Bypassing Tree Growth Models to Predict Timber Harvest from Lidar
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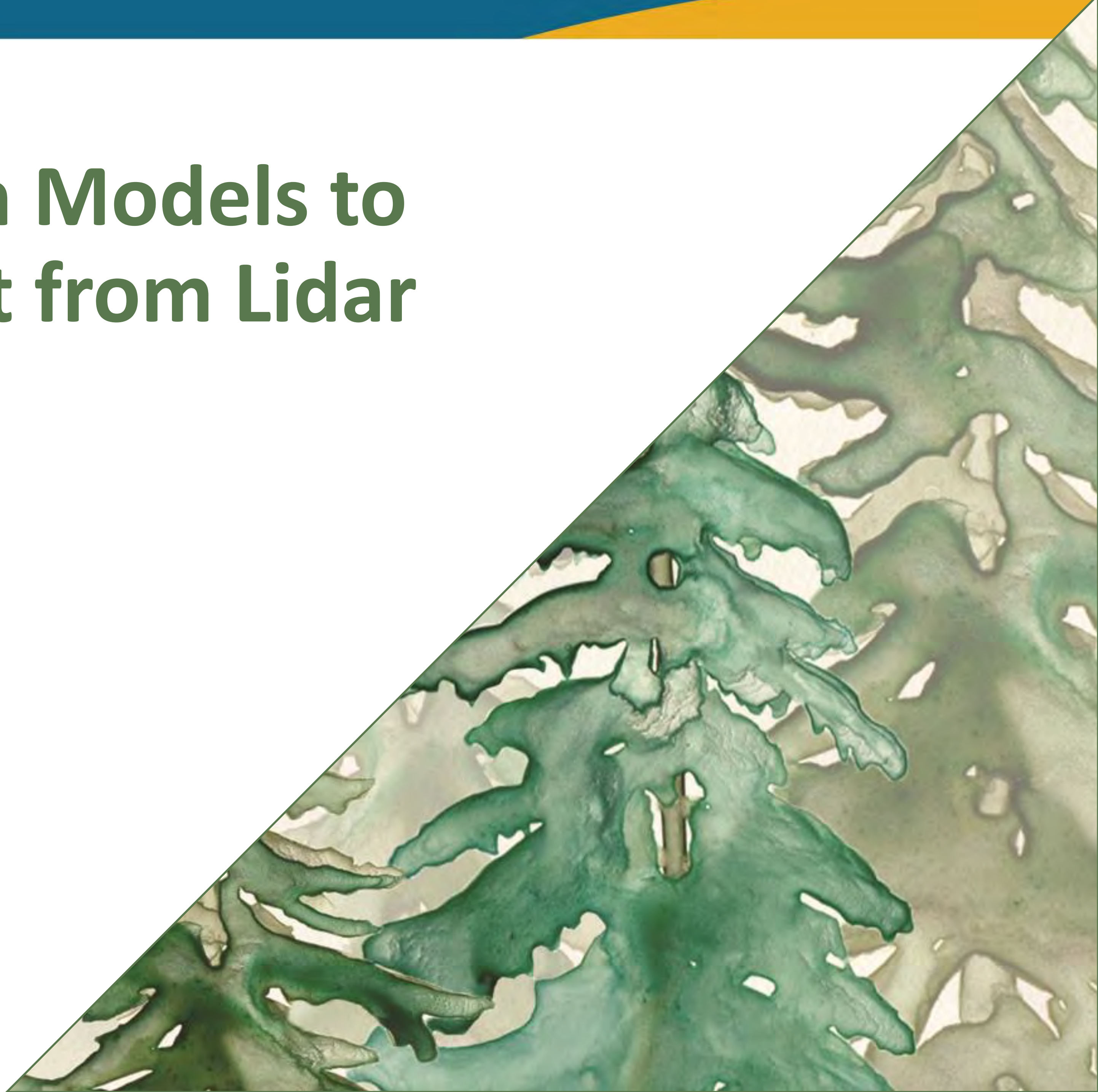
1921-2021
Celebrating 100 Years

