LiDAR Remote Sensing in support of Forest Inventory and Assessment

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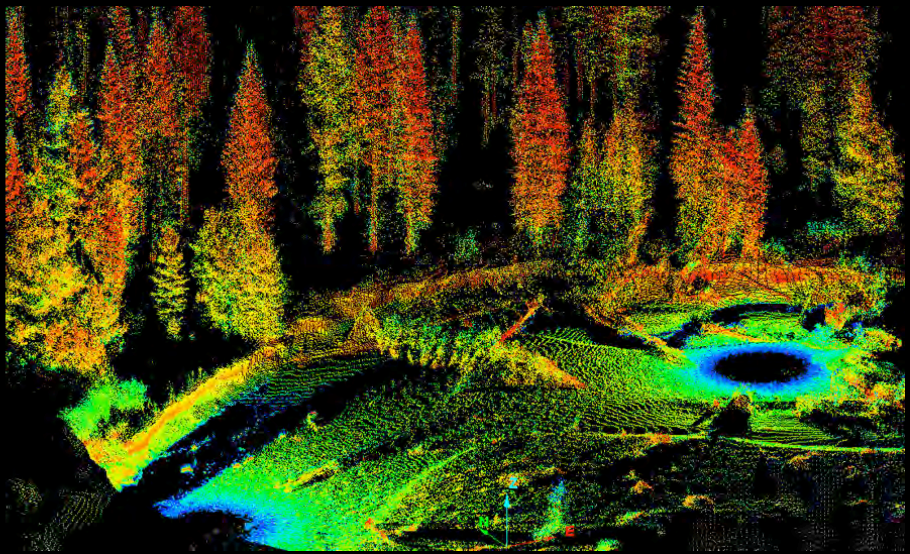
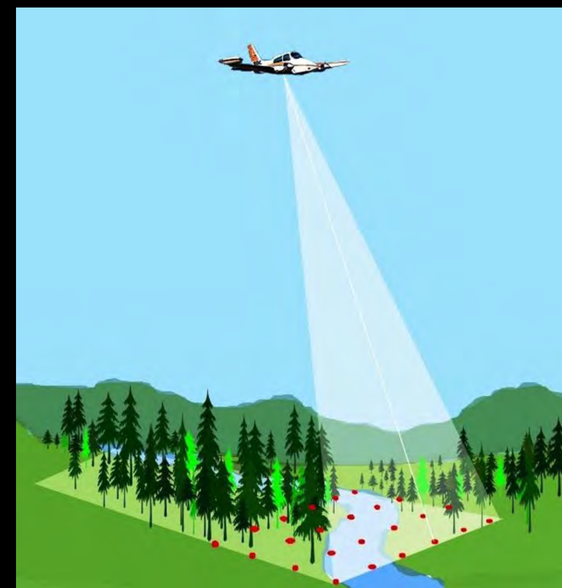


MichiganTech

The Biometrics, Ecosystem Assessment, and Modeling (BEAM) Laboratory



Co-directors: Mike Falkowski (remote sensing), Robert Froese (biometrics/modeling), and Ann MaClean (GIS)

Mission:

The BEAM lab is broadly focused upon employing spatial information to characterize, measure, and monitor forest status and function across large spatial extents. We specialize in use of remote sensing and GIS data in conjunction with advanced statistical algorithms and models to support the information needs of both land managers and ecosystem scientists.

Expertise:

Scientists, students, and technicians within the BEAM lab have expertise in a variety of areas including forestry, forest biometrics, wildlife ecology, fire ecology, statistics, remote sensing, and GIS.

Forest Resources & Environmental Science

Forest Information Needs

Sustainable resource management requires multi-scale information across large areas (landscapes)

- Landmanagers are ever increasingly required to evaluate the impacts management decisions have upon multiple resources across large spatial and temporal extents

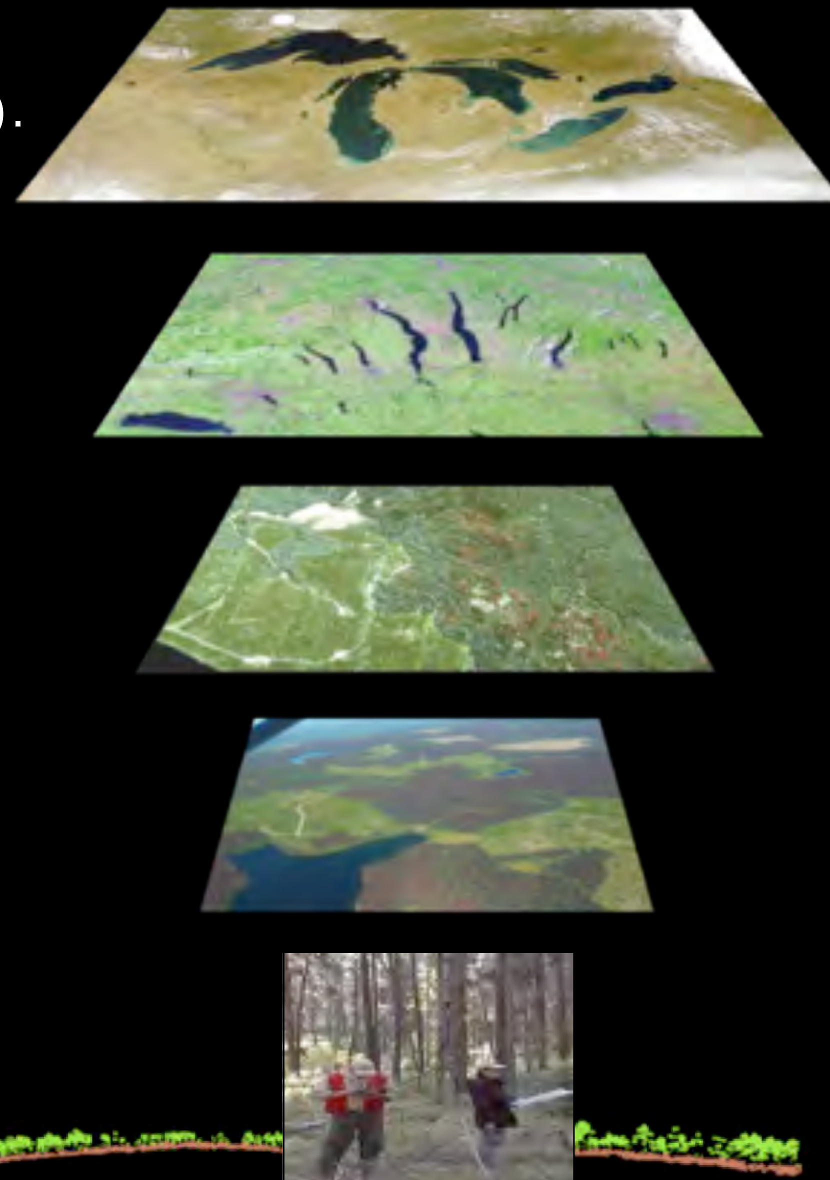
- The development of effective management protocols often requires detailed inventory data across large spatial extents

Research Summary - Goal & Approach

Goals:

Developing efficient methods to measure forest structure and composition across large spatial extents (Primarily achieved via Remote Sensing).

Use such measurements to answer applied research questions in the forest, ecological, and wildlife sciences.



Approach:

Fundamental field measurements

Linking Cutting edge spatial technologies

Models

Powerful statistical algorithms

and established ecological theory

Presentation Overview

- Discuss recent developments in remote sensing of vegetation composition and structure, with a specific focus on operational forest inventories

- Demonstrate the efficacy of LiDAR remote sensing for measuring/estimating detailed forest characteristics at the tree, stand, and landscape level.

- Introduce a series of applied research projects in forest science and ecology that utilize remotely sensed vegetation measurements (some completed and some in progress). These include:
    - The assessment of wildlife habitat suitability
    - Investigating the relationships between butterfly abundance and vegetation structure
    - Wildlife ecology research on Isle Royale (Wolves, Moose, Beavers, and LASERs)

Myth #1 - Remote Sensing can Do Anything!

• Remote Sensing was often oversold in the early years of the discipline/ technology... and still can be today.

• RS cannot do everything... RS simply provides information that can broaden our perspective making large area studies more efficient.

http://www.thecarconnection.com/image/100182441_used-car-salesman

"Hey, hey, hey! Are you folks nuts? I'm telling you, *this* is the car for you!"

Myth #2 - Remote Sensing Eliminates the Need for Field Data!

Many people think that Remote Sensing has the ability to provide all the information required to perform large-scale research or inventory projects:

i.e. Remote Sensing = No Fieldwork

This is NOT true

Each Remote Sensing method provides only a layer of information.

The RS data must always be either calibrated or ground-truthed with field field data

RS, however, does provide a means to extend field measurements across lager spatial extents.

Supporting Operational Forest Inventory with RS

Operational Forest Inventory Seeks to Answer the Following Questions:

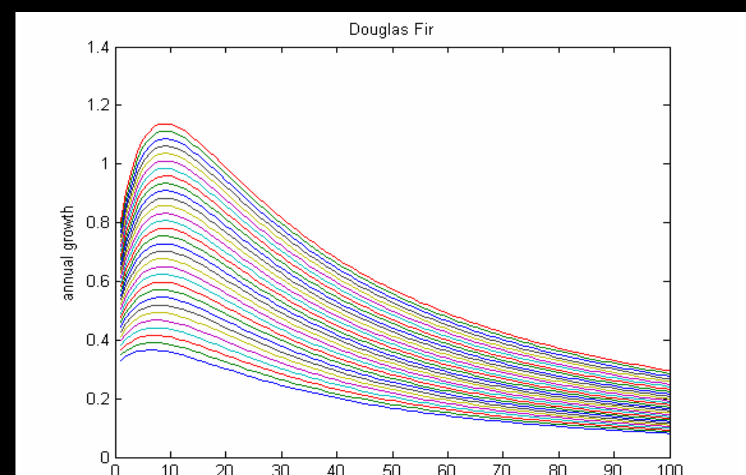
Inventory

- What do we have? e.g., species composition
- How much do we have? e.g., basal area, volume, etc.
-

Can Remote Sensing Help?

- What about the future? e.g., removals, growth, mortality, impacts of disturbance & management

Stand Inventories



Growth and Yield Forecasts

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Remote sensing for forest inventory and assessment

"Remote sensing is not a panacea for existing shortcomings in forest measurement and often has shown little utility to operational management needs… Integrating remote sensing [in forest inventory and monitoring] is perceived as difficult and costly by potential data users in the field [of forestry]." (Peterson et al., 1999)*

Forest Monitoring and Remote Sensing: A Survey of Accomplishments and Opportunities for the Future. A report prepared by the RAND Corp. for the White House Office of Science and Technology Policy.

Supporting Operational Forest Inventory with RS

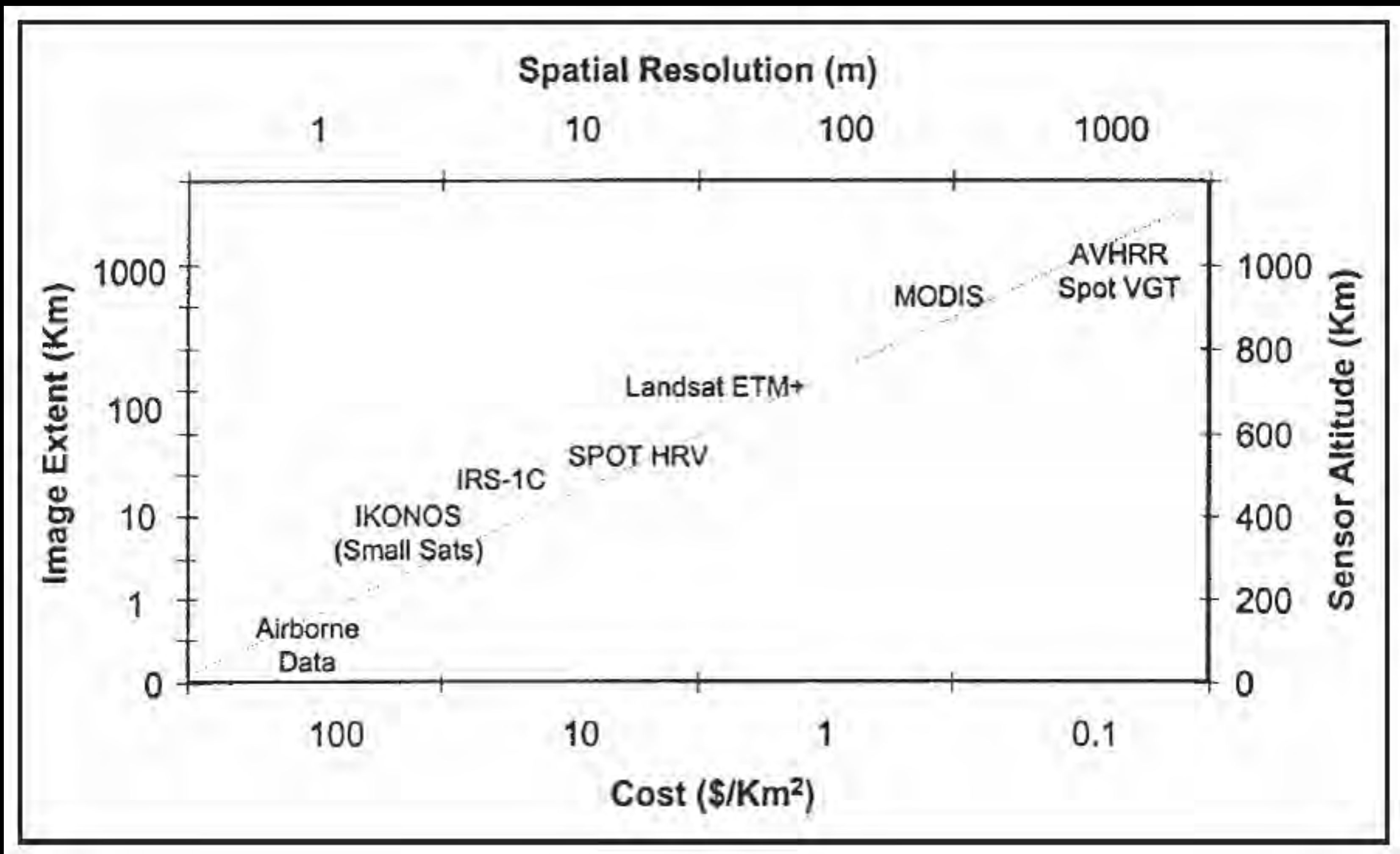
Remote Sensing For Forest Inventory and Assessment:

From Holmgren and Thuresson 1998:

‘It is concluded that satellite images seldom contain enough information to support the decision process in applied forestry. Although regional level applications may be useful, few successful and reliable applications for local forest inventory, planning or damage monitoring have evolved.’

Satellite remote sensing for forestry planning—A review
Scandinavian Journal of Forest Research Volume 13, Issue 1 & 4, 1998, Pages 90 - 110 Authors: Peter Holmgren[a]; Thomas Thuresson[b]

Supporting Operational Forest Inventory with RS



Relationship Between Spatial Precision, Extent, and Cost (Source: Franklin, 2002).

