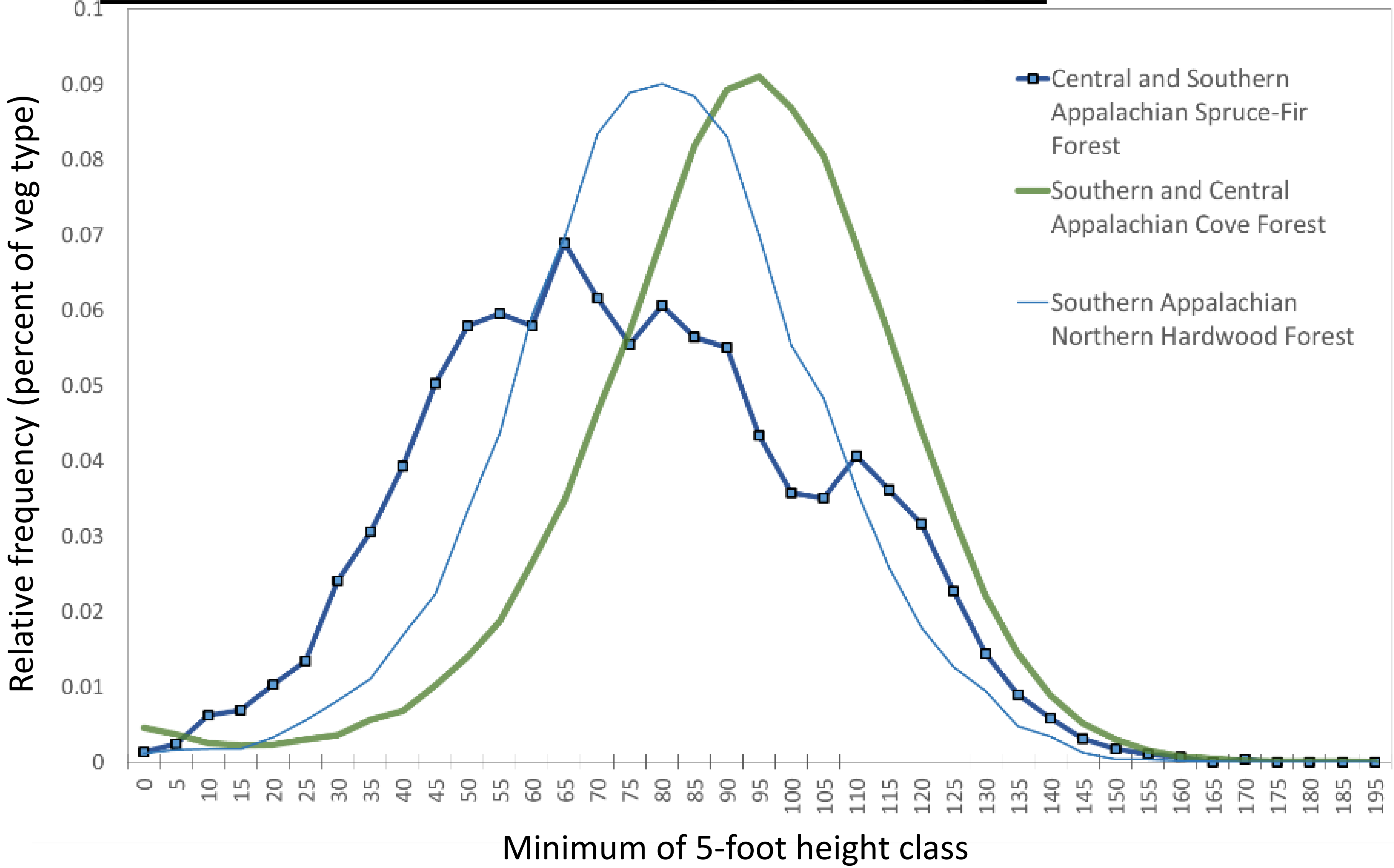
for selected xeric Landfire existing vegetation types



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



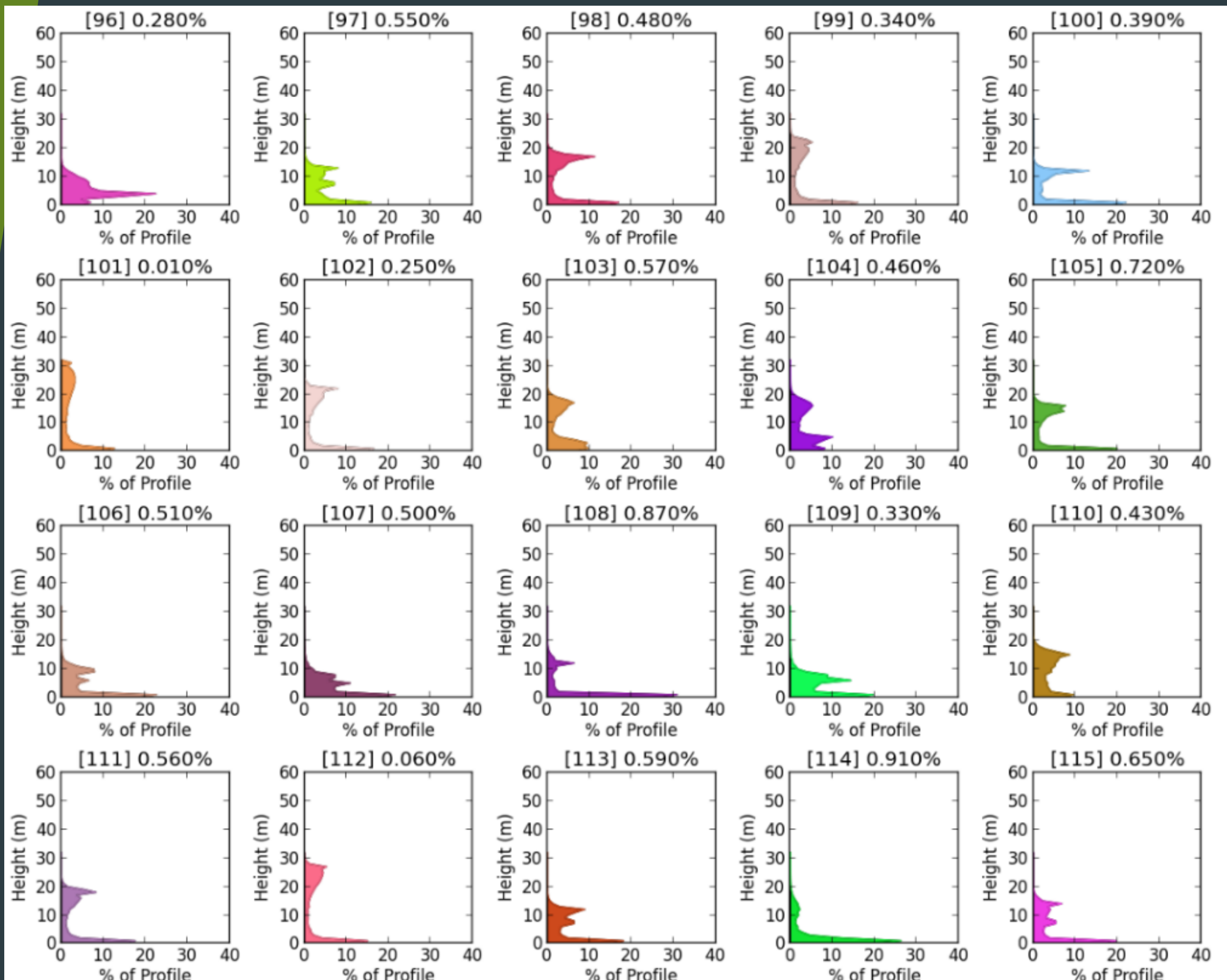
N= Spruce-fir forests: 2,904; Cove forests: 77,956; Northern Hardwood: 11,802