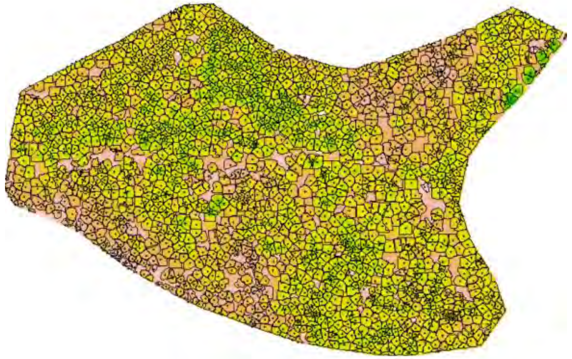


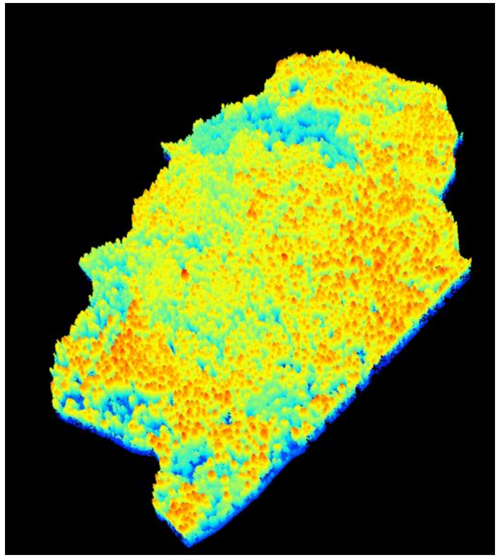
Motivation

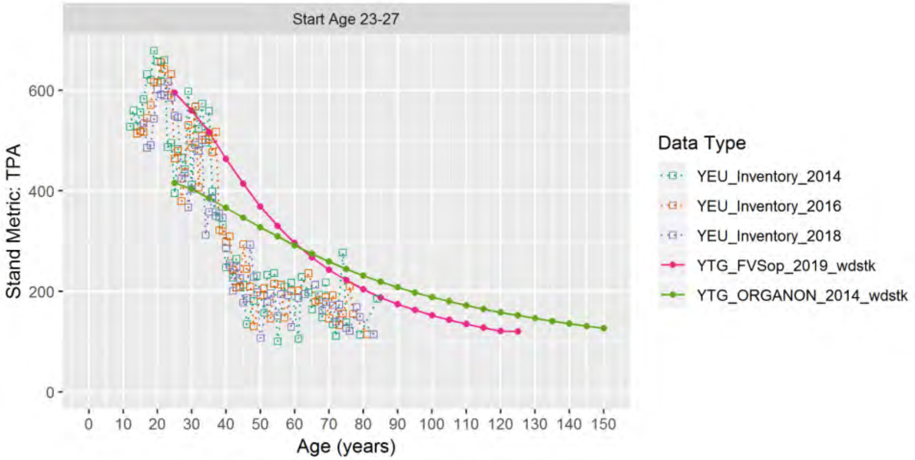
- Publicly available Lidar datasets could be a useful resource for forest managers with no access to proprietary acquisitions
- Broad coverage but limited resolution; increasingly obsolete
- Obsolescence problem exists even for organizations capable of funding their own acquisitions
- Goal: accessible, non-proprietary techniques to extend the shelf-life of Lidar data in forest management applications

Approaches to Lidar-informed growth modeling

- Forest inventory:
  - Grid metrics from detailed ground plots
  - Segmented individual tree objects
  - Combined hyperspectral imagery, Lidar
- Forest growth modeling:
  - Existing individual-based models
  - Proprietary Lidar-based growth models
  - Phenomenological models







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Focus

- Western Oregon, primarily Douglas-fir plantations
- Lidar acquisitions 2009, 2012
- Timber sale scaling data from 2014 through 2020
- Target: predict total harvest volume (gross and/or net MBF)

Rationale

- Lidar data provide reliable tree height but no direct diameter
- Height predicts volume reasonably well
- For t tree objects in a stand, estimate volume at time of acquisition:
  - $Stand\ MBF_{acq} = \sum_1^t MBF\ as\ f(zheight)$
- Timber sale scale data provide a census of volume
- For l logs in a sale, measure exact volume at the time of harvest:
  - $Stand\ MBF_{hrv} = \sum_1^l MBFlogs$
- Predict harvested MBF_{hrv} using estimated MBF_{acq}, time since acquisition
  - $Stand\ MBF_{hrv} = a * Stand\ MBF_{acq} + b * (Date_{hrv} - Date_{acq}) + c * etc.$

Datasets

- 2 ppm Lidar data from DOGAMI
  - ftp://lidar.engr.oregonstate.edu/
  - 121 stands [confidential locations]
  - 655,000 tree objects, height metrics for max, %iles, mean
  - From 50 to 150 crop tree objects per acre
- Timber sale scale data and sale GIS [confidential locations]
  - Post-harvest area mapped
  - Complete list of individual log dimensions, species
  - Sum of all log volumes is a complete census of trees at harvest

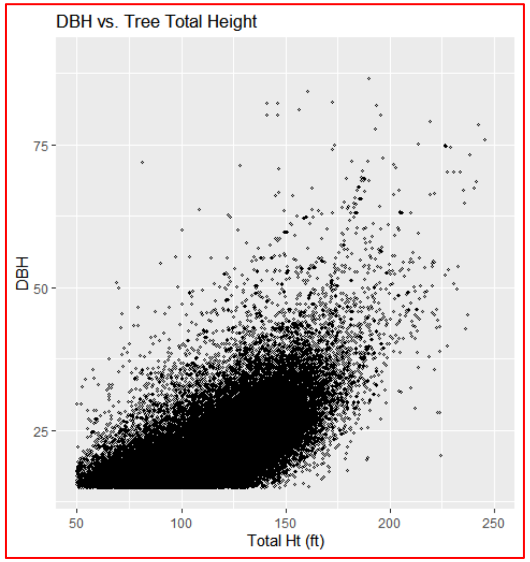
Lidar data processing

- All processing implemented in R
  - Point cloud tasks: lidR: https://github.com/Jean-Romain/lidR
  - Other spatial tasks: sf: https://r-spatial.github.io/sf/
- Segmentation using the Dalponte 2016, variable radius
- Tree object metrics: zmax, 95^{th} and 75^{th} percentile, mean