Supporting Operational Forest Inventory with RS

Traditional RS data lack the precision required for operational inventory:

Landsat data - Many trees per pixel

Landsat (30 m spatial resolution)

Supporting Operational Forest Inventory with RS

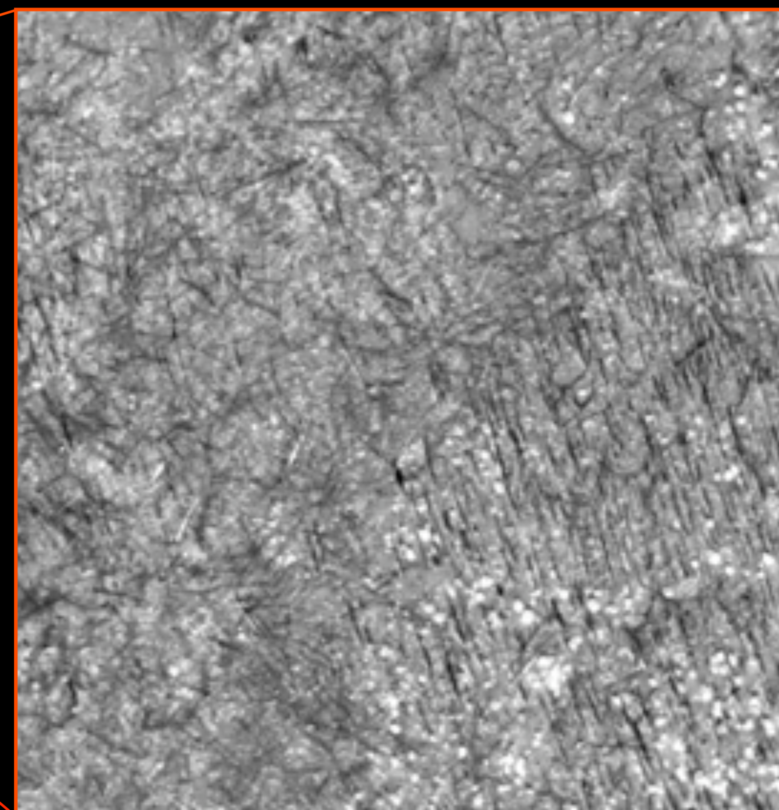
Cutting edge sensors provide increased spatial detail:

- High Spatial Resolution Satellites

Many trees per pixel

Many pixels per tree

Landsat (30 m spatial resolution)



WorldView (50 cm spatial resolution)

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Cutting edge sensors provide increased spatial detail:

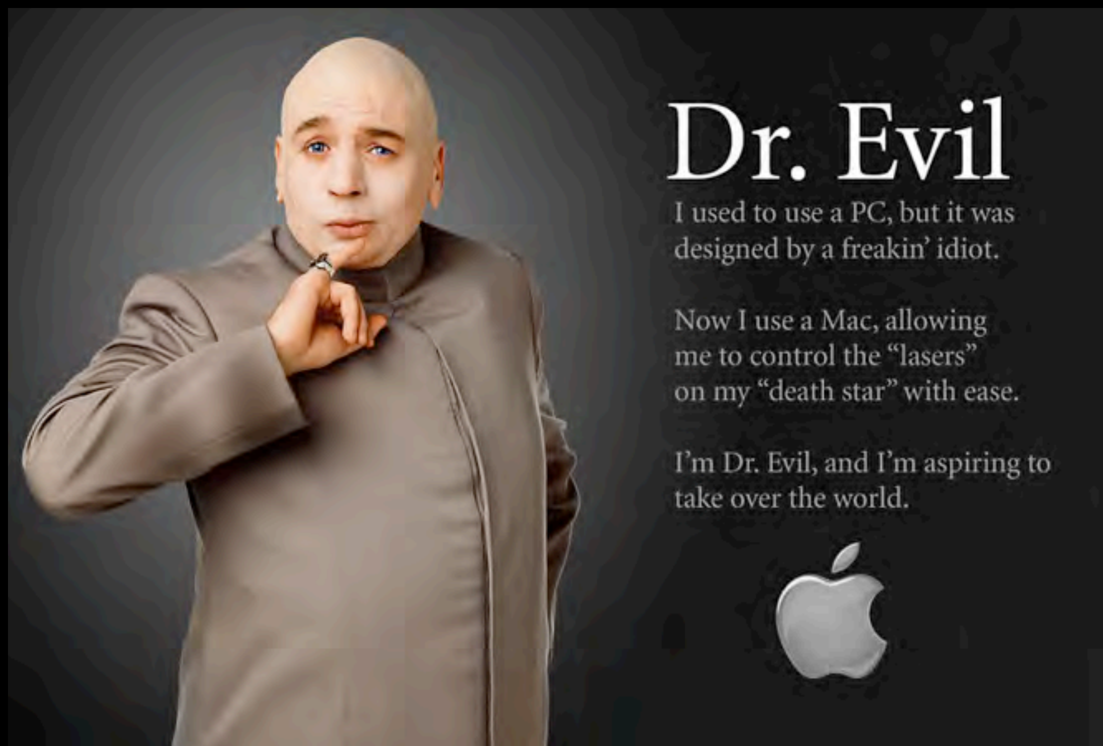
LiDAR: Measures 3-dimensional forest properties

Aerial Photo (10 cm)

LiDAR (> 10 points m^2)

Source: USFS PNW Research Station

What is LiDAR (Light Detection and Ranging)?



It's a LASER……. Range Finder!

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How does LiDAR work?

LiDAR - Light Detection and Ranging

The Basic LiDAR Equation:

$$d = (t*s)/2$$

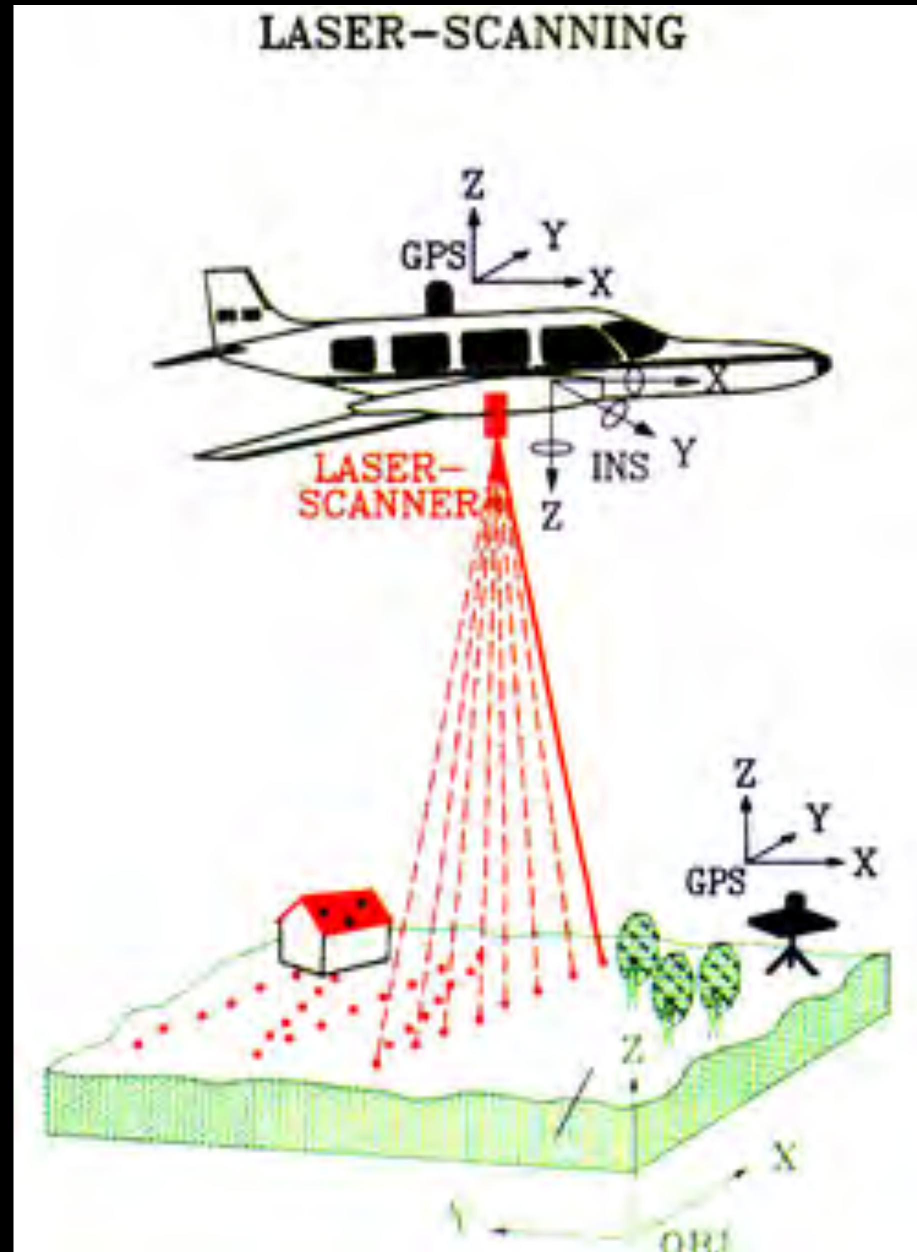
$d = (t*s)/2$

d = Distance (m)

t = Time (sec)

s = Speed of Light (299,792,458 m sec^{-1})

Light (SPEED IS KNOWN!!)



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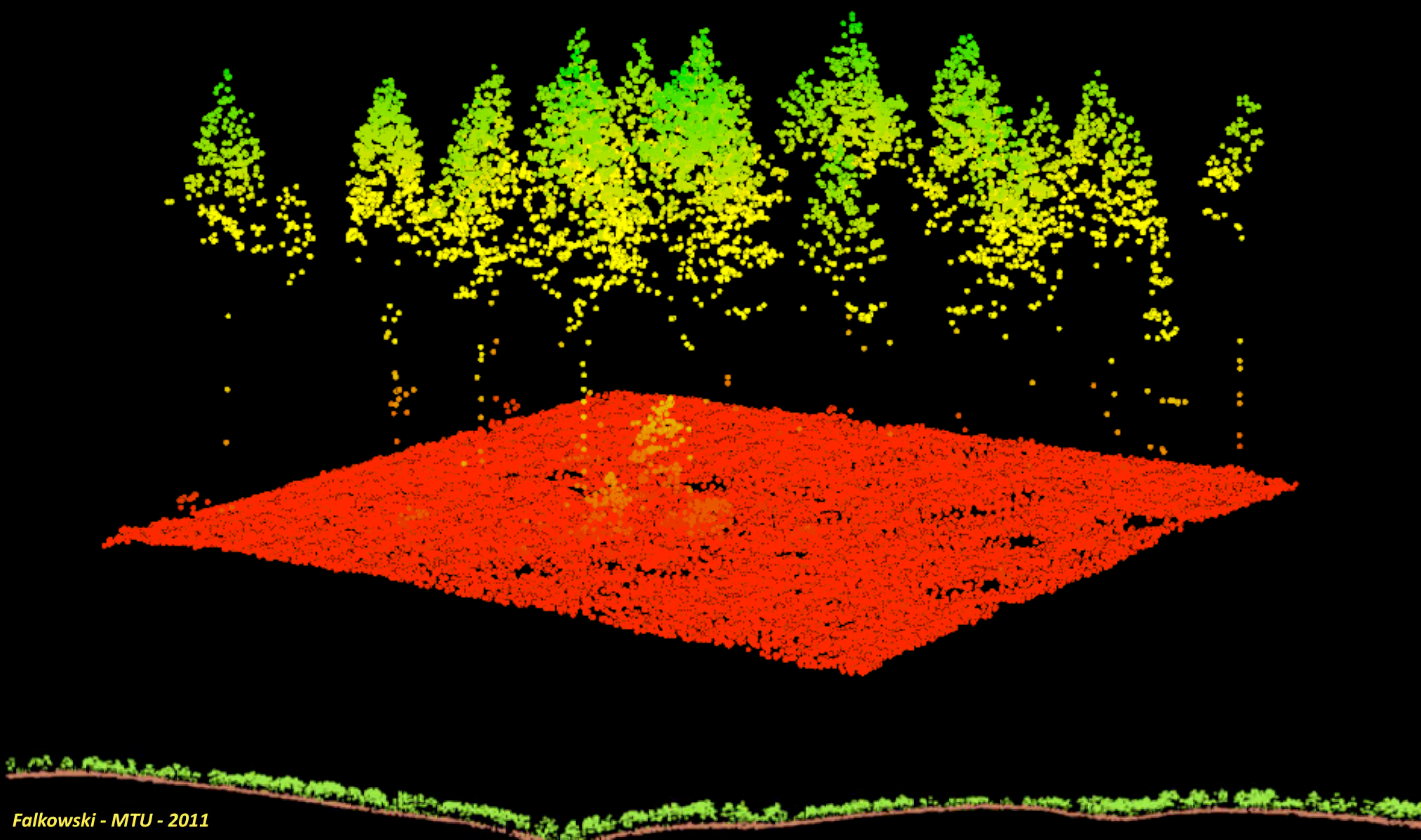
What do LiDAR data look like?

3-D point clouds



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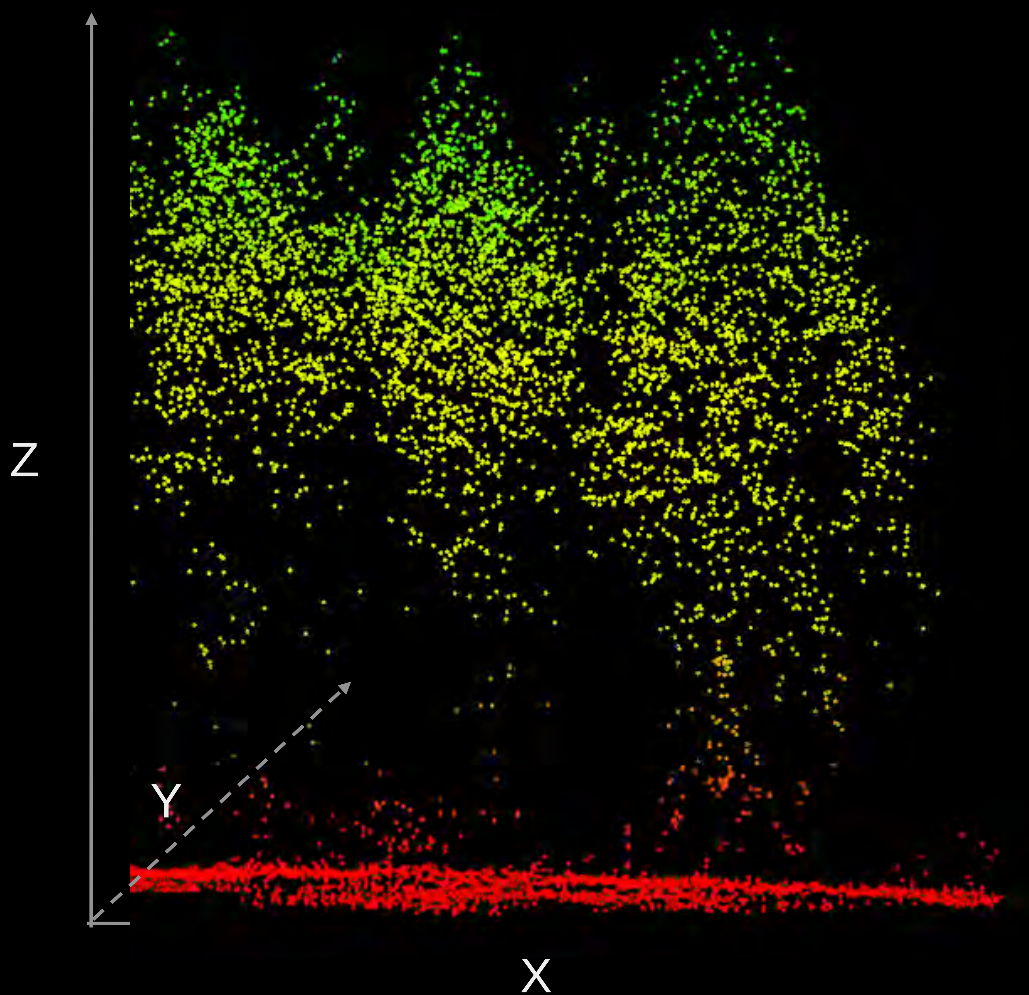
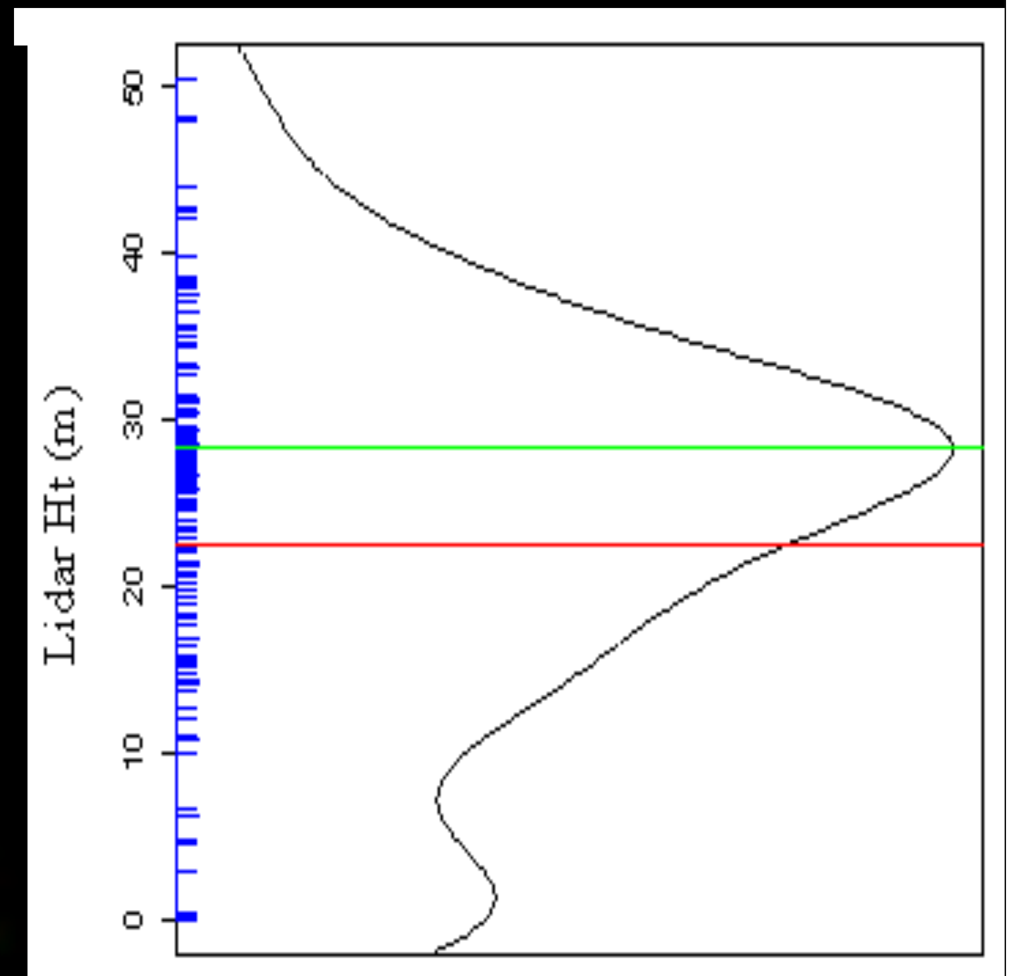
What do LiDAR data look like? - Plot-level Height distributions