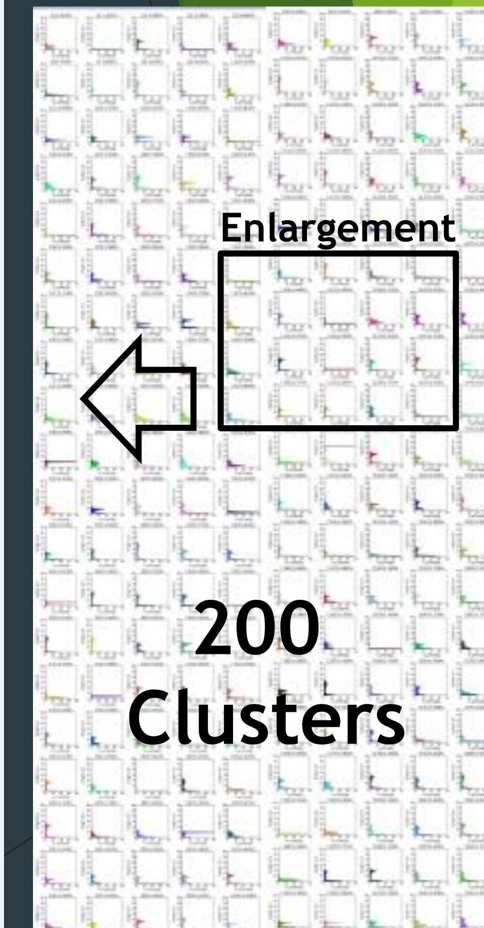
Mean height of stands of different origin years