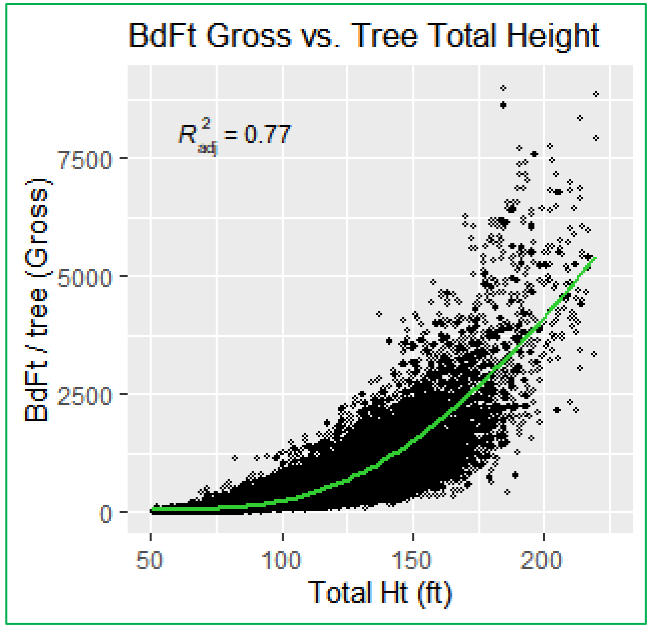
SaleNum	treeID	zmean	zmax	z75th	z95th
5221	3	93.30557	163.34	133.0100	149.9780
5221	491	73.80012	151.38	110.2800	133.5900
5221	494	40.42528	85.64	67.2375	74.6435
5221	4	99.42761	141.56	112.0875	127.8695
5221	486	94.87019	155.77	125.4650	144.2490
5221	485	115.36573	154.92	136.2600	148.6100

Volumetric model

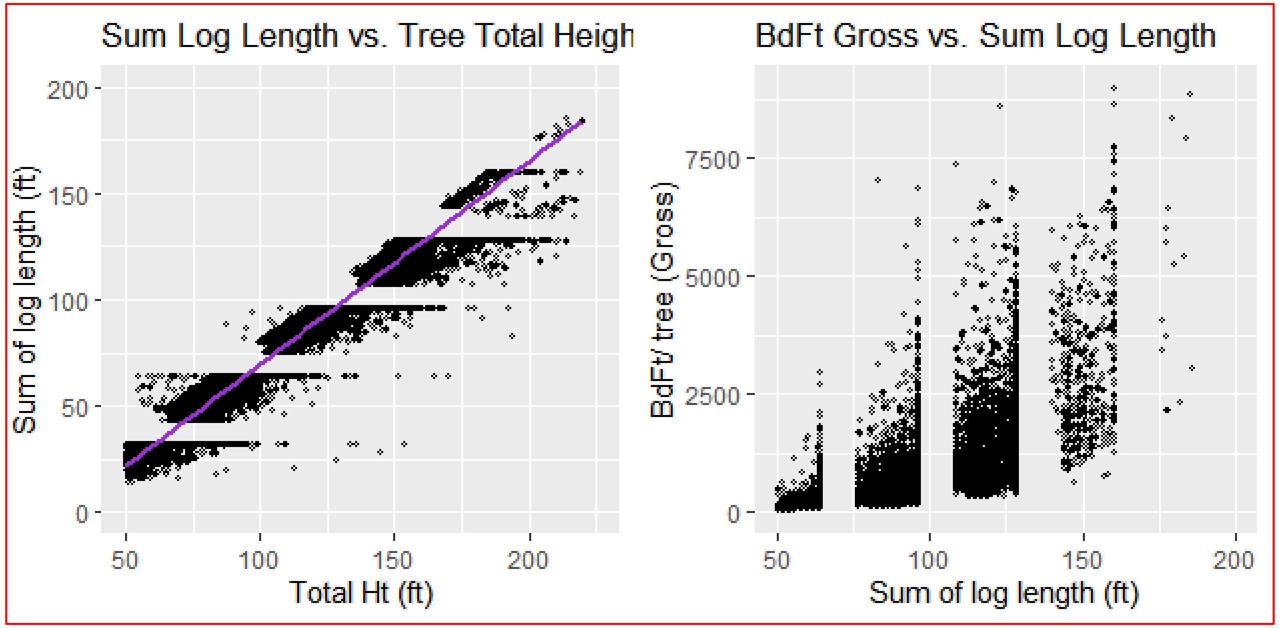
- Predict tree volume as a function of Lidar metrics
- Weak diameter, log count/length relationships to height
- Reasonable correlation of volume to total height