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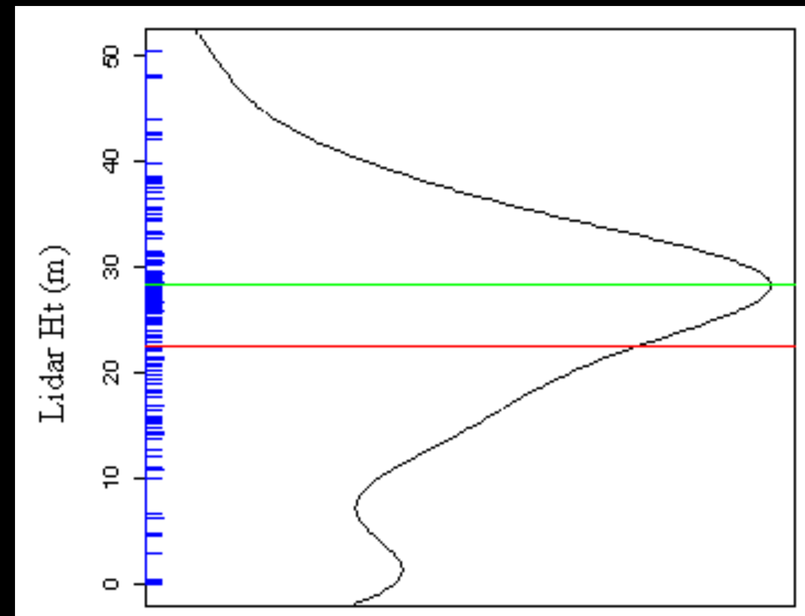

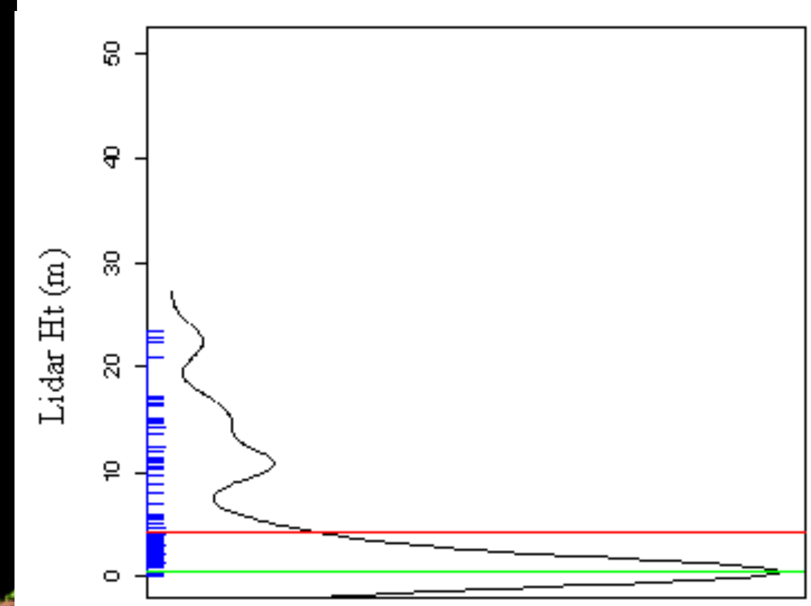

Supporting Operational Forest Inventory with RS

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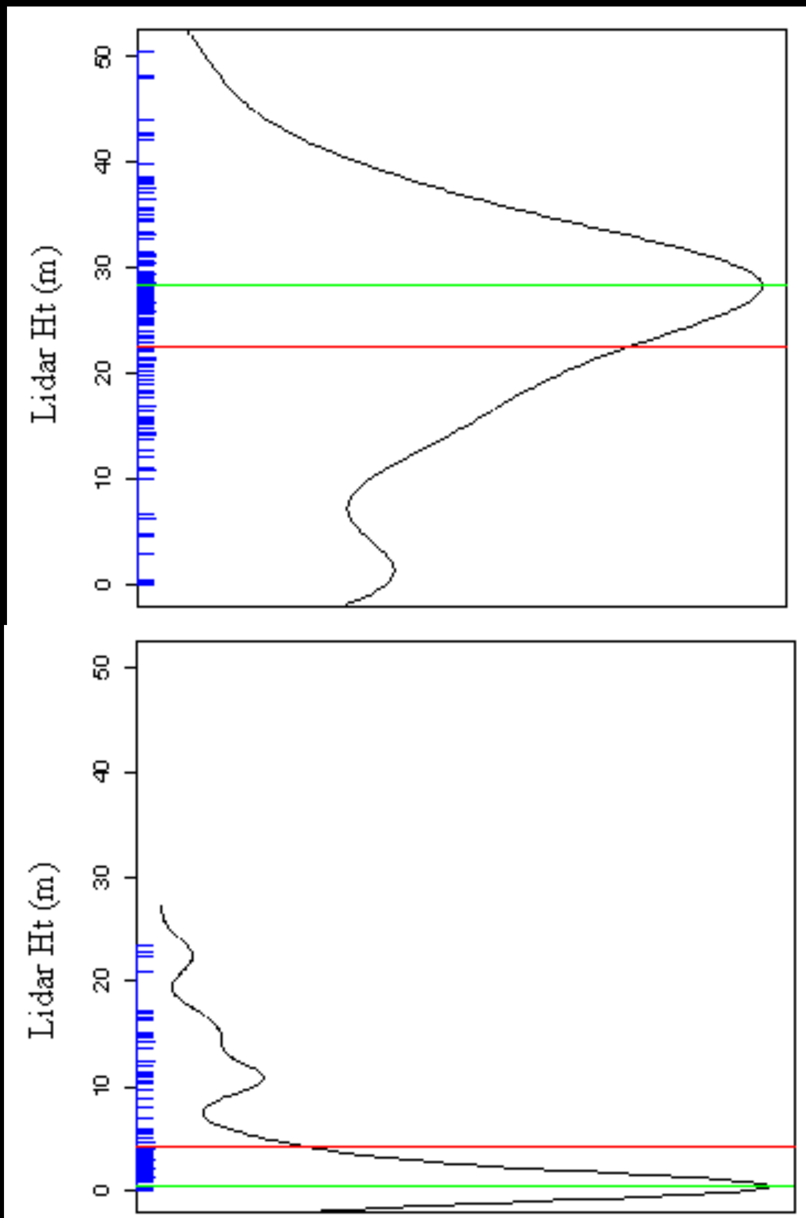

Common LiDAR-Derived Vegetation Metrics

Metric name	Metric description
HMIN	Minimum Height
HMAX[a]	Maximum Height
HRANGE	Range of Heights
HMEAN[a,b]	Mean Height
HMEDIAN[a,b]	Median Height
HMODE[b]	Modal Height
NMODES	Number of Modes
HAAD	Average Absolute Deviation of Heights
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HSTD	Standard Deviation of Heights
HVAR	Variance of Heights
HSKEW	Skewness of Heights
HKURT	Kurtosis of Heights
HCV	Coefficient of Variation of Heights
H05PCT	Heights 5th Percentile
H10PCT	Heights 10th Percentile
H25PCT[b]	Heights 25th Percentile
H50PCT	Heights 50th Percentile (Median)
H75PCT[c]	Heights 75th Percentile
H90PCT	Heights 90th Percentile
H95PCT[c]	Heights 95th Percentile
CANOPY[a,b]	Canopy Cover (Vegetation Returns/Total Returns * 100)
STRATUM0	Percentage of Ground Returns = 0 m
STRATUM1	Percentage of Non-Ground Returns > 0 m and <= 1 m
STRATUM2[b]	Percentage of Vegetation Returns > 1 m and <= 2.5 m
STRATUM3	Percentage of Vegetation Returns > 2.5 m and <= 10 m
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TEXTURE	Standard Deviation of Non-Ground Returns > 0 m and <= 1 m
PCT1	Percentage 1st Returns
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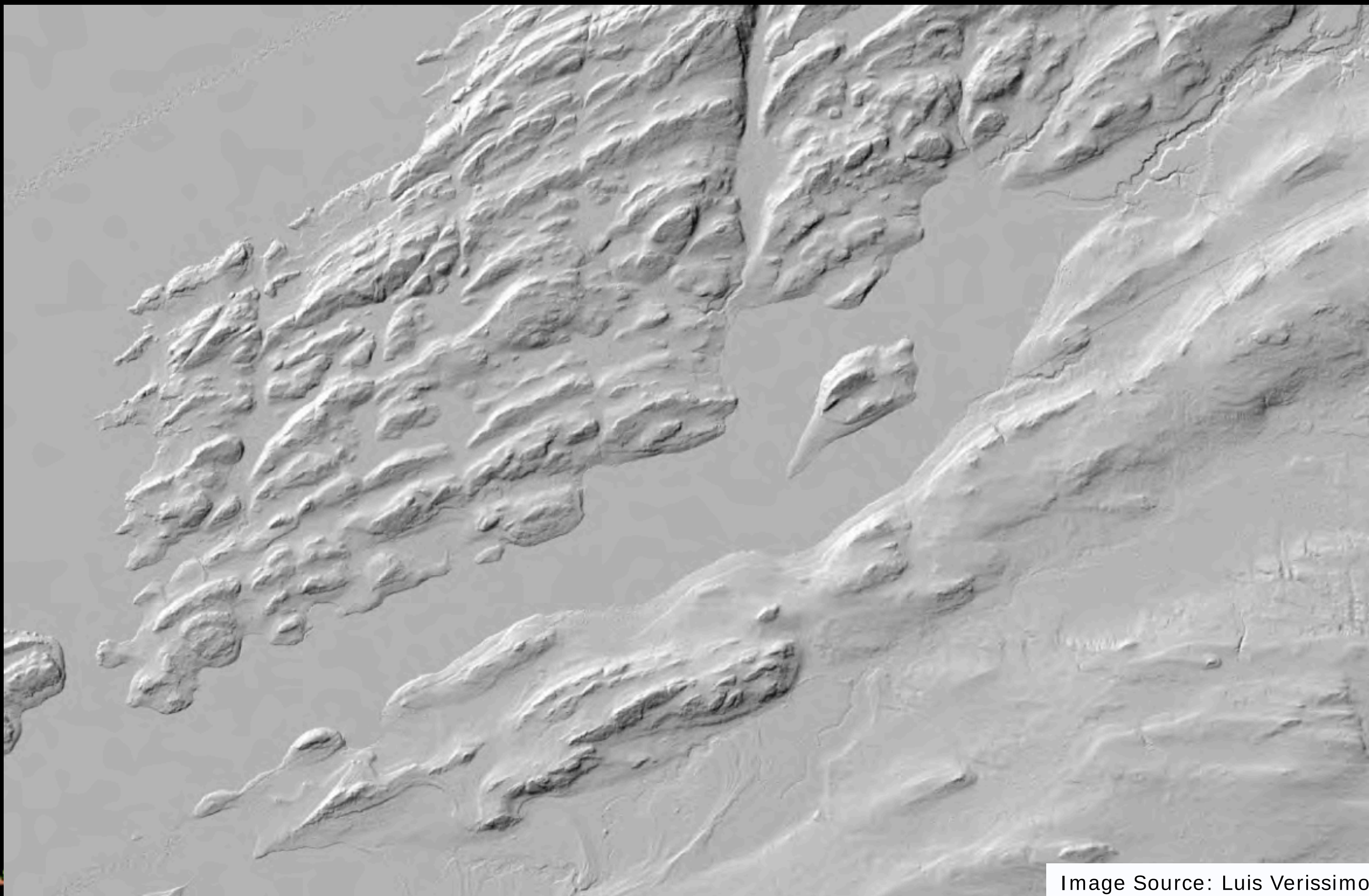
Supporting Operational Forest Inventory with RS

What do LiDAR data look like?



Supporting Operational Forest Inventory with RS

What do LiDAR data look like?