Pisgah and Nantahala NFs, NC

The Structural Typology
LiDAR relative density profiles for clusters

Height

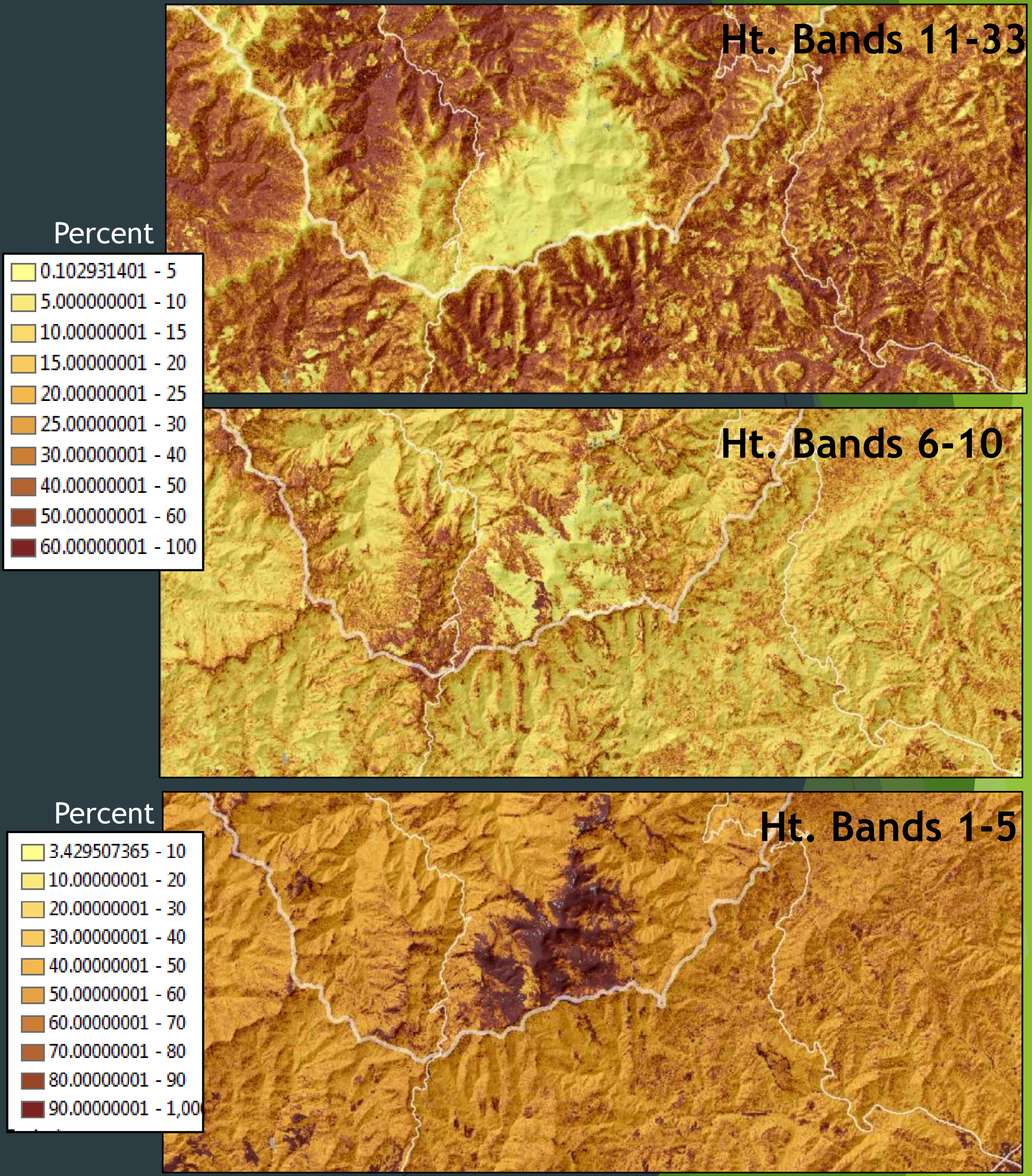




5-foot height band’s percent of profile

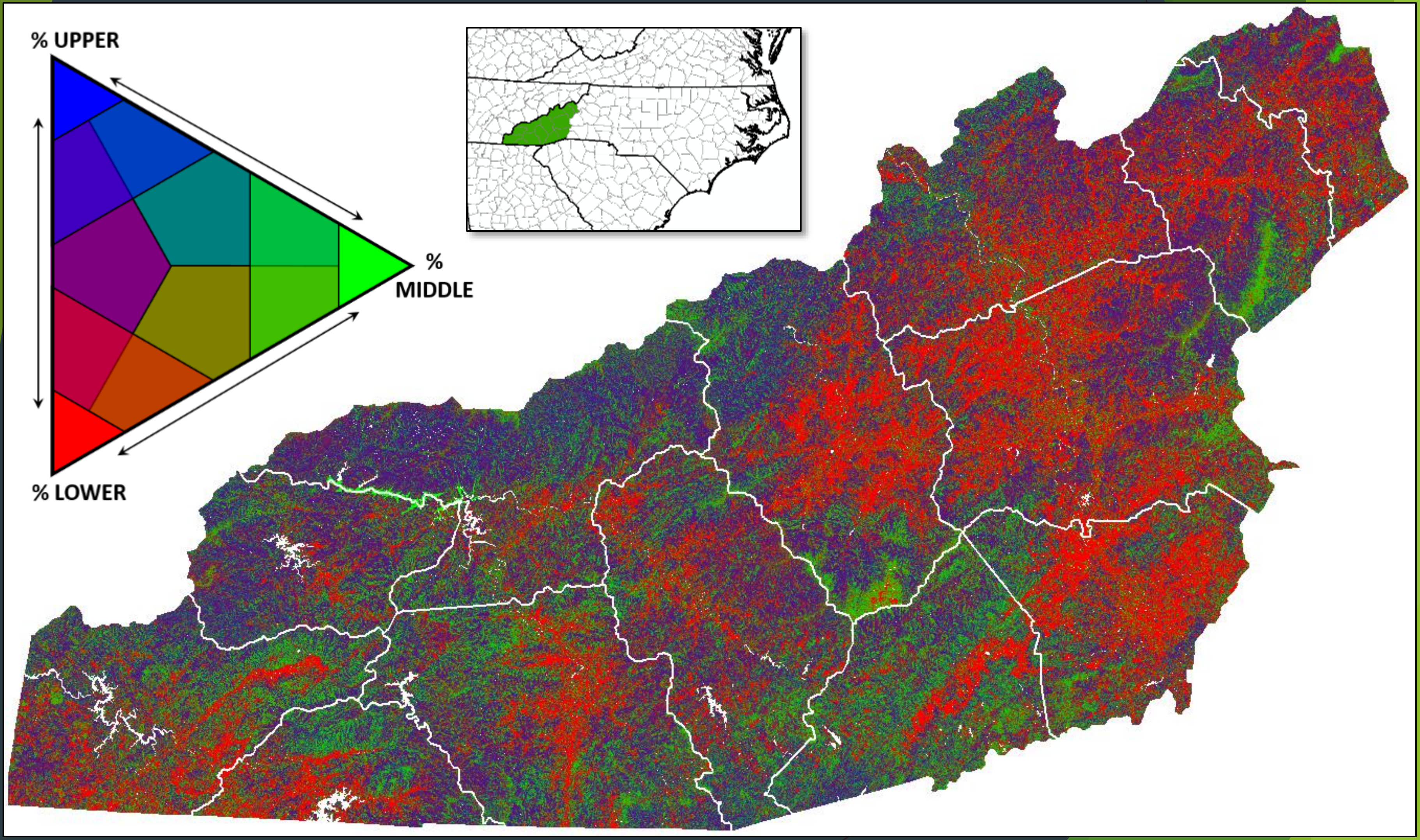
The Structural Typology

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



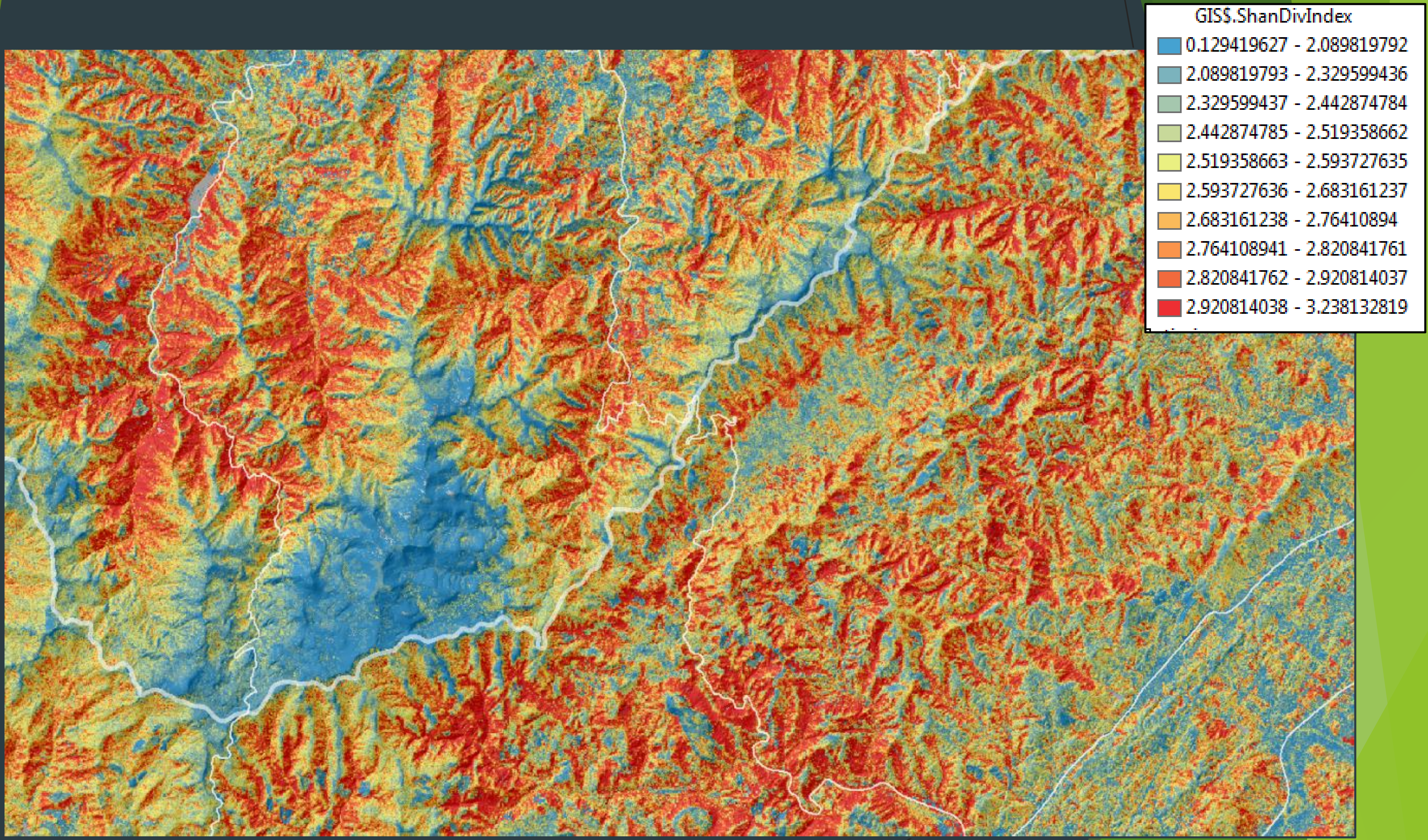
The Structural Typology