Tht → BdFt



Tht → Log Length → BdFt



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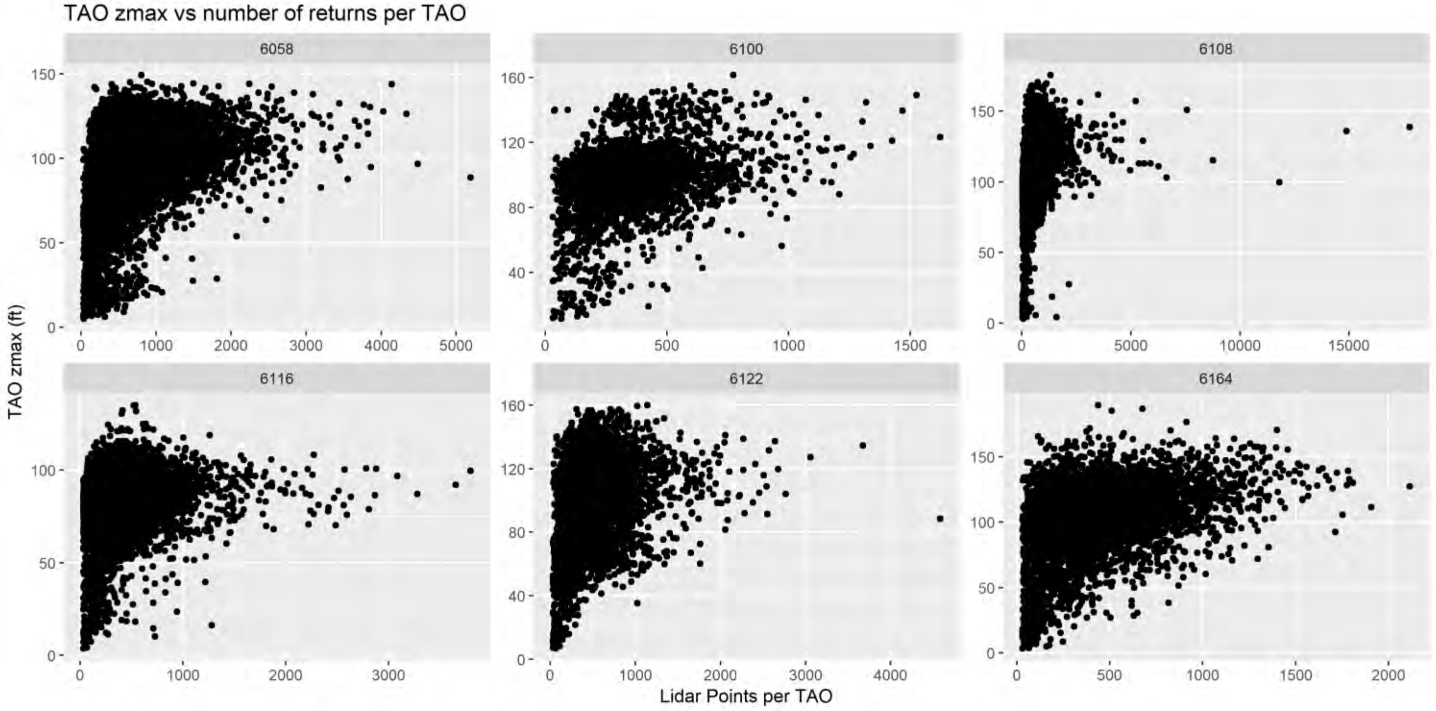
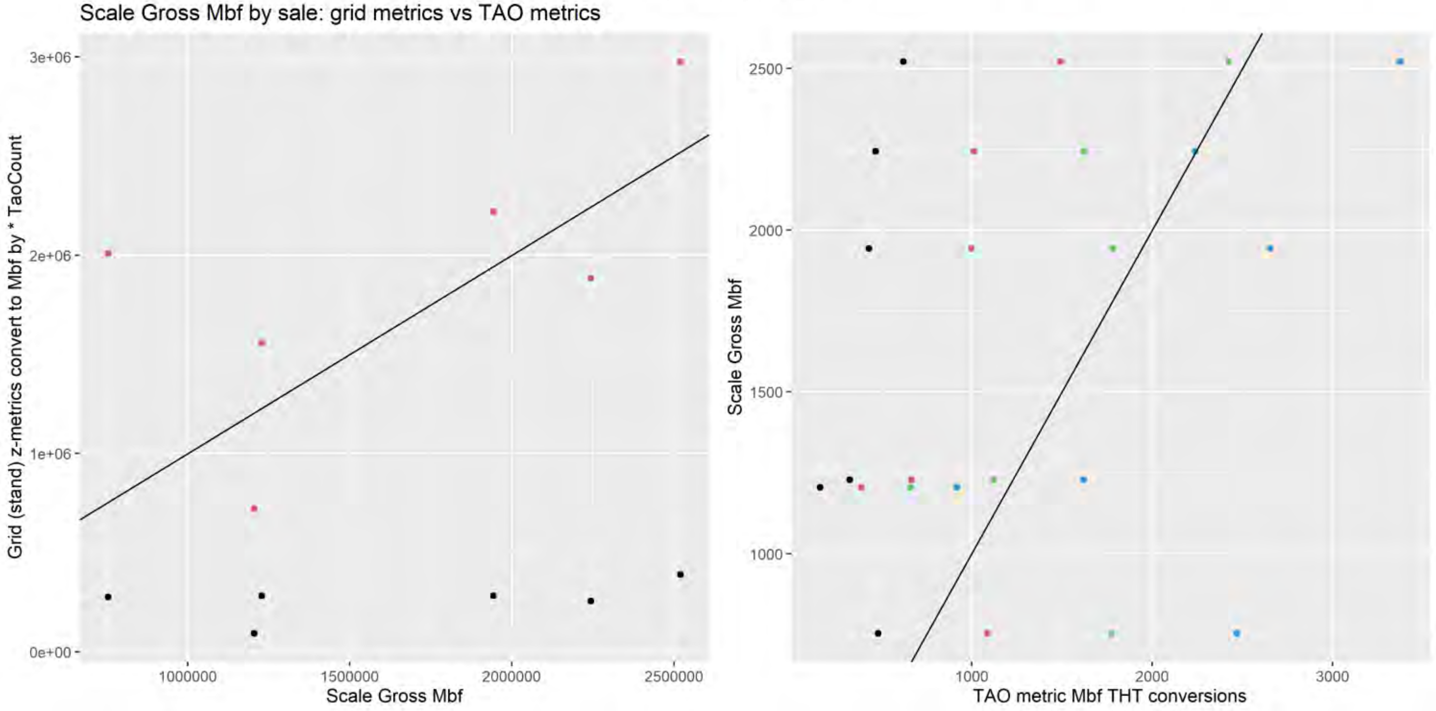
Scale v. Lidar