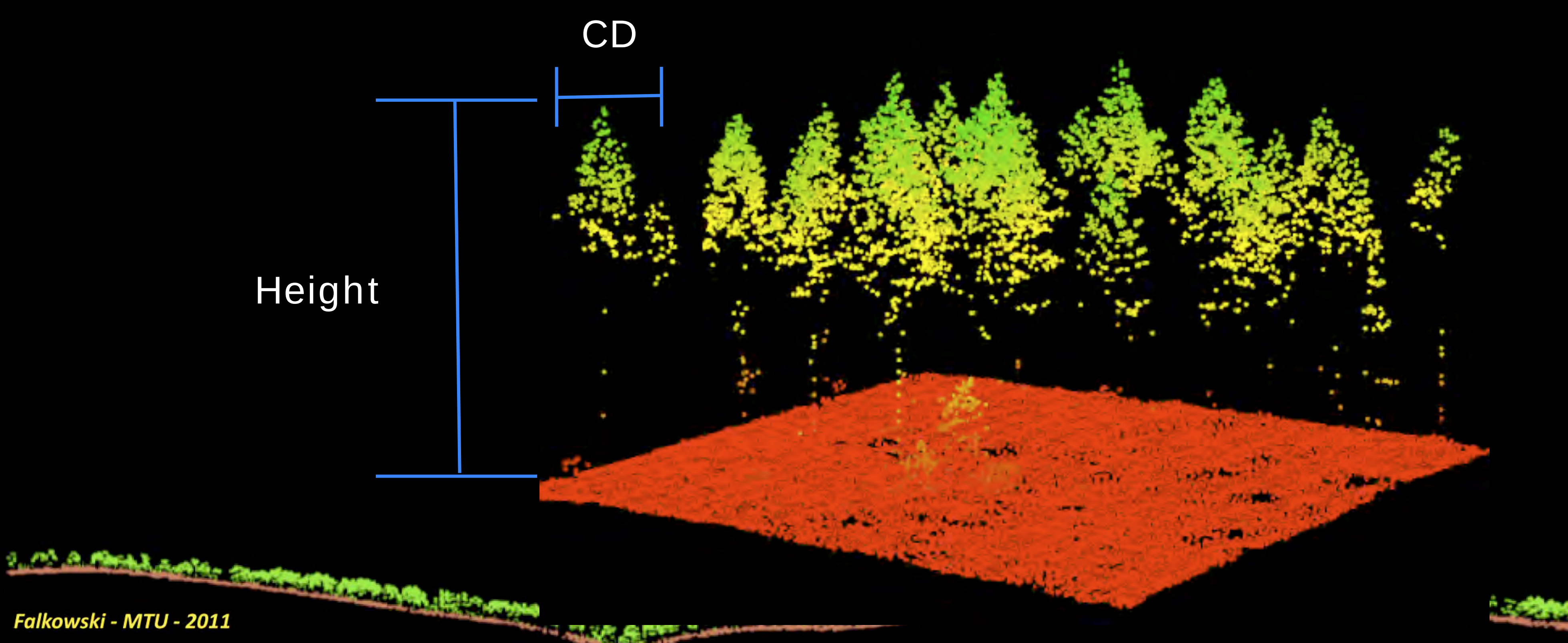
Supporting Operational Forest Inventory with RS

Operational Forest Inventory Seeks to Answer the Following Questions:

Inventory

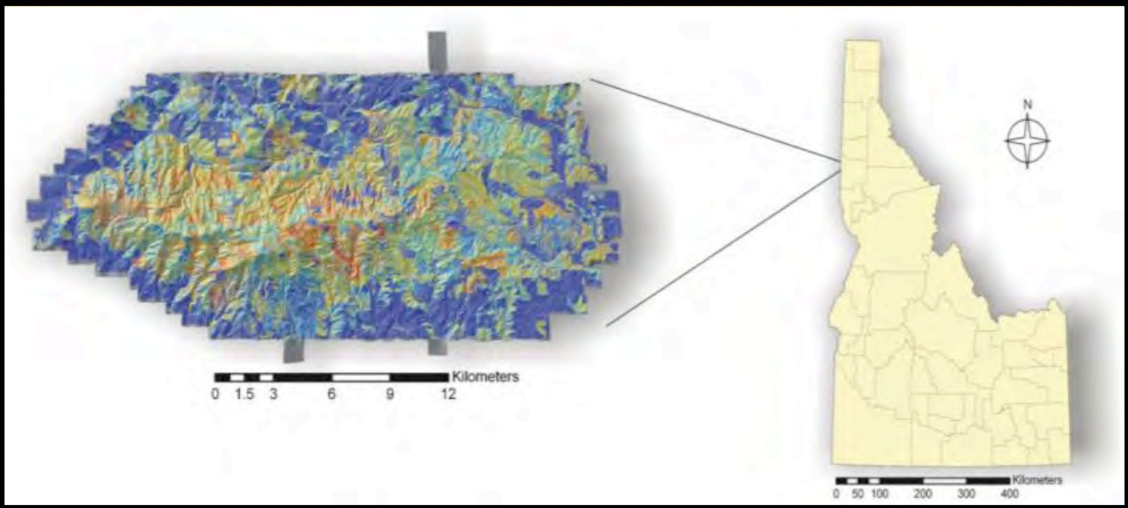
- What do we have? e.g., species composition
- How much do we have? e.g., basal area, volume, etc.
- How is it spatially arranged? e.g., vertical and horizontal structure, dia. distrib, age class distrib.

Individual Tree Crown (ITC) measurement



Supporting Operational Forest Inventory with RS

Study area: Moscow Mountain, Near Moscow, ID



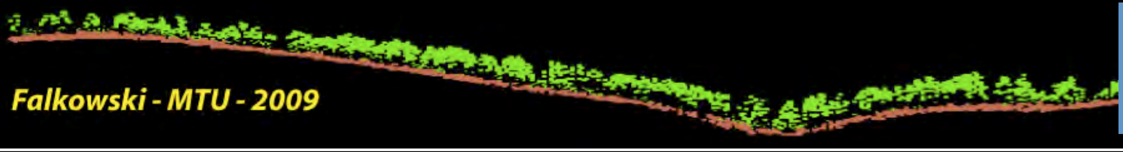
- 30,000 ha of mixed conifer forest
- Diverse in terms of species composition and forest structure
- Primarily managed for timber production
- Topographically complex

Sample Design and Data Collection:

81 forest inventory plots (1/10 acre (0.04 ha)) located using a stratified sampling design

Standard forest inventory data collected at each plot (Species, DBH, Ht, Crn Dia., etc.)

LiDAR Data: LiDAR data acquired with an ALS40 with a point density ~0.5 pulses per sq. m (considered low resolution by today's standards)



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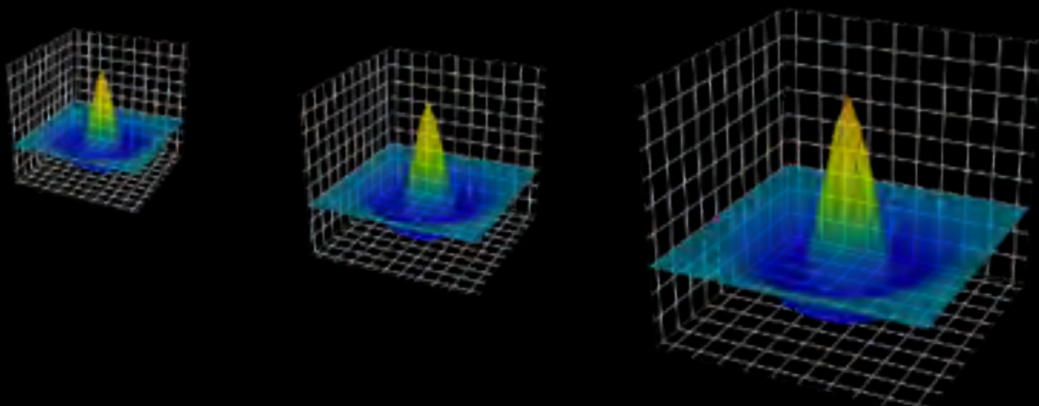
Falkowski, M.J., et al. 2005. Evaluating ASTER Satellite Imagery and Gradient Modeling for Characterizing Wildland Fire Fuels. *Forest Ecology and Management*, 32, 126-138.

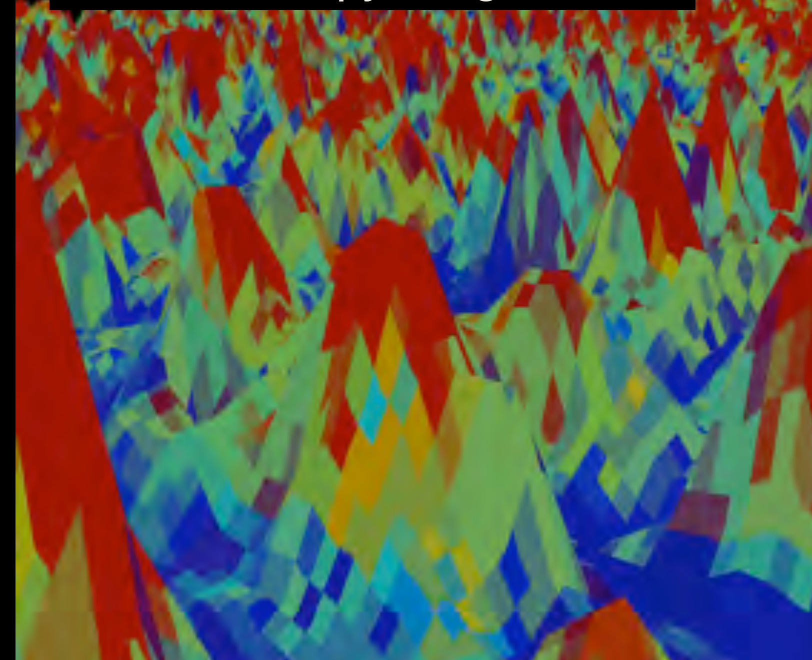
Example - Direct Measurement of Individual Trees via LiDAR (ITC)

Automated image processing for measuring individual tree dimensions (height and crown diameter) from LiDAR RS data

Mexican Hat Wavelet



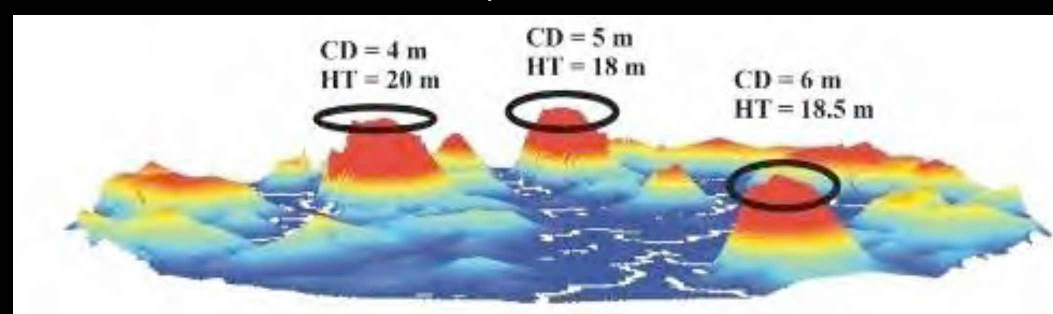
LiDAR Canopy Height Model



Wavelet Dilation Eq.

$$\psi_{a,b}(\lambda) = \frac{1}{a}\psi\left(\frac{\lambda - b}{a}\right)$$

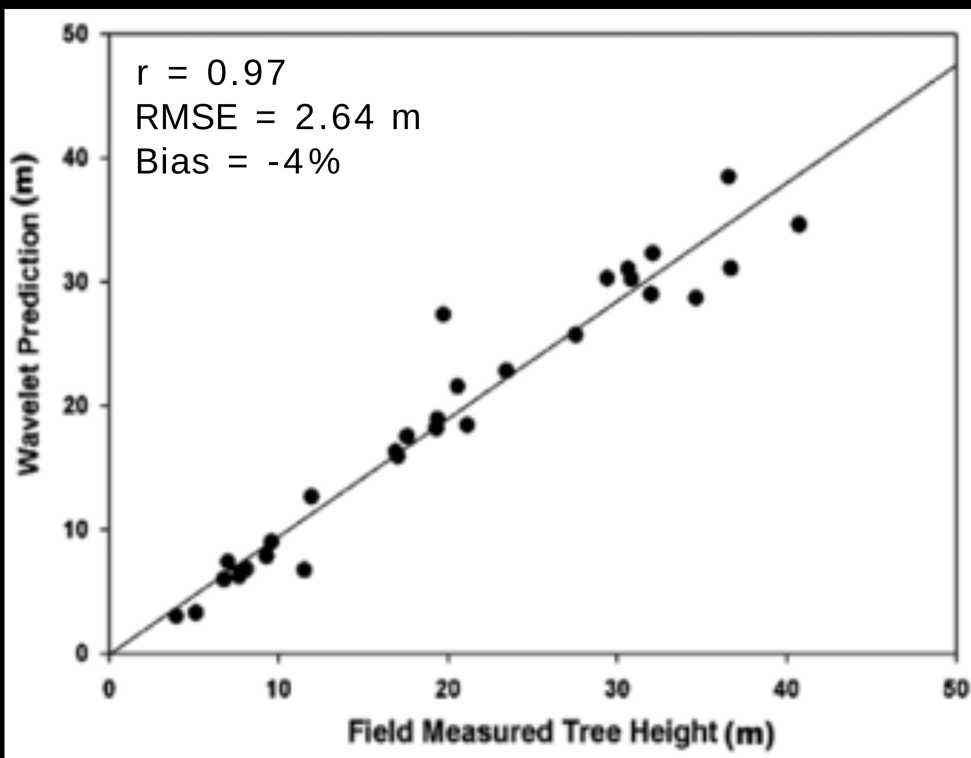
Result – Location, Crown Dia. and Ht.



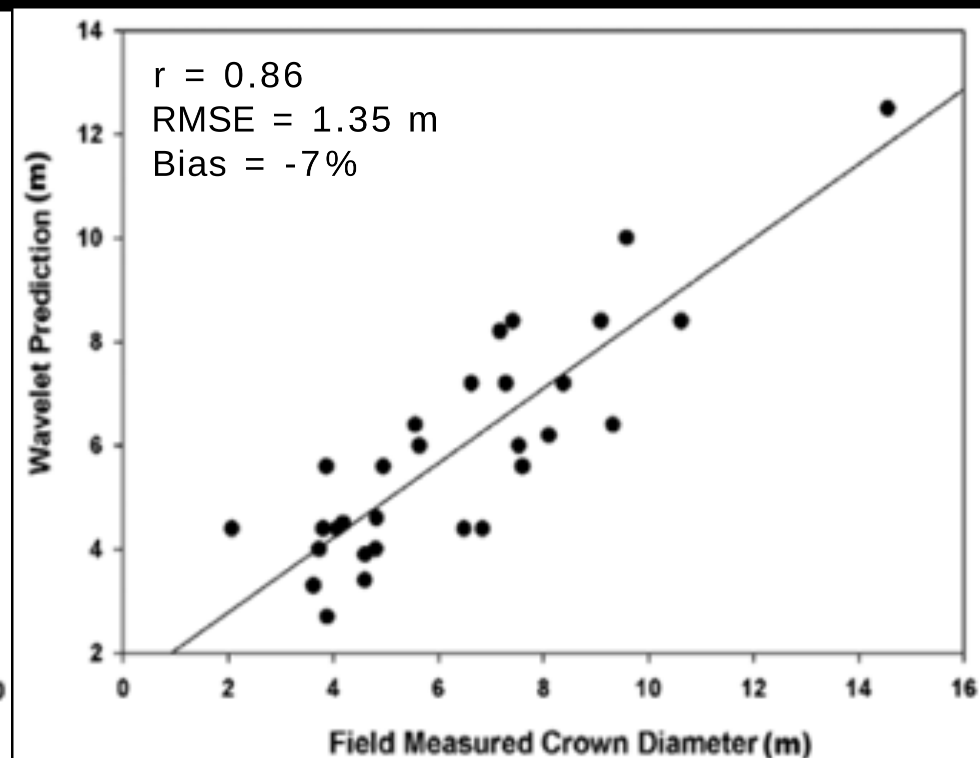
Example - Direct Measurement of Individual Trees via LiDAR (ITC)

Results: Open canopy forests (canopy cover >50%)

Tree Height



Tree Crown Dia.



Falkowski, M.J., et al. 2006. Automated estimation of individual conifer tree height and crown diameter via Two-dimensional spatial wavelet analysis of lidar data, *Canadian Journal of Remote Sensing*, Vol. 32, No. 1, pp. 153-161.