Tri-polar (R-G-B) colors on three height zones



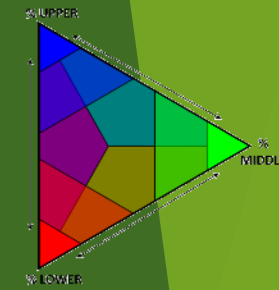
The Structural Typology

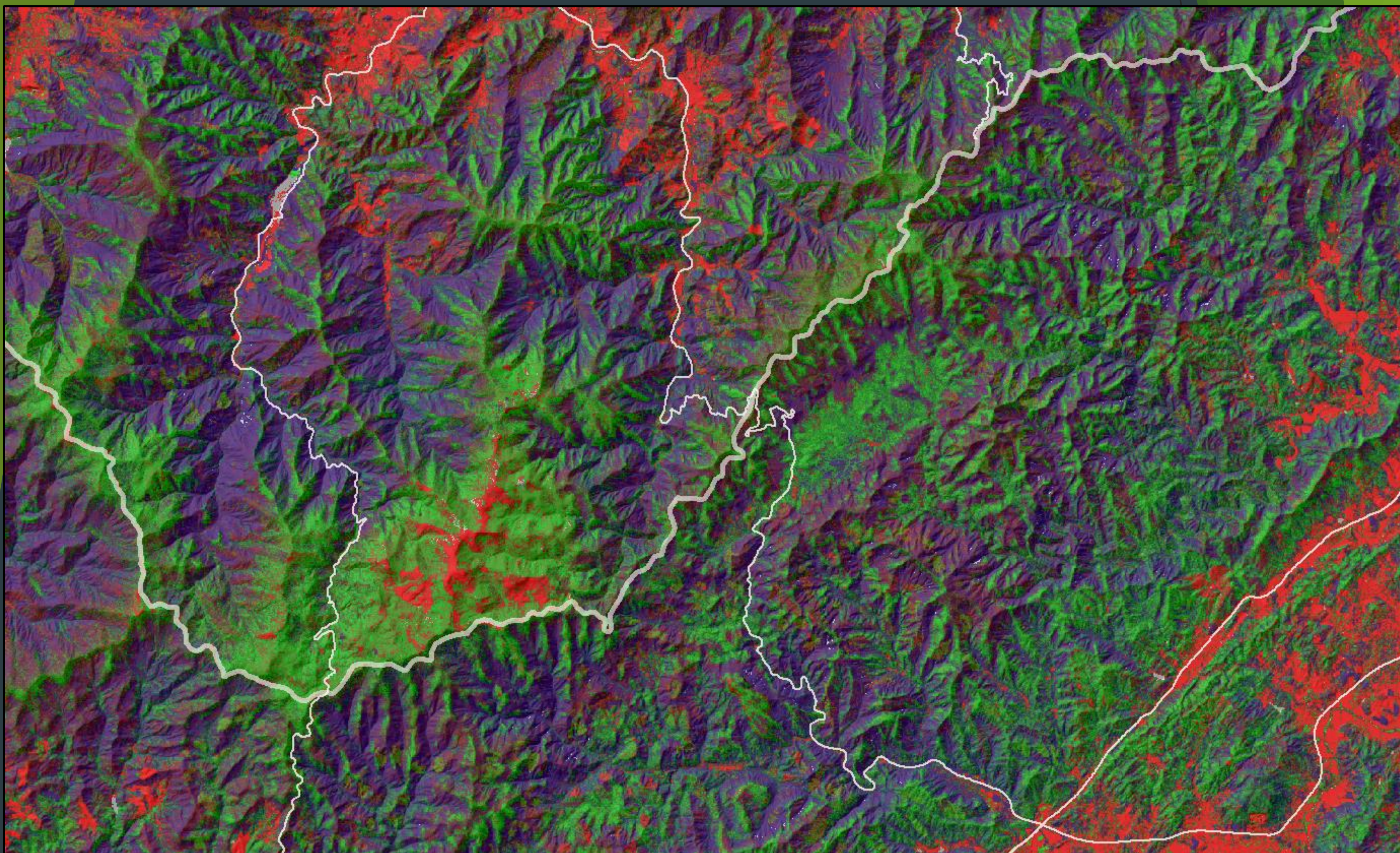
Shannon's Diversity of 33 relative height densities of 200 LiDAR cluster groups for the Greater Shining Rock - Pink Beds Area



The Structural Typology

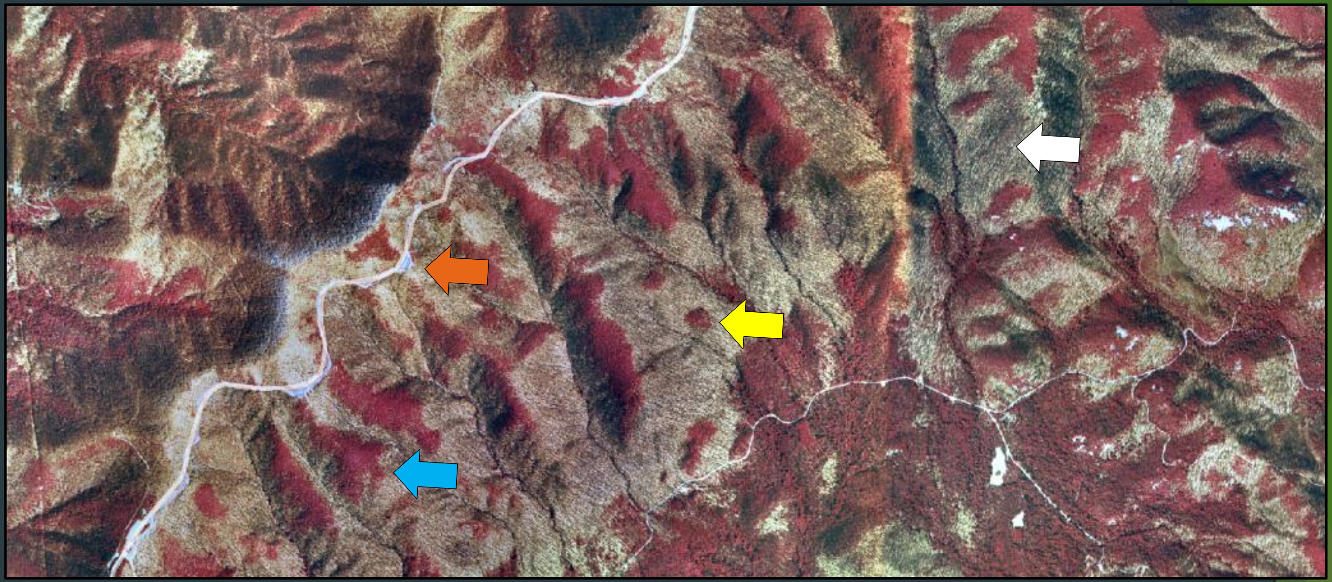
Shining Rock Wilderness-Pink Beds, Pisgah