- Difficult to reconstruct trees from scaled logs: no reliable TPA
- Volume per log in Scribner MBF
- Most straightforward volume measurement:
  - Lidar: Σ estimated MBF over tree objects
  - Sales: Σ measured MBF over logs





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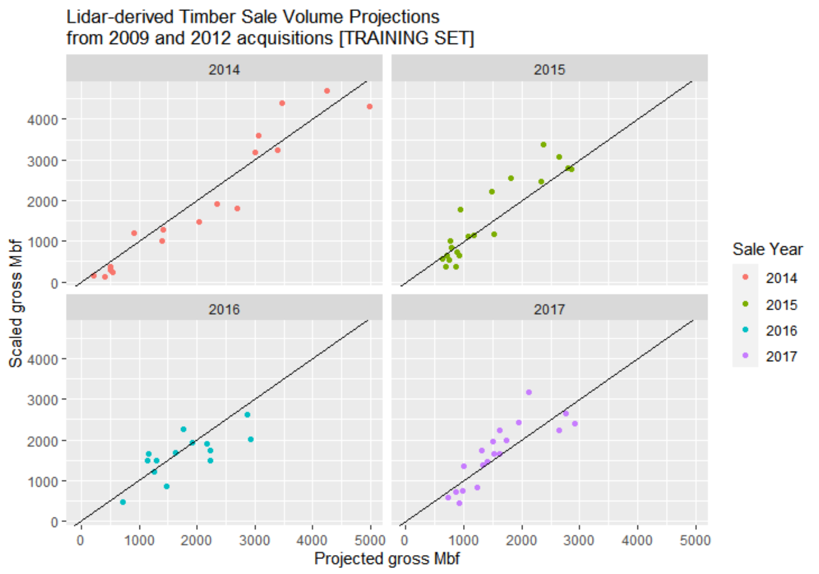
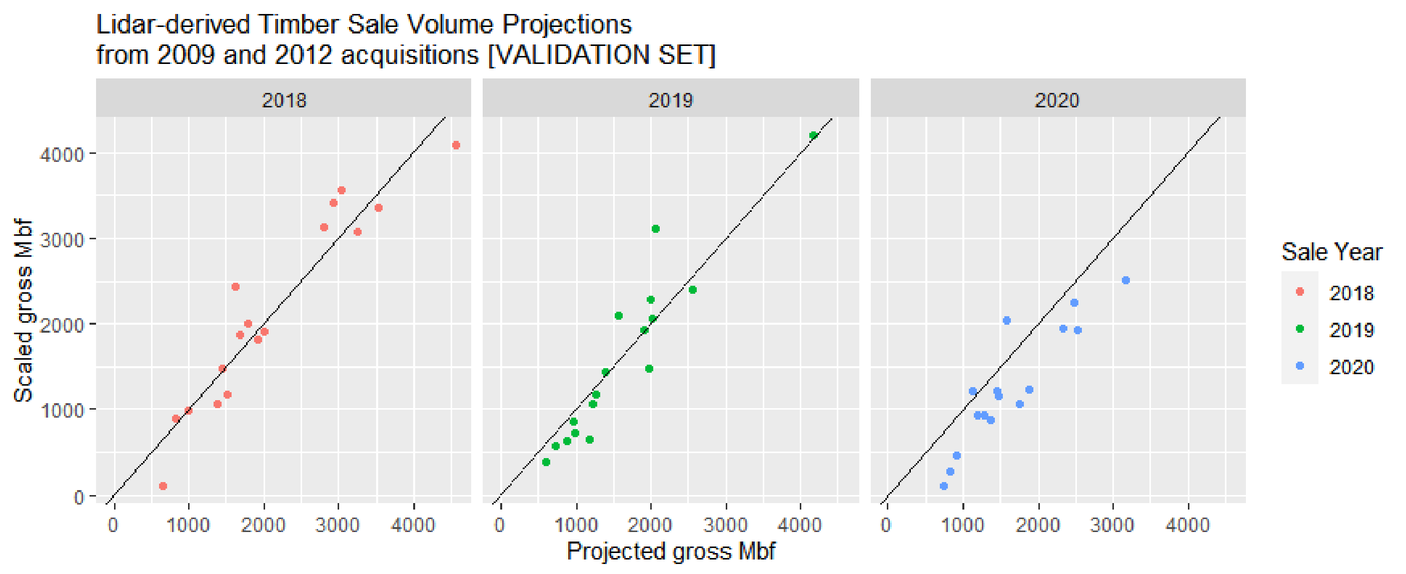
[Individual Tree] Growth Model Bypass