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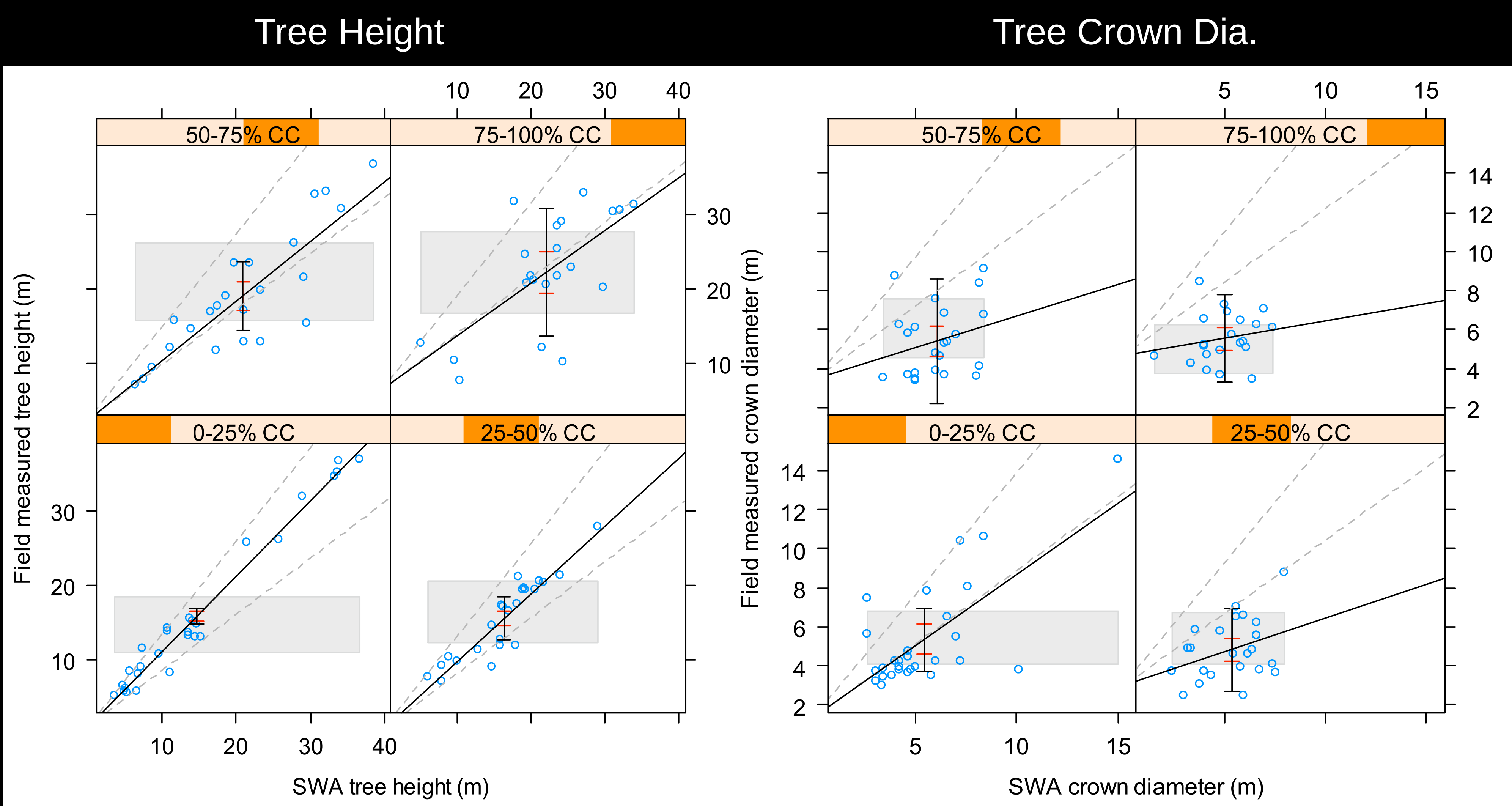
Example - Direct Measurement of Individual Trees via LiDAR (ITC)

Results: All canopy conditions (canopy cover 0 - 100%)



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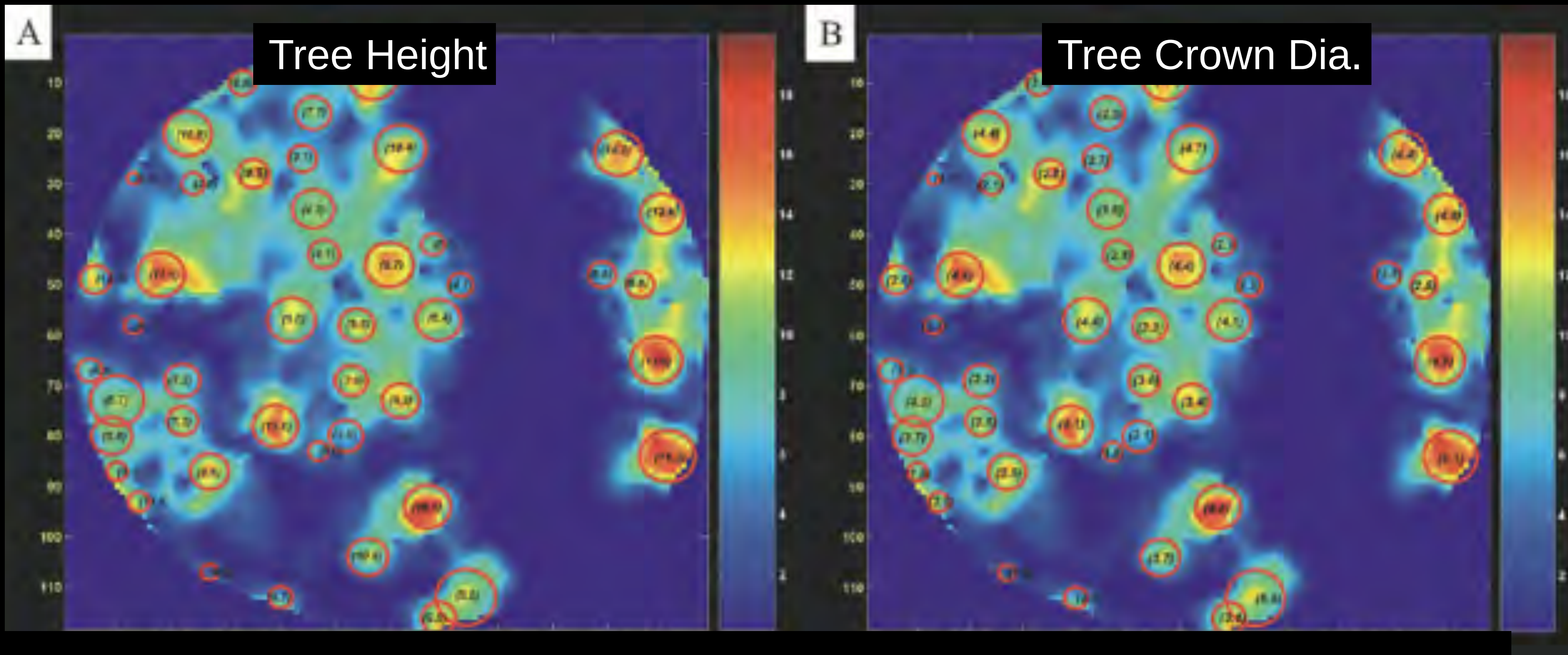

- What do we have? How much do we have? How is it arranged? Future conditions?

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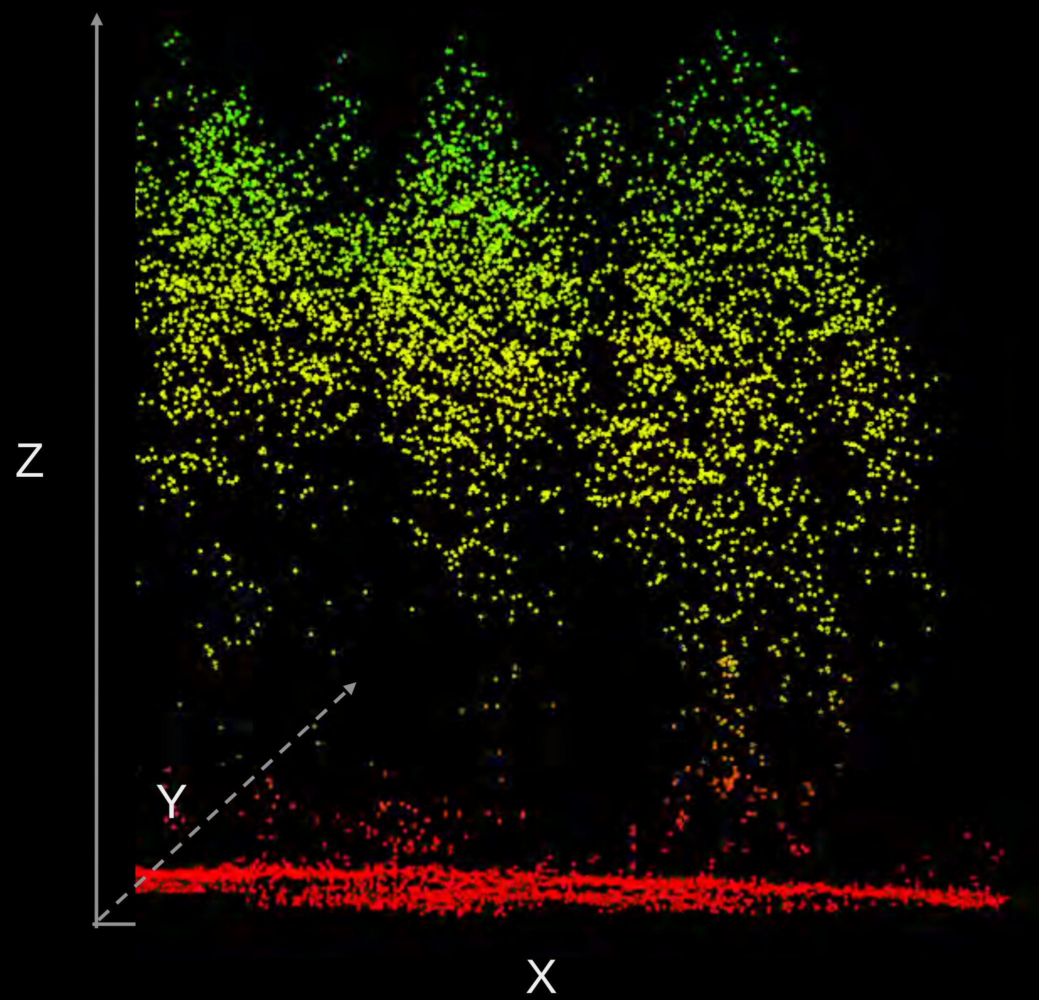
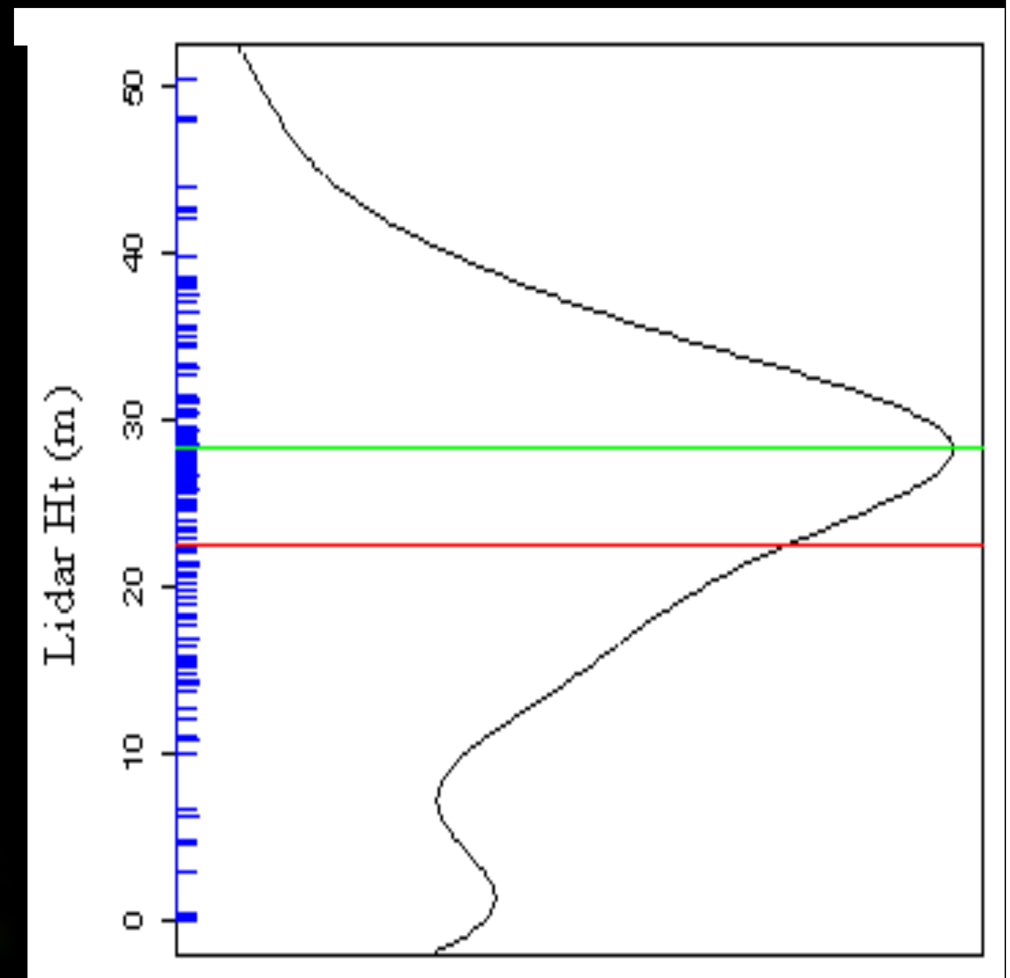
Supporting Operational Forest Inventory with RS

Plot and Stand Inventories (Area Based Approach)

Plot-level Height distributions





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Supporting Operational Forest Inventory with RS

Plot-level Height distributions are indicative of coincident forest structure

Common LiDAR-Derived Vegetation Metrics

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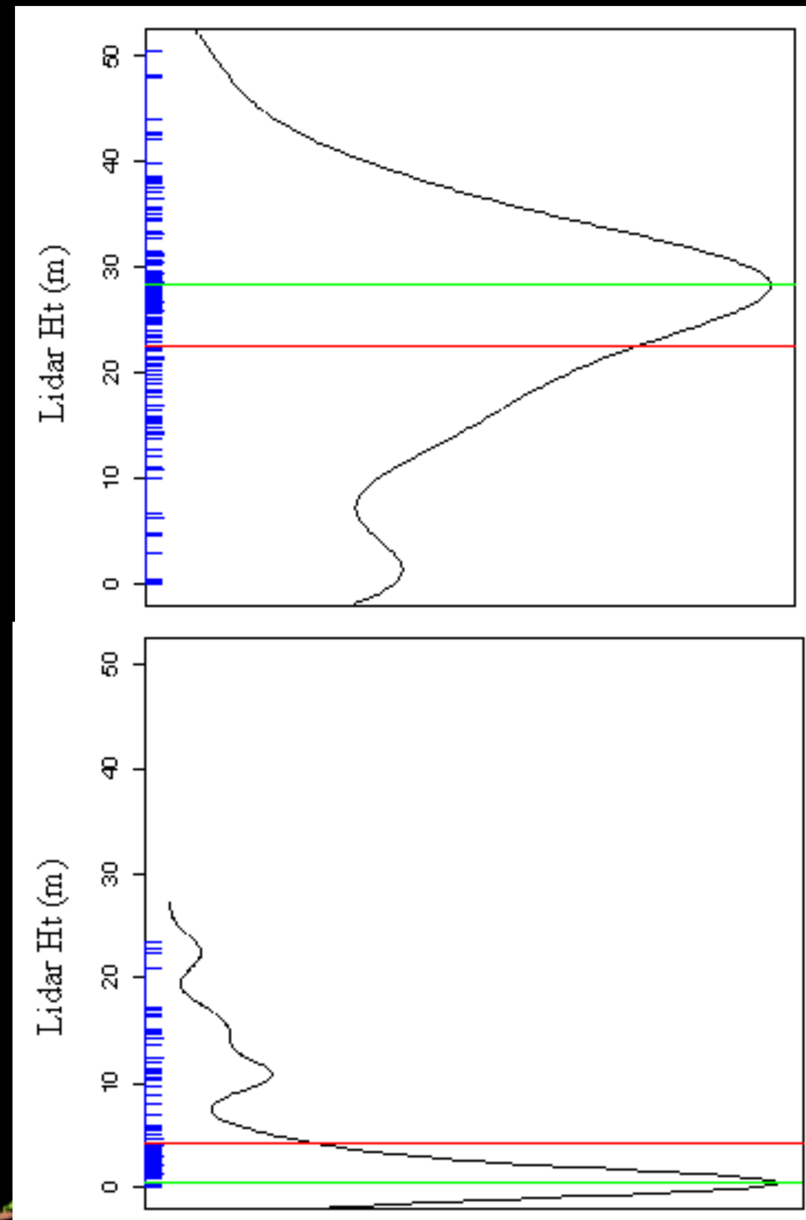
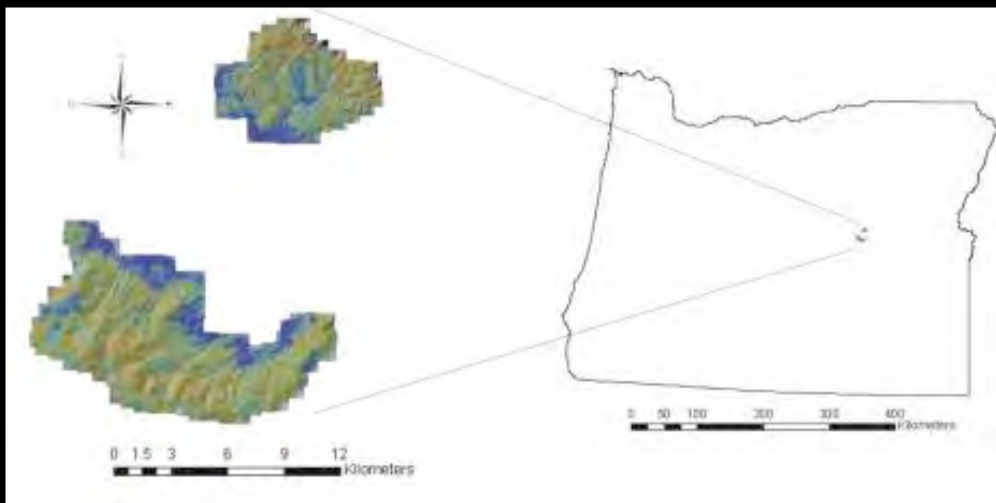


