% see Manuri 2017; Knapp et al 2018 Table 1 for lidar metric definitions.

\section{Discussion}

Logical: It is desirable to develop models that have clear biological interpretation; the variables pools arrived at via our approach can be reasonably interpreted to have direct analogs to ecologically significant variables. Lidar height, density, and distribution metrics are analogous to variables used in aerial stand volume tables that are used in forest inventory. Also, the inclusion of the vertical distribution variable, in our case height skewness, may help the model to account for intermediate tree crown in the over-story and suppressed trees in the understory \cite{Li et al 2008}. Close agreement in magnitude between RMSE and RMSEcrossval suggests that the model is not overfit and suitable for generalization.

Issues influenced the analysis of this data set: 1) the potential for multicollinearity when a large number of independent variables are involved; 2) the choice of variables for, and the comprehensibility of, regression equations.

Latent variables – overfitting may occur, independent (validation) data used to determine the optimal number of latent variables (?? Maybe Naesset e tal 2005). Close agreement in magnitude between RMSE and RMSEcrossval suggests that the model is not overfit and suitable for generalization.

Regional Lit comparison: Lidar based regional models have been developed to estimate biomass in boreal, temperate deciduous, temperate coniferous, and tropical forests \cite{Naesset 2004, Nelson 2004,Lefsky 2005,Naesset 2008, Asner 2012}.

Lefsky et al. (2002) were successful at developing a unified equation for predicting aboveground biomass in multiple biomes (Temperate Deciduous Broadleaf, Temperate Coniferous Needleleaf, Boreal Coniferous Needleleaf), there was no replication in each biome. When all sites are considered together, mean height squared is the best overall predictor of above-ground biomass. (Lefsky et al 2002)

Lefsky et al 2005 A we were able to look at 5 sites within the Temperate Coniferous Needleleaf biome, using sites with varying environment and composition. They created equations that predicted stand structure variables (e.g. aboveground biomass and LAI) across an environmental and compositional gradient. Aboveground biomass were consistently predictable along a productivity and species composition gradient from the true fir forests of Mt. Rainier to Ponderosa pine forests at Metolius, and at the high productivity forests of Cascade Head, the coast range, and H.J. Andrews (Lefsky et al 2005 A).

(Lefsky et al 2005 A and 2002) offer a regional confirmation of the continental-scale hypothesis offered in Lefsky et al. (2002), in which the geographic generality of an equation predicting aboveground biomass was demonstrated.

Lefsky et al 2005 A found broad consistency in lidar-stand structure relationship over this region, and a relative lack of importance of environmental conditions (Lefsky et al 2005 A).

While the range of environmental conditions and composition examined in this paper is narrower than in Lefsky et al. (2002), the number of site locations examined is larger, and thus confirms the result for the Pacific Northwest region of the USA (Lefsky et al 2005 A).

Given this wide range of conditions, and the earlier results of Lefsky et al. (2002 and 2005 A), it is reasonable to ask if, in forests dominated