- Predict harvested MBF_{hrv} using estimated MBF_{acq}, time since acquisition
  1. $Stand\ MBF_{hrv} = a * Stand\ MBF_{acq} + b * \left(Date_{hrv} - Date_{acq}\right) + c * etc.$
  2. $Stand\ MBF_{hrv} = a * Stand\ MBF_{acq} + b * \left(Year_{acq}\right) + c * etc.$
  - a = estimated parameter for Lidar-derived MBF
  - b = estimated parameter for time
  - c = other potentially useful parameter(s), site index, elevation, etc.
- Model (1) with time interval receives greatest empirical support (minimum AIC value)
  - **AIC (1)** **1808.54 [$R^2 = 0.954$]**
  - AIC (1), with site index: 1810.24 [$R^2 = 0.954$] (site index parameter not significant)
  - AIC (2) 3482.35 [$R^2 = 0.954$]

Validation

- Withhold later harvests from model construction
  - Training set (2014, 2015, 2016, 2017)
  - Validation set (2018,2019, 2020)

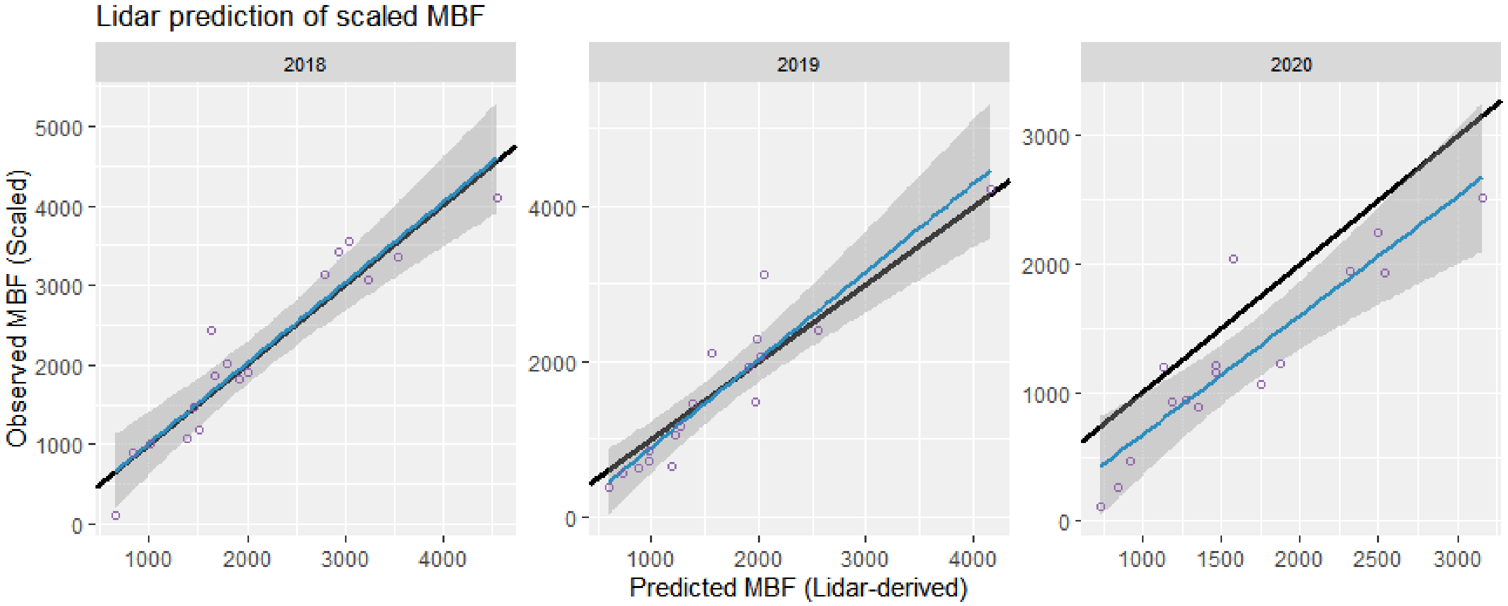




Validation

- Performance assessment in terms of bias and accuracy with linear models of observed MBF vs. predicted MBF
  - Slope not different from 1: true for all years
  - Intercept not different from 0: true for all years