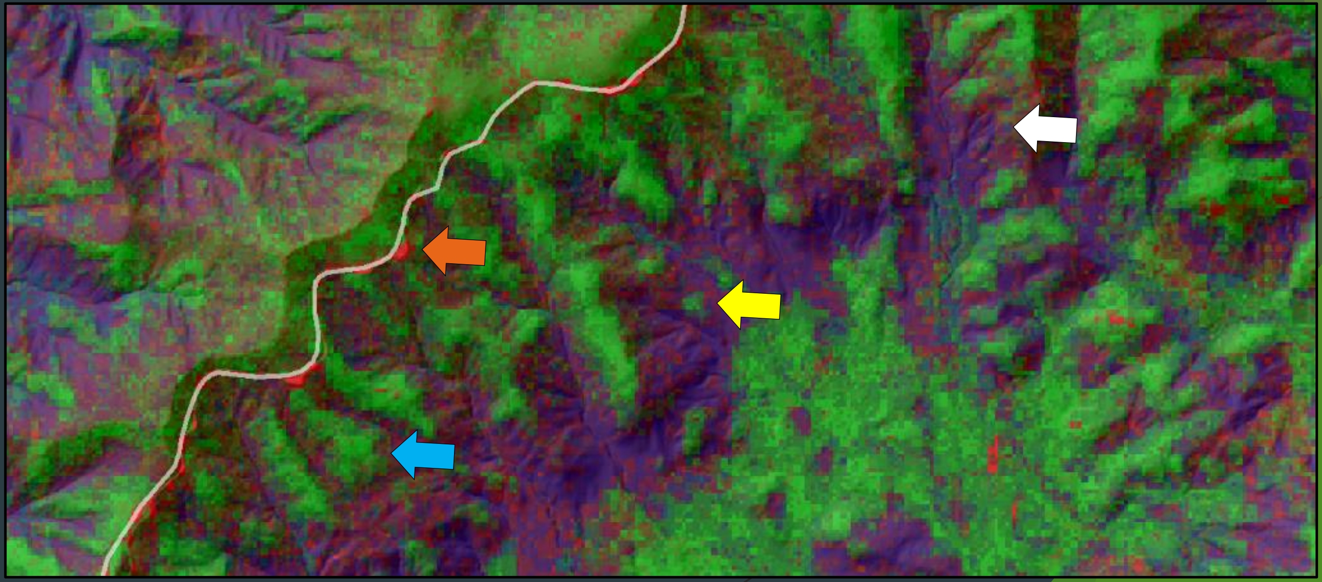


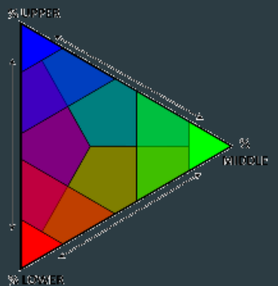


The Structural Typology

Detectability of key understory attributes Pink Beds, Pisgah NF

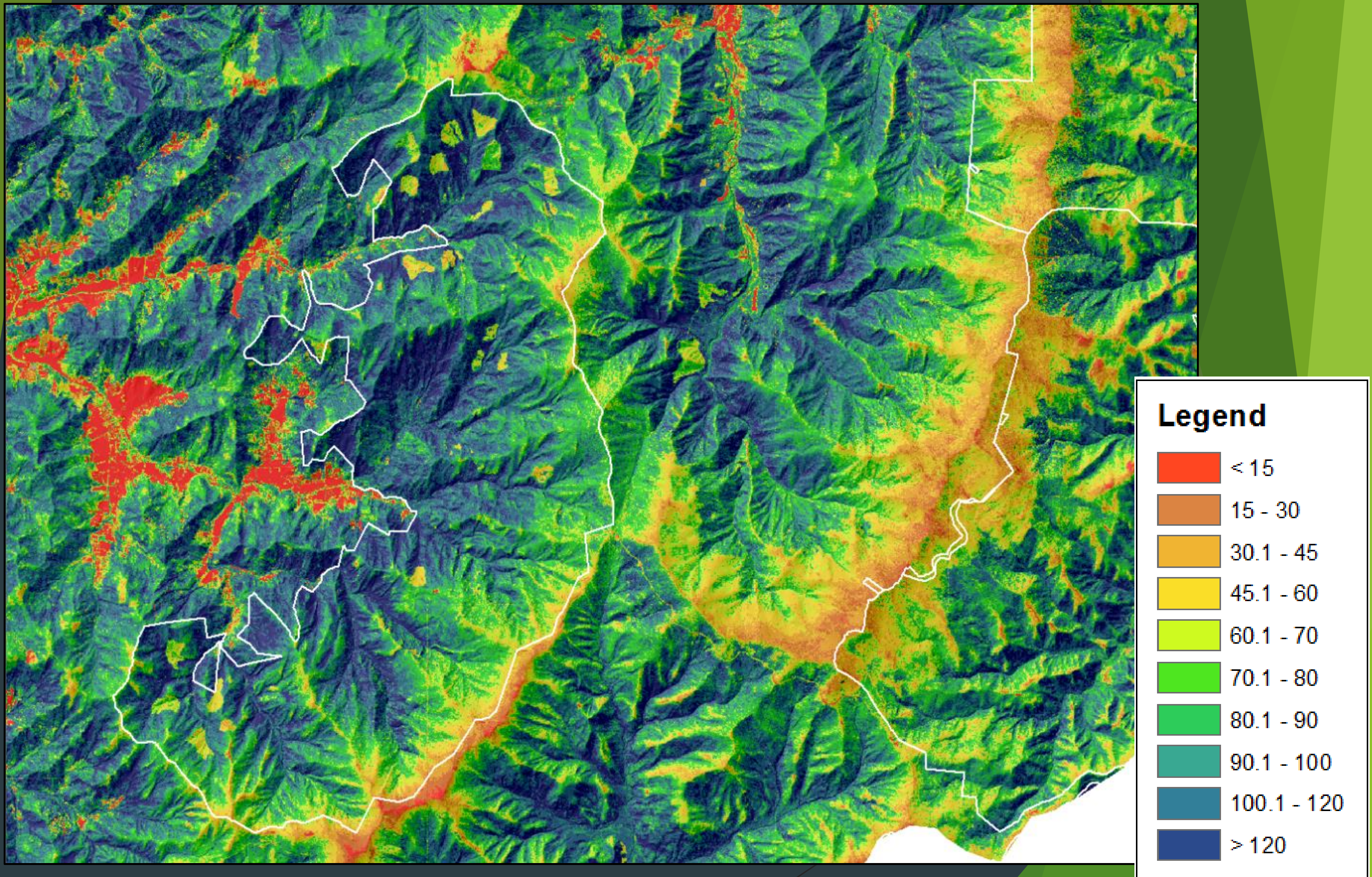






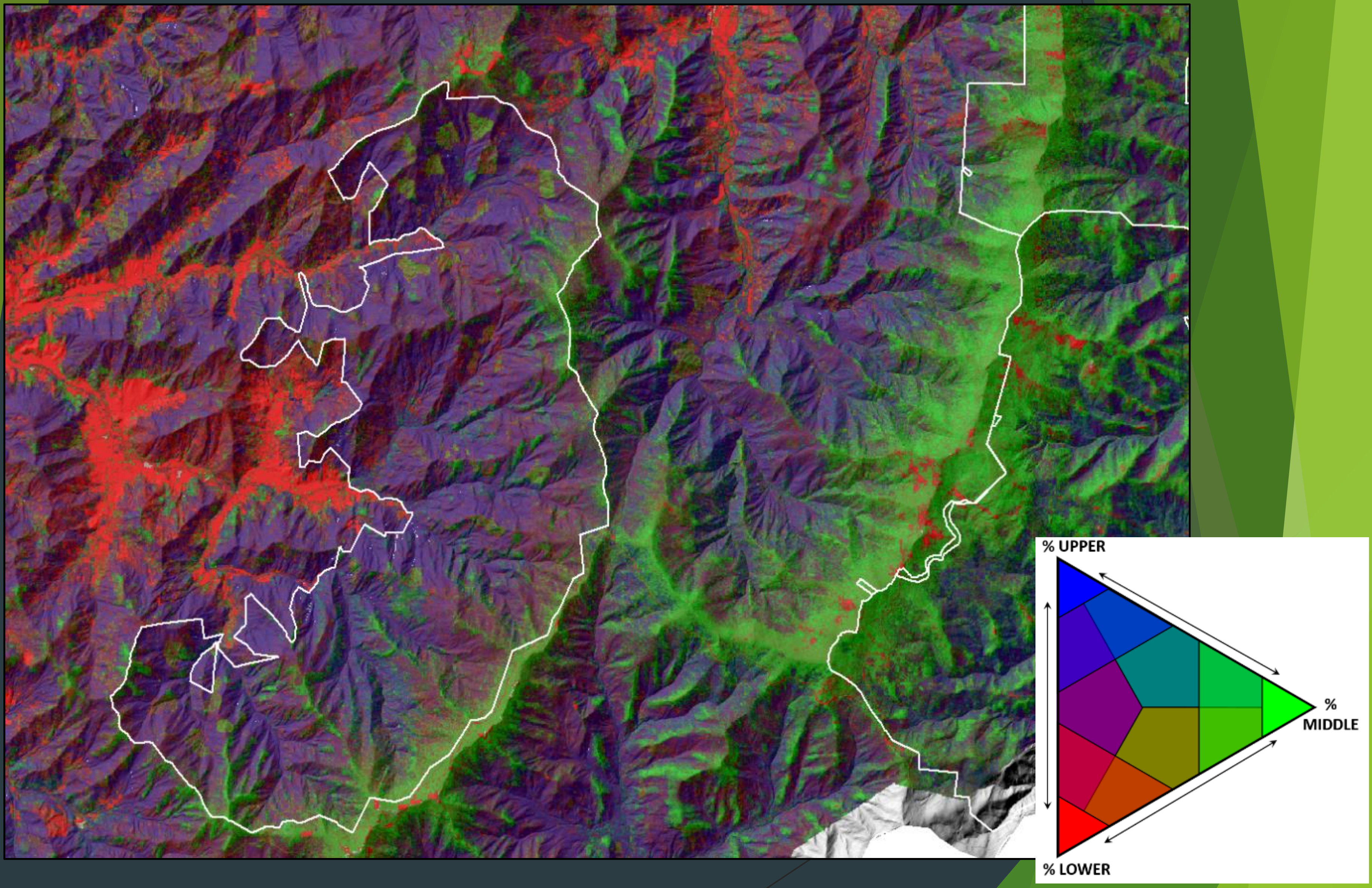
Maximum canopy height

Mount Mitchell and Pisgah NF