Supporting Operational Forest Inventory with RS

Study area: Damon Project Area, Malheur N.F., John Day, OR

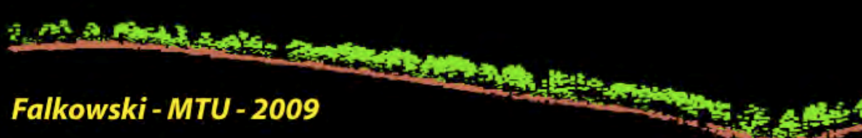


- 12,000 ha of mixed conifer forest
- Dry forest types (PIPO, PSME, with some ABGR, LAOC, PICO, POTR mixed in)

Sample Design and Data Collection:

88 Stands inventoried via variable radius plot sampling scheme

LiDAR Data: LiDAR data acquired with an ALS40 with a point density ~0.5 pulses per sq. m (considered low resolution by today's standards)



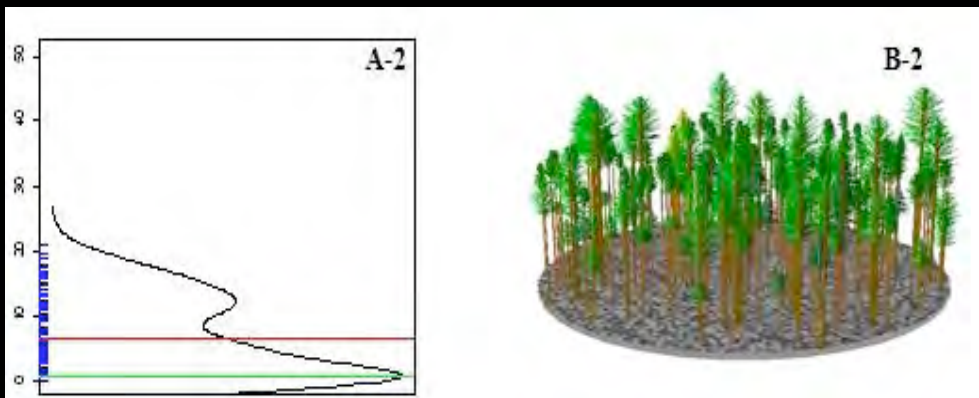
Falkowski - MTU - 2009

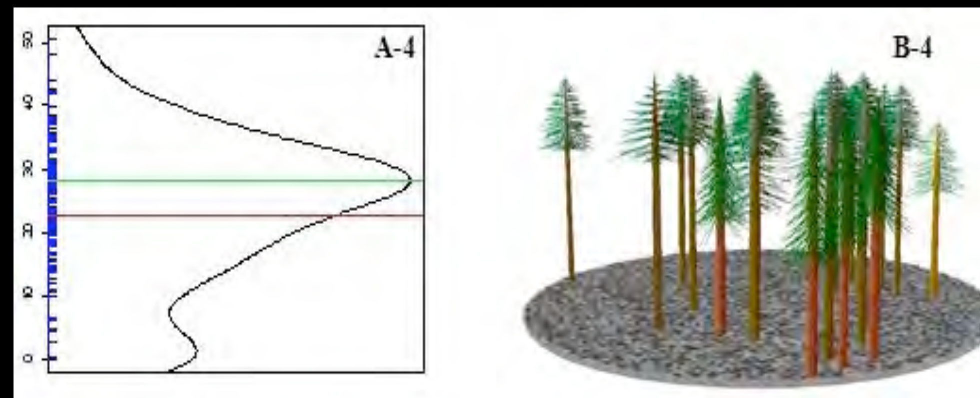
Falkowski, M.J., et al. Landscape-scale parameterization of a tree-level forest growth model: A *k*-NN imputation approach incorporating LiDAR data. Canadian Journal of Forest Research, Vol. 40, 184-199.

Example - Stand Inventories via LiDAR (ABA)

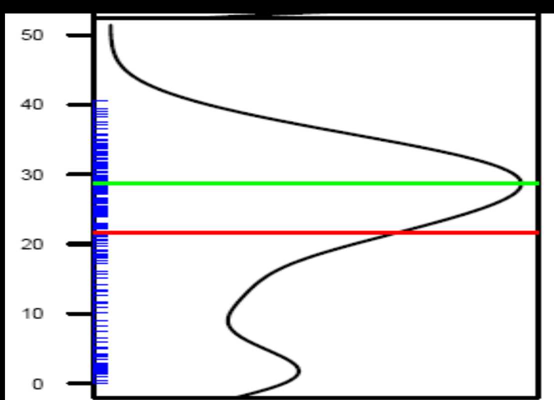
Rationale: FI Plots w/ similar LiDAR Ht. distributions should have similar tree-level forest structure

Reference Dataset (Forest inventory data and associated LiDAR data)





Target Dataset (LiDAR data at new FI plot)



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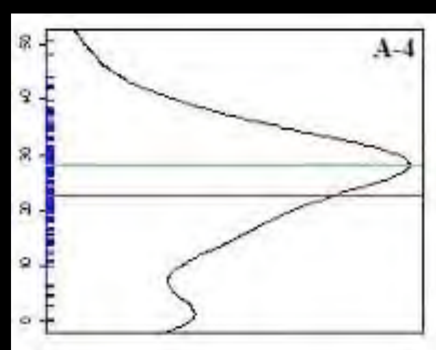
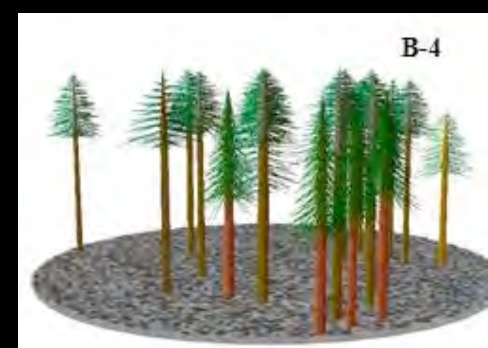
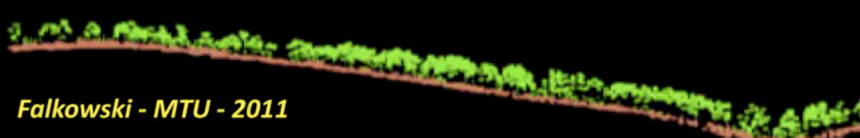


∴ Unknown Inventory Data ≈





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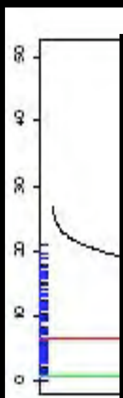
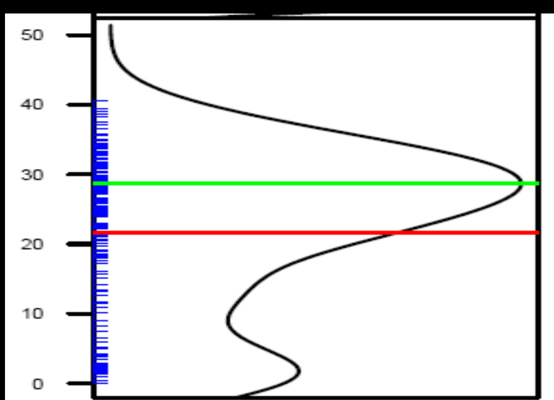


What do we have? How much do we have? How is it arranged?

What about species? Future Conditions?

Target Dataset (LiDAR data at new FI plot)



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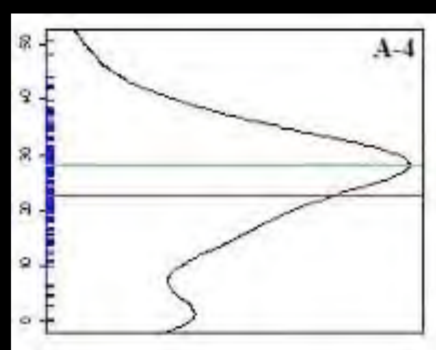
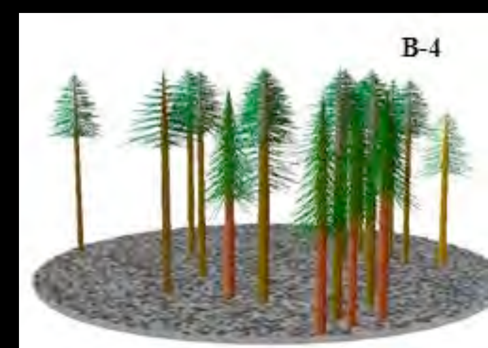


∴ Unknown Inventory Data ≈



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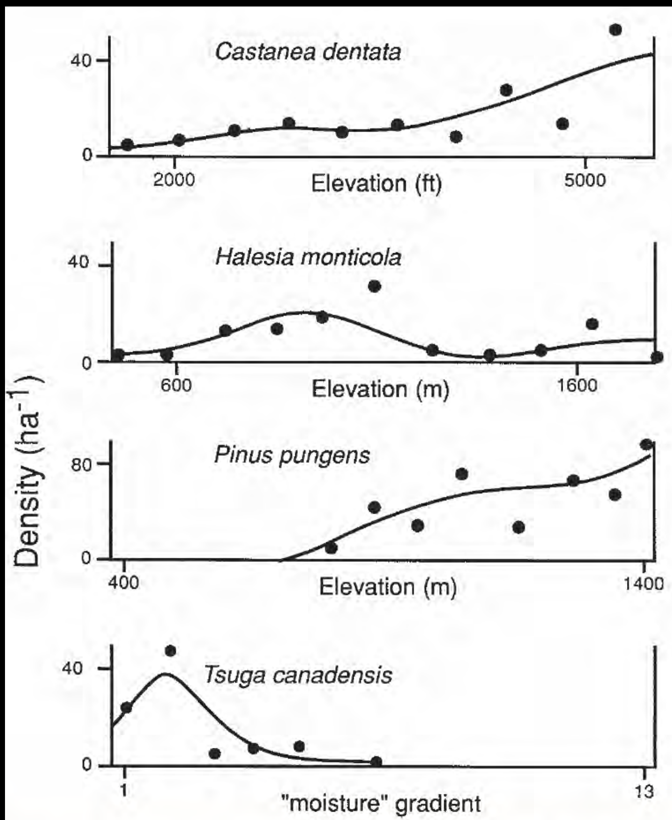
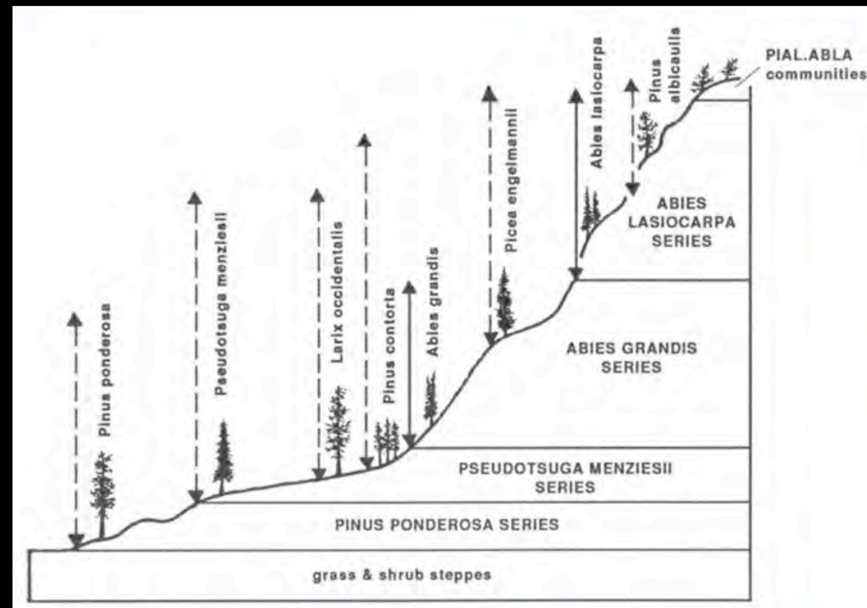
Falkowski, M.J., et al. Landscape-scale parameterization of a tree-level forest growth model: A *k*-NN imputation approach incorporating LiDAR data. Canadian Journal of Forest Research, Vol. 40, 184-199.

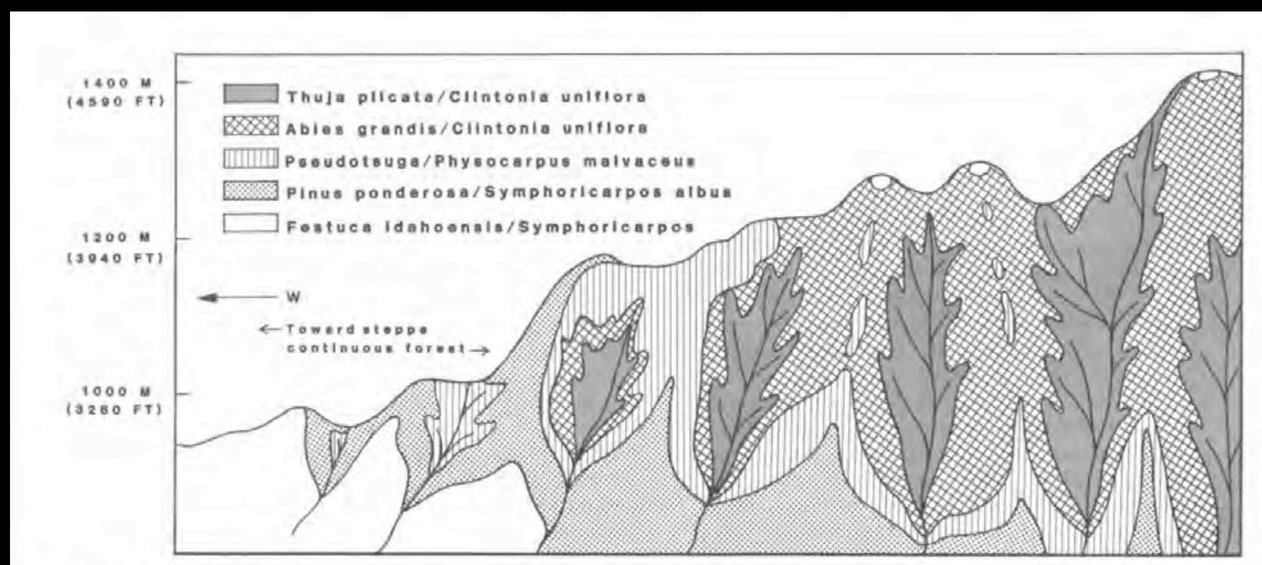
Example - Stand Inventories via LiDAR (ABA)