Sale Year	Model Parameter (95% CI)		Goodness of Fit	
	Slope	Intercept	R^2	AIC
2018	1.01 (0.82, 1.2)	3.51 (-441, 448)	0.890	253.8
2019	1.13 (0.89, 1.36)	-225.52 (-651, 200)	0.867	253.8
2020	0.93 (0.68, 1.18)	-252.46 (-692, 187)	0.807	232.8



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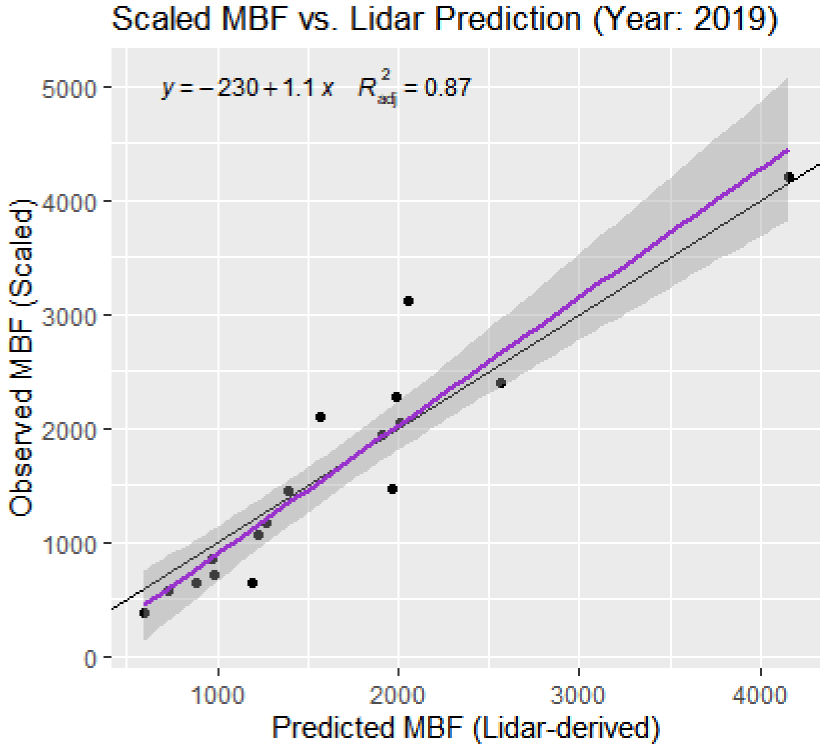
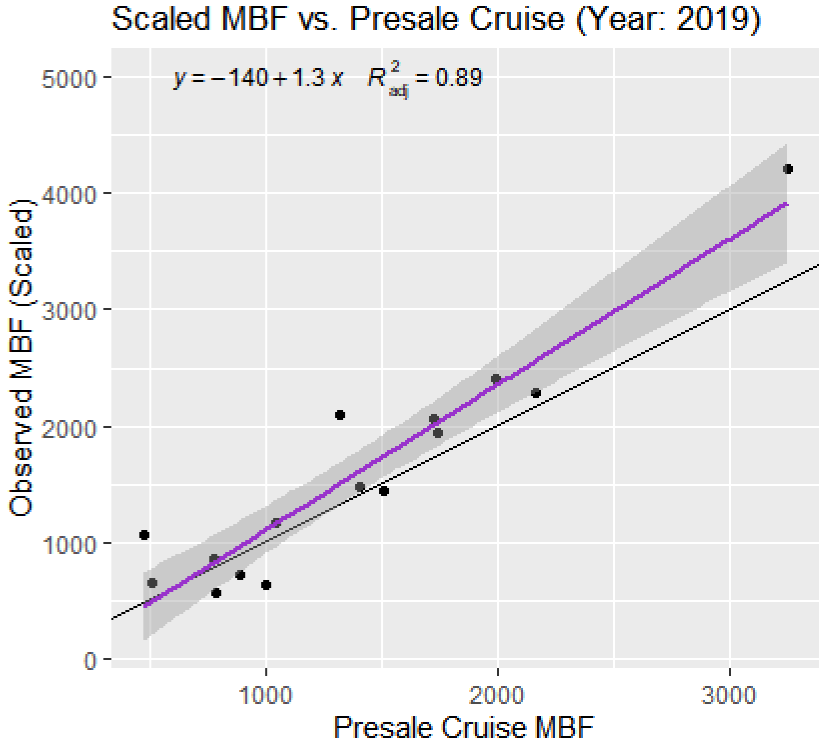
Performance vs. Presale Cruise