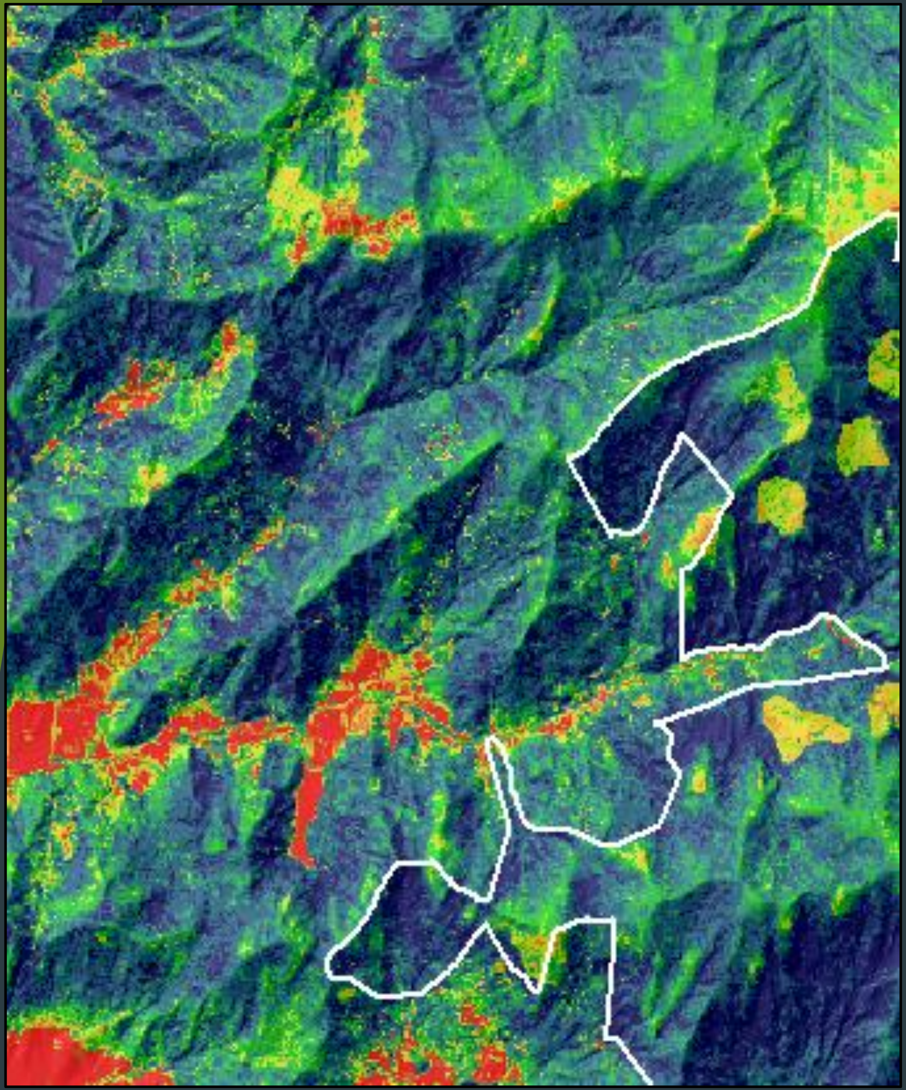
The Structural Typology

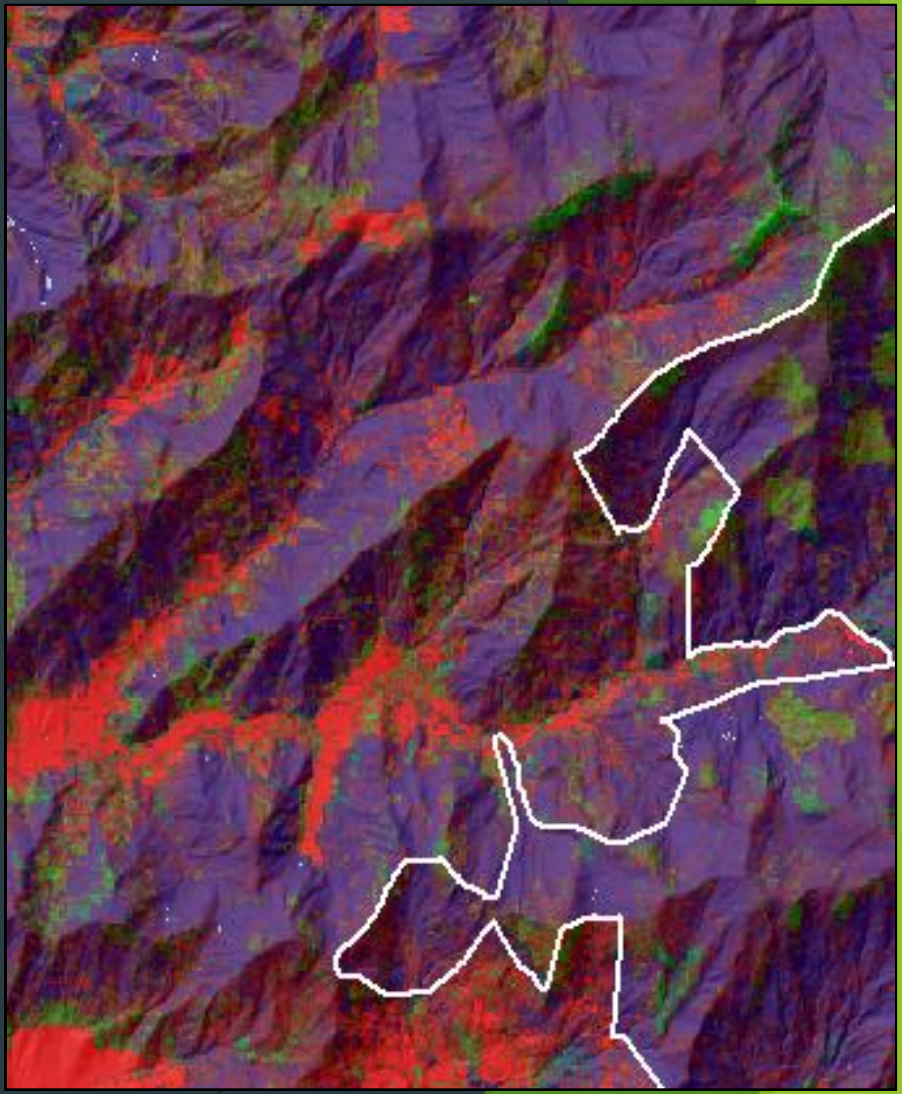
Mount Mitchell and Pisgah NF



Concluding thoughts on applied use

Type-averaging reduces the precision of key measures, like height, while conveying more information in a comprehensible package