Biophysical gradients influence forest species composition



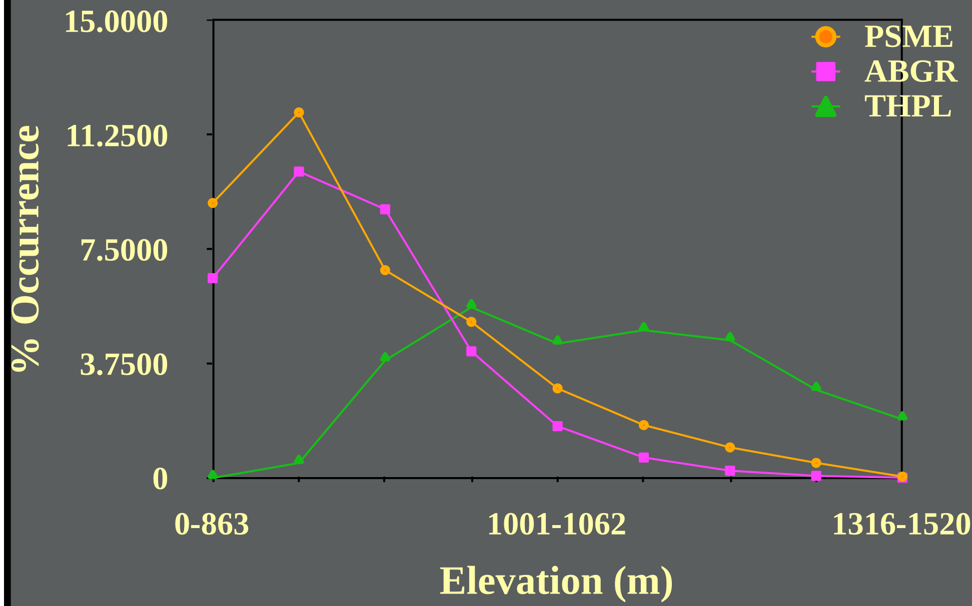
Whittaker, 1967

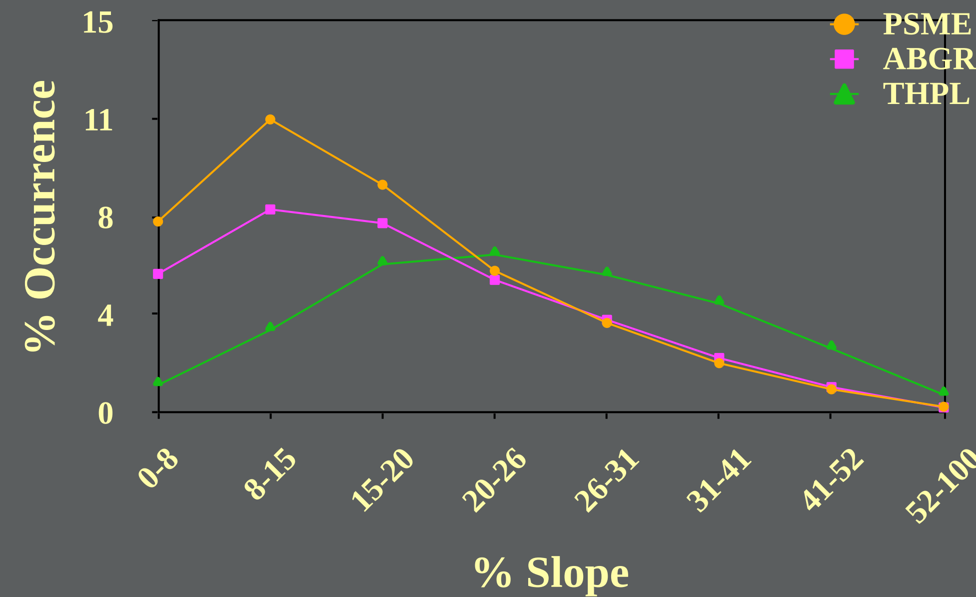


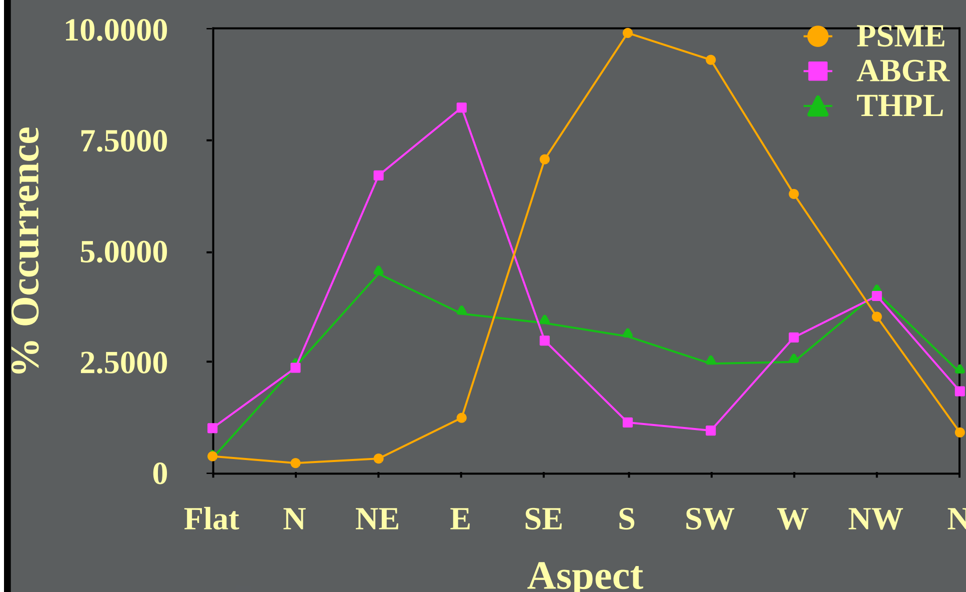


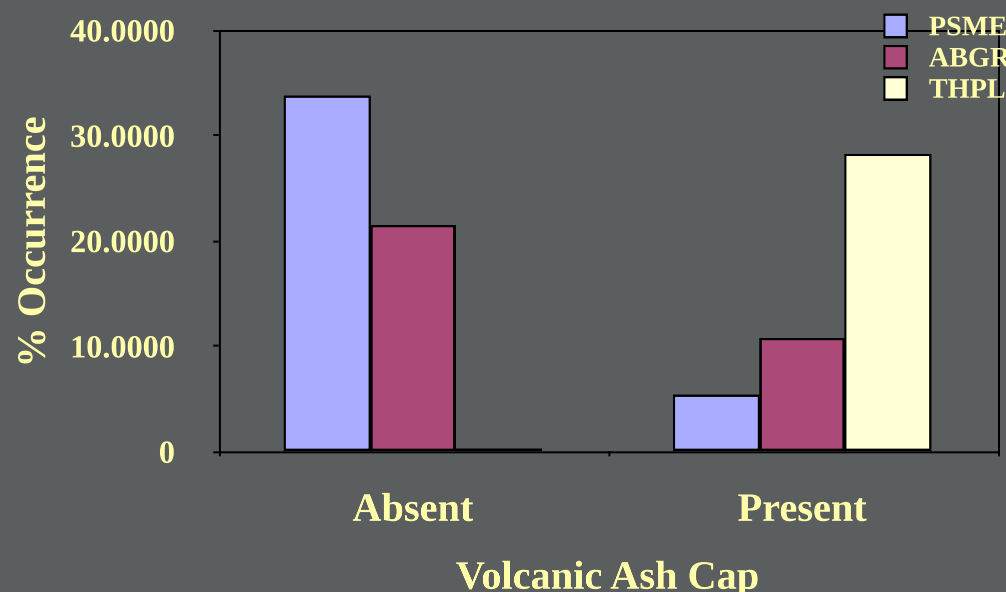
Daubenmire, 1956; 1968; 1980

Example - Stand Inventories via LiDAR (ABA)







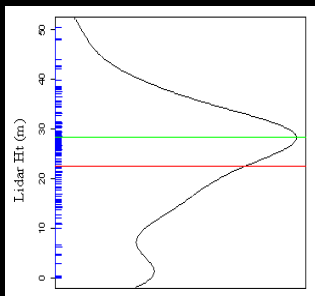


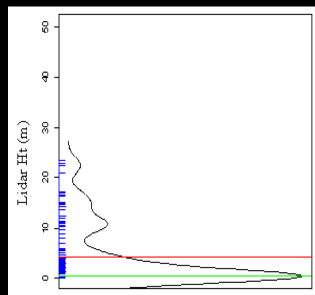
Falkowski - MTU - 2011

Falkowski, M.J., et al. 2005. Evaluating ASTER Satellite Imagery and Gradient Modeling for Characterizing Wildland Fire Fuels. *Forest Ecology and Management*, 32, 126-138.

Example - Stand Inventories via LiDAR (ABA)

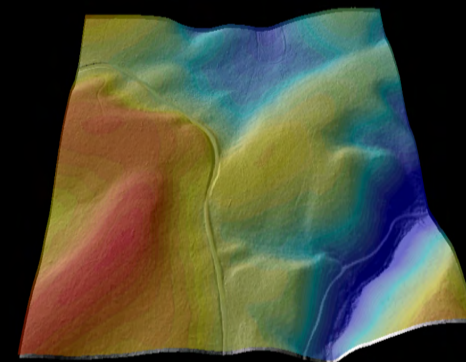
LiDAR Heights



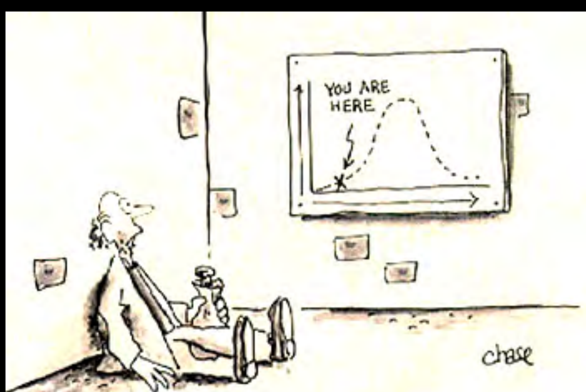


Plot Data

LiDAR DEM



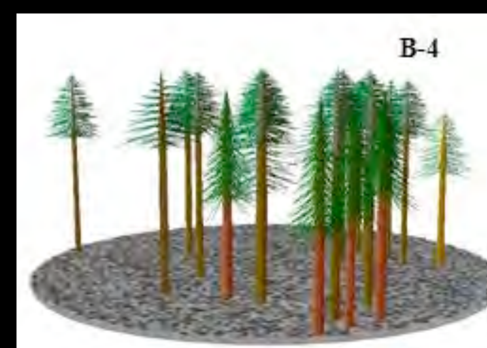
Imputation model



Unfortunately, Bill has been an outlier his entire life

Unknown Inventory Data

≈



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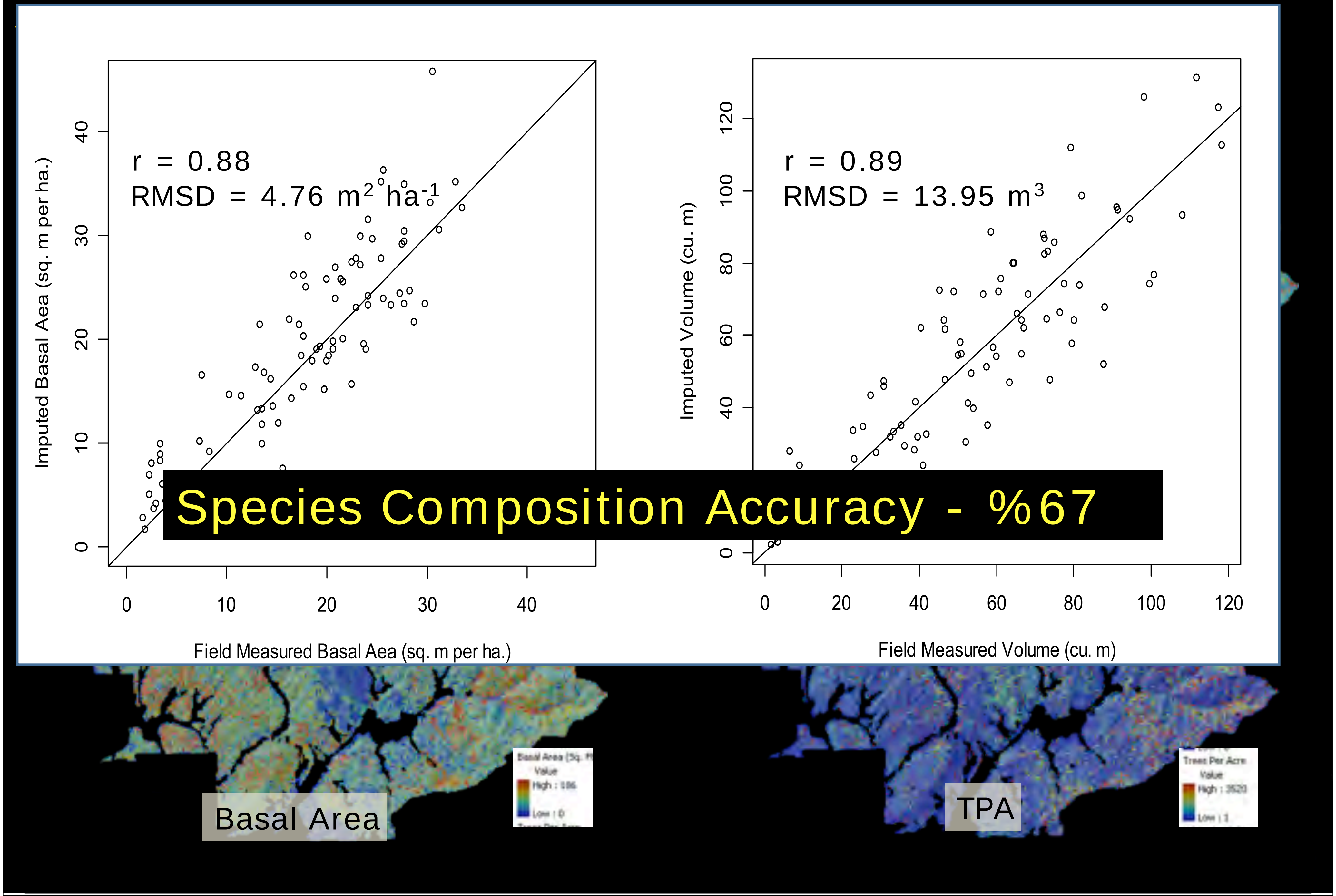
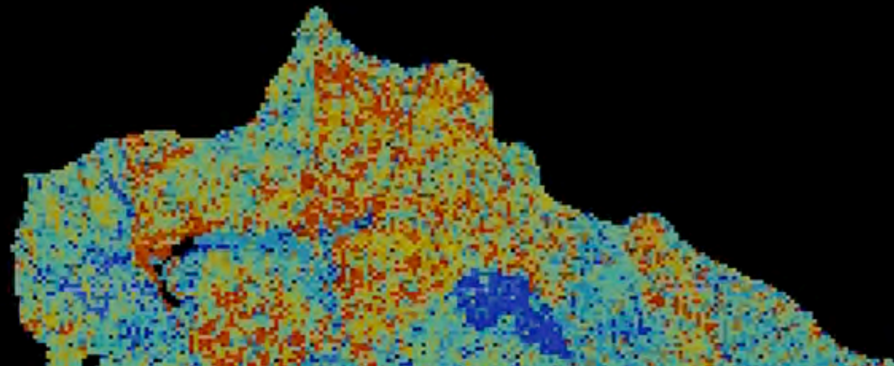
Example - Stand Inventories via LiDAR (ABA)

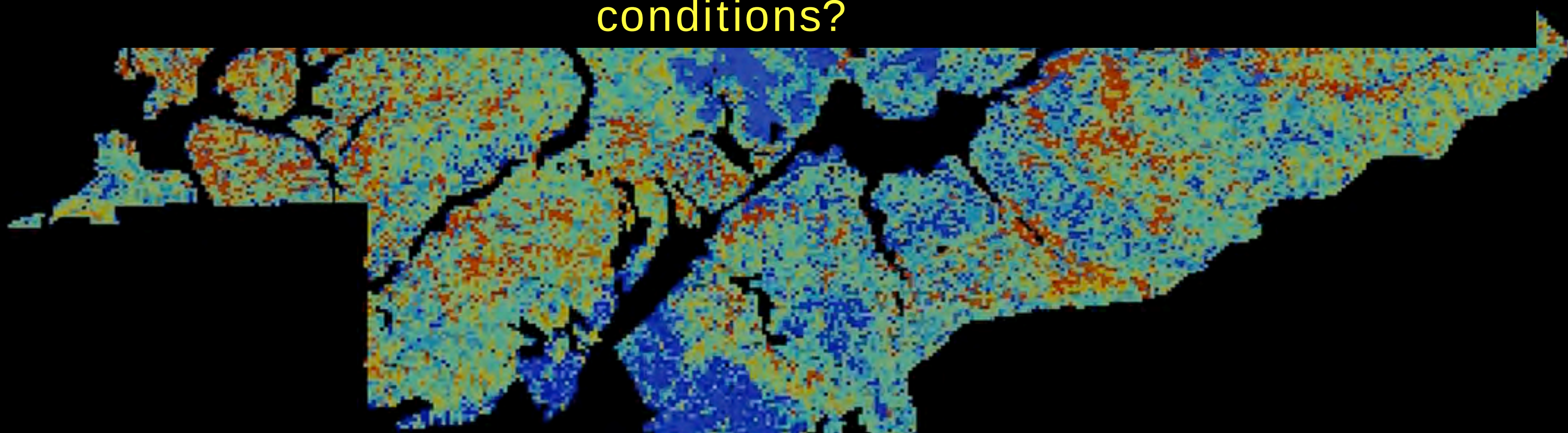


Example - Stand Inventories via LiDAR (ABA)

Application: Spatial FVS growth projections (100 Year Basal Area Projection)



What do we have? How much do we have? How is it arranged? Future conditions?