- Harvest prediction for 2018 through 2020 could have been made in 2017
- Compare to accuracy of corresponding pre-sale cruises
- Example: 2019





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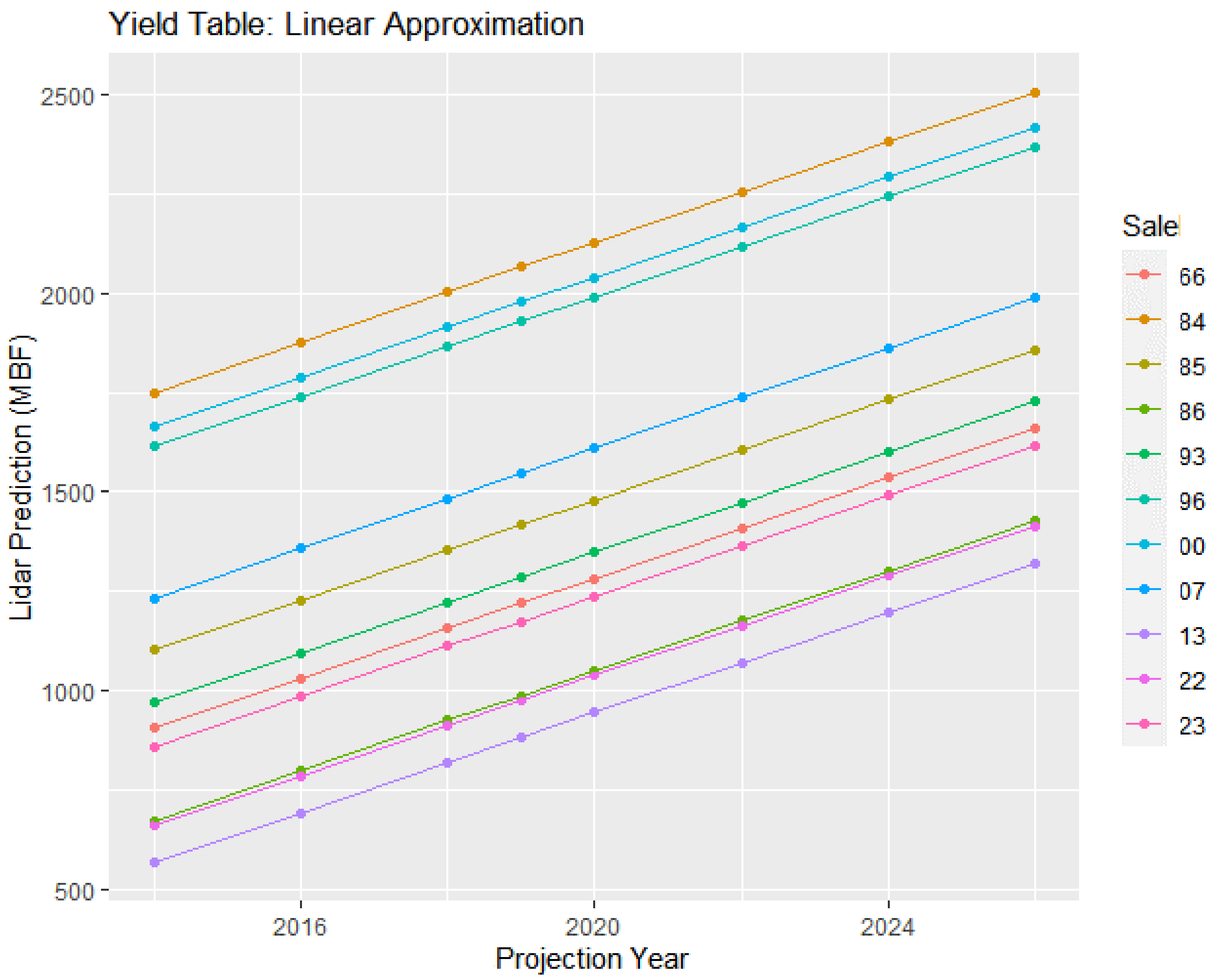
Yield Tables

- Linear yield approximation
- Non-linear regression more realistic
- Suggestion of (over-projection) bias by 2020—departure from linear approximation?



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Early Practical Uses

- Cruise flagging and check cruise prioritization
- Detect inventory anomalies
- Inventory effort allocation
- Post-wildfire loss estimation
- Due diligence, timberland appraisal

Next Steps

- Unresolved:
  - How to work with thinning, partial harvests, or other complex silviculture
  - How far forward reasonable predictions are sustained
  - Log size distribution – could solve with similar methods
  - Geographic relevance – likely needs ‘variants’
  - Nonlinear least squares regression function appropriate for yield tables
  - Performance relative to individual-based projections from contemporary data
- Combined with other methods:
  - Species composition – address with field sampling or machine learning
- Unsuited for:
  - Realistic tree lists – may not be possible with 2 aerial ppm Lidar
  - Long-term predictive yield modeling – insufficient time since first acquisitions

END