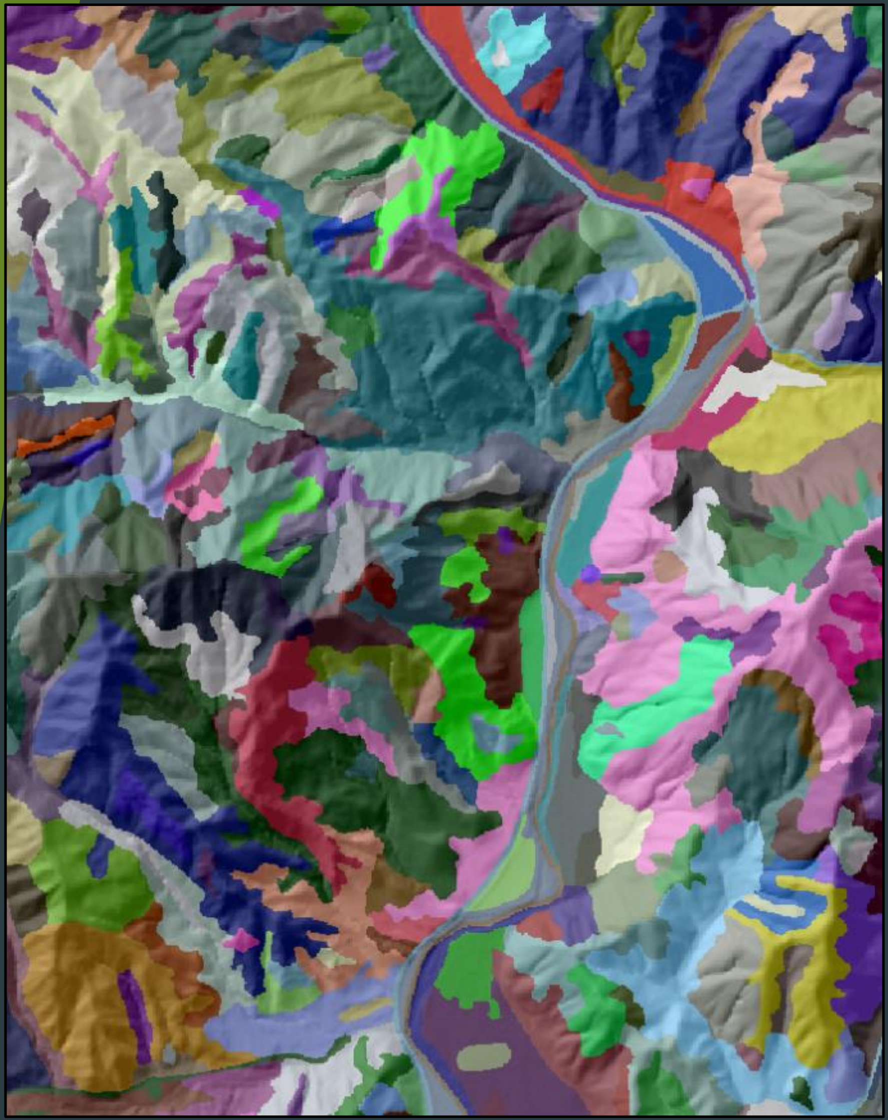




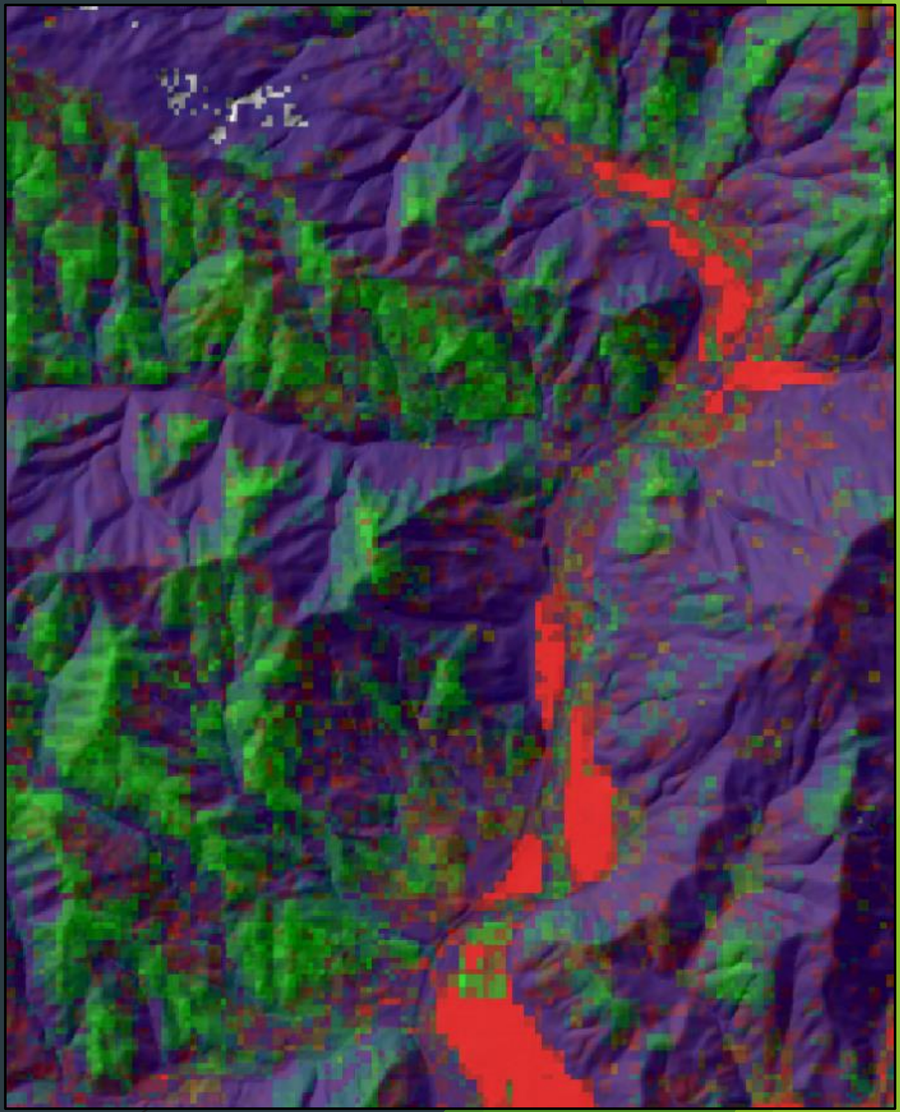
Concluding thoughts on applied use

Raster v. polygon approaches to veg mapping—complementality

Compositional Typology

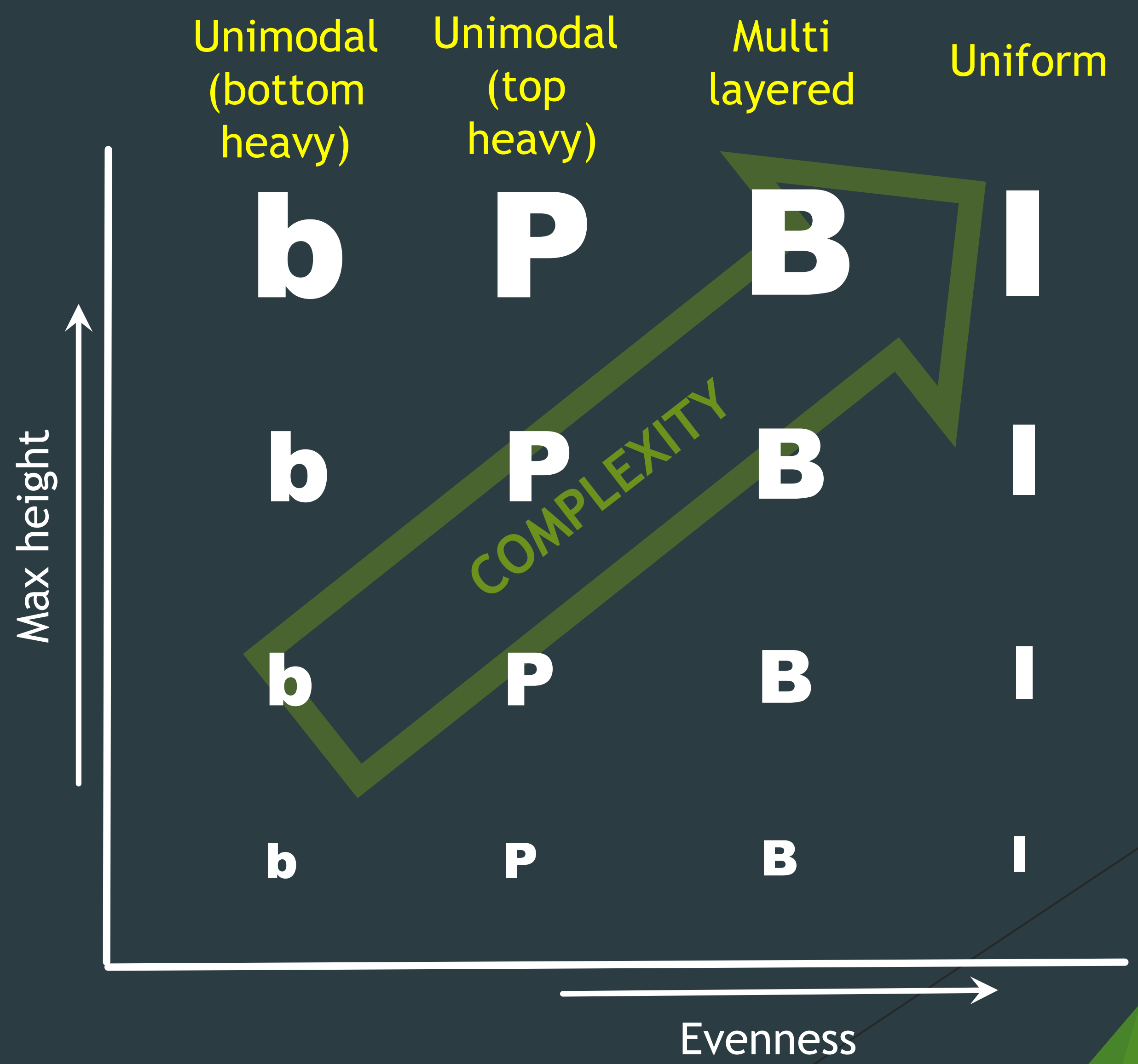


Structural Typology



Concluding thoughts on applied use

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