~14,800 Acre (~6,000 ha)

Falkowski, M.J., et al. Landscape-scale parameterization of a tree-level forest growth model: A *k*-NN imputation approach incorporating LiDAR data. Canadian Journal of Forest Research, Vol. 40, 184-199.

Presentation Overview

- Discuss recent developments in remote sensing of vegetation composition and structure, with a specific focus on operational forest inventories

- Demonstrate the efficacy of LiDAR remote sensing for measuring detailed forest characteristics across large spatial extents

- Introduce a series of applied research projects in forest science and ecology that utilize remotely sensed vegetation measurements (some completed and some in progress). These include:

    - The assessment of wildlife habitat suitability

    - Investigating the relationships between butterfly abundance and vegetation structure

    - LiDAR/Wildlife Ecology research on Isle Royal

Application - Assessing Wildlife Habitat Suitability

Wildlife and forest structure:

- Forest structure often determines wildlife habitat suitability

- Structural characteristics (e.g., tree height, canopy cover, shrub cover, abundance and size of snags trees, etc.) are important factors explaining 1) the presence of many wildlife species, 2) the functional use of the habitat (e.g. nesting, foraging, cover, roosting), and 3) the overall diversity of wildlife species in a particular area.

Goal:

- Use LiDAR derived estimates of forest structural parameters to generate spatially explicit predictions of habitat suitability for 4 different woodpeckers

Application - Assessing Wildlife Habitat Suitability

Habitat suitability models: Hypotheses of species-habitat relationships developed by the USFWS


HABITAT SUITABILITY INDEX MODELS:
DOWNY WOODPECKER

Fish and Wildlife Service

U.S. Department of the Interior

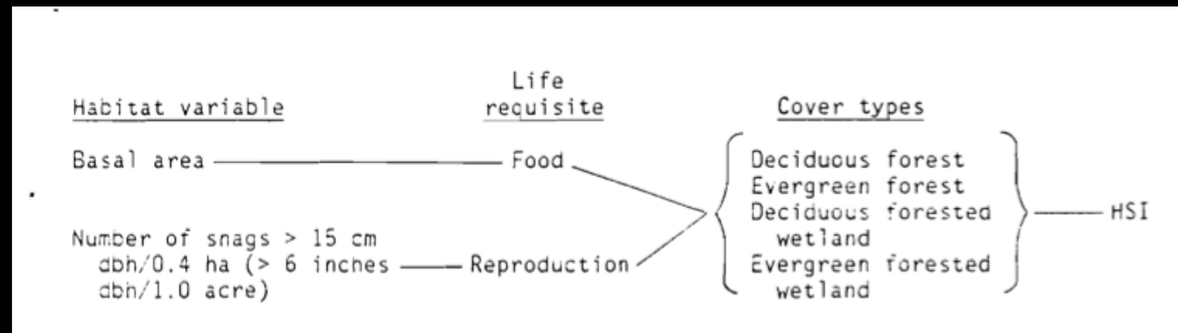
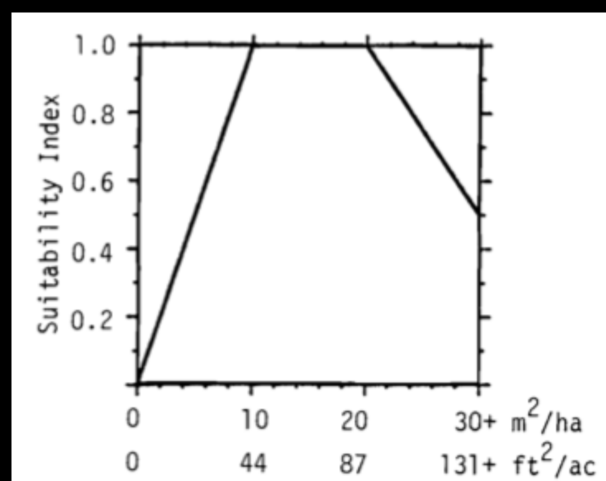


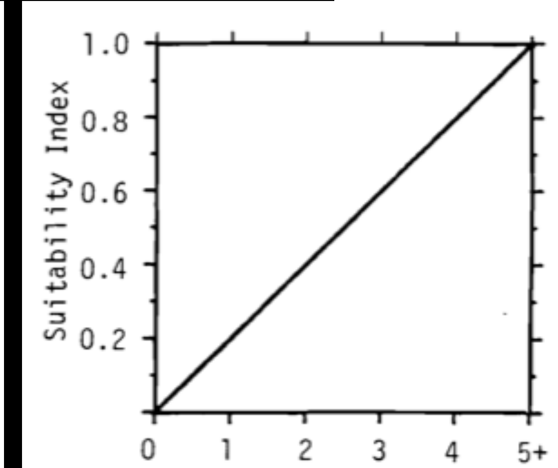
Figure 1. Relationships of habitat variables, life requisites, and cover types in the downy woodpecker model.

Basal Area

Snag Density

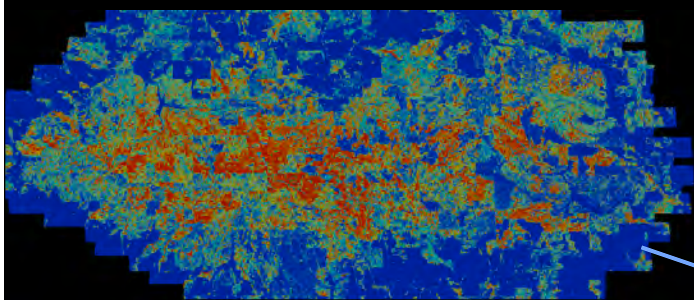
Number of snags > 15 cm dbh/0.4 ha (> 6 inches dbh/1.0 acre).



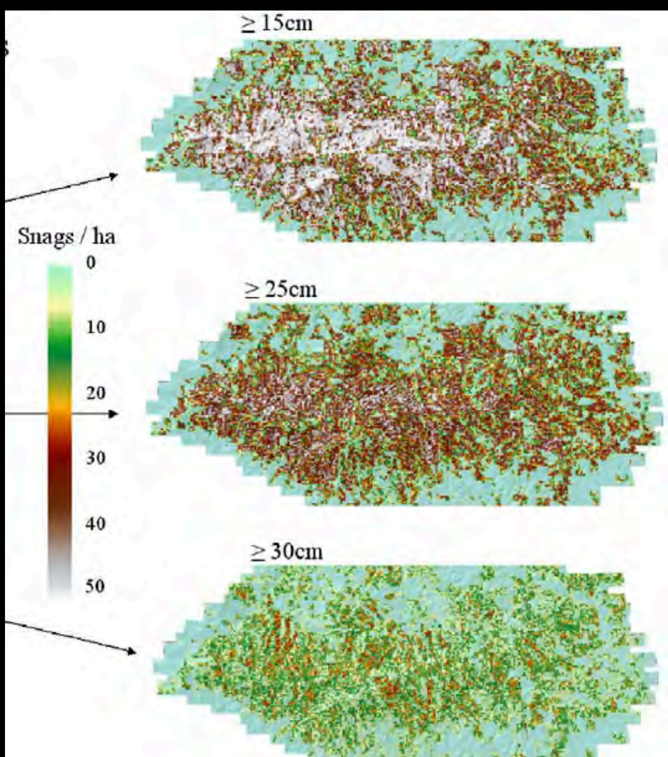


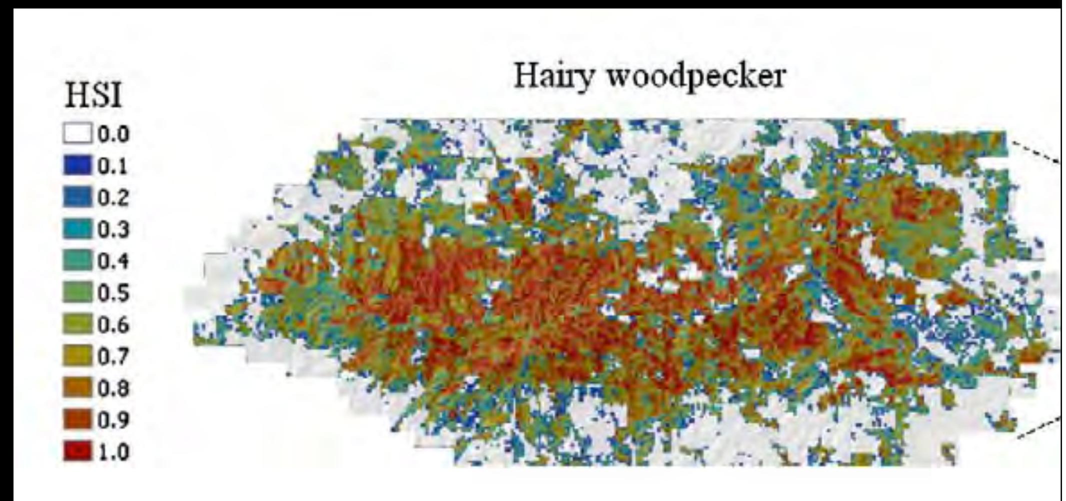
Application - Assessing Wildlife Habitat Suitability

LiDAR-Derived Basal Area



LiDAR-Derived Snag Density

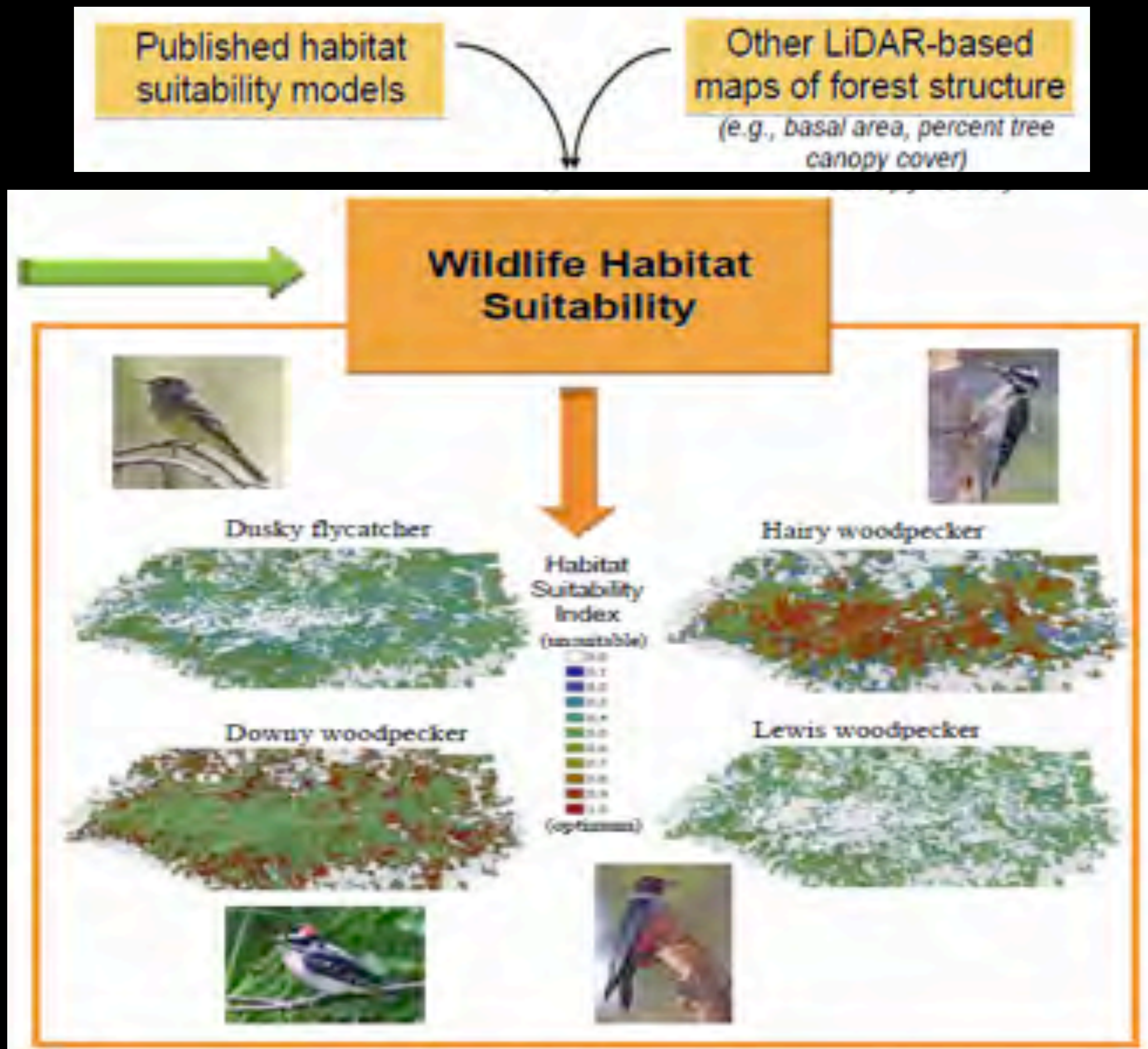




Downy Woodpecker

Martinuzzi, S., Vierling, L.A., Gould, W.A., Falkowski, M.J., Evans, J.S., Hudak, A.T., and Vierling, K.T. 2009. Mapping snags and understory shrubs for a LiDAR-based assessment of wildlife habitat suitability. Remote Sensing Environment. 113(12):2533-2546

Application - Assessing Wildlife Habitat Suitability



Martinuzzi, S., Vierling, L.A., Gould, W.A., Falkowski, M.J., Evans, J.S., Hudak, A.T., and Vierling, K.T. 2009. Mapping snags and understory shrubs for a LiDAR-based assessment of wildlife habitat suitability. Remote Sensing Environment. 113(12):2533-2546

Conclusions

- Novel remote sensing systems with high spatial fidelity and increased sensitivity to three-dimensional vegetation structure can characterize vegetation structure and composition at unprecedented levels of detail and accuracy... across very large spatial extents.

- Vegetation composition and structure data derived from such sensors can be used to answer a variety of applied questions in both forestry and ecology.

- Applications include supporting operational forest inventory and assessment, conducting wildlife habitat suitability assessments, and characterizing relationships between organisms (birds, moose, butterflies, etc) and vegetation characteristics.

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The End – Thanks! Questions?

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Special thanks to:

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Field assistants: Jen Clawson, Tessa Jones, Arjan Meddens, Kris Poncek, Curtis Kvamme, K.C. Murdock, Jacob Young, Julius DeWald

Industry Partners:

The Cost of LiDAR

rich5/jof-forestry/jof-forestry/jof00211/jof2643d11a | phillipa | S=10 | 12/22/10 | 10:45 | 4/Color Fig: 2 | doi: | artno: JF-10-021

A Comparison of Accuracy and Cost of Light Detection and Ranging versus Stand Exam Data for Landscape Management on the Malheur National Forest

Susan Hummel, A[redacted] Hudak, E[redacted] Uebler, M[redacted] Falkowski, and K[redacted] Megown

Table 4. Estimated per acre cost to acquire and process LiDAR data.

Area (ac)	Damon study costs ($/ac)	Minimum costs ($/ac)	Average costs ($/ac)	Maximum costs ($/ac)
30,000	2.63	2.27	3.03	3.79
50,000	NA	1.88	2.59	3.29
70,000	NA	1.72	2.39	3.07
90,000	NA	1.63	2.29	2.95

NA, not applicable.

- Damon study costs include cost to acquire and process stand exam data across the 30,000 acre project area... plots covered 18% of the total area

- LiDAR costs include costs to acquire and process LiDAR across the 30,000 acre project area... across 100% of the total area