Concluding thoughts on applied use

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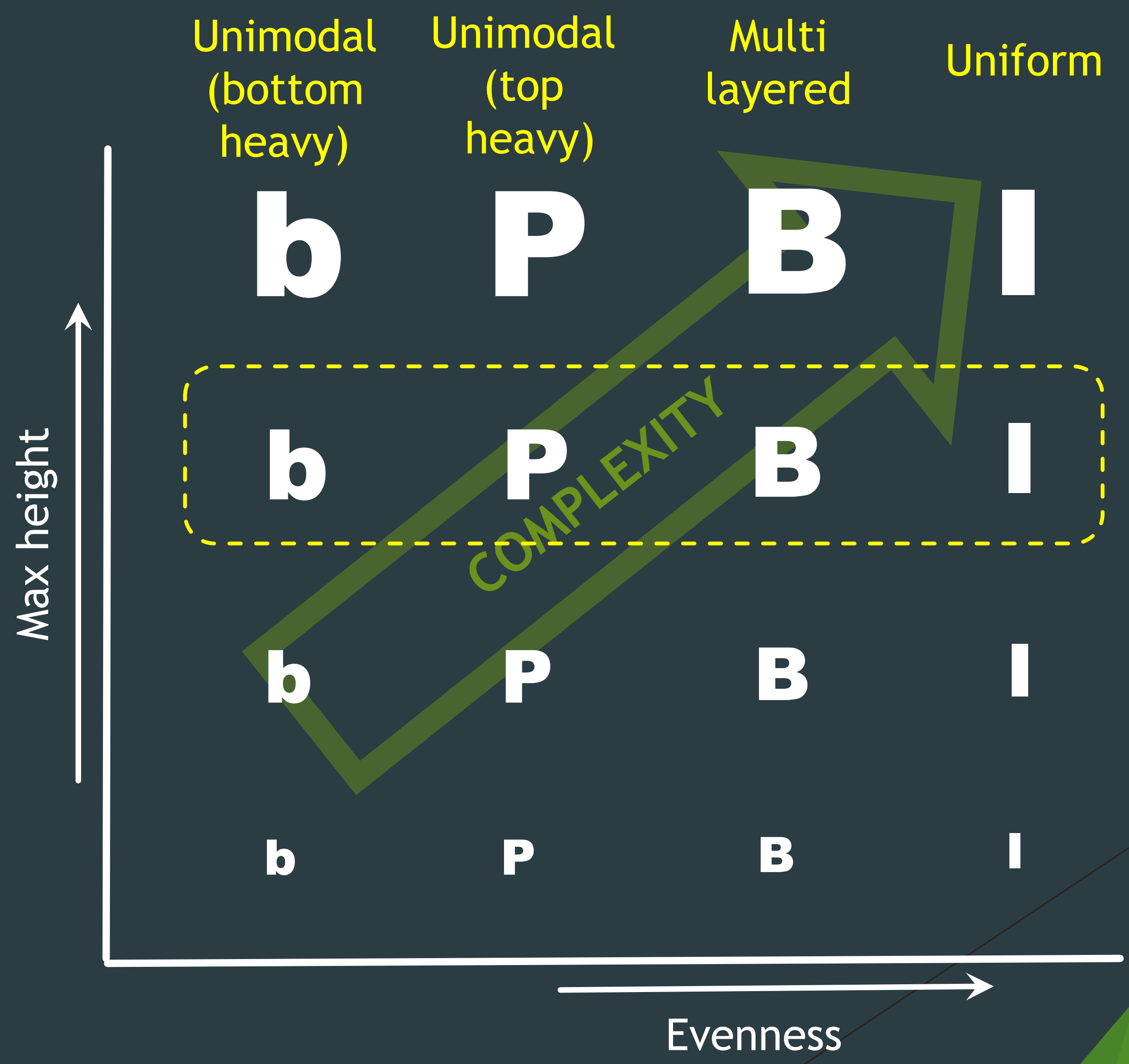

While clustering generates this whole matrix of possibilities, local canopy ht. is most precise, suggesting a complementary use of both datasets may be most useful.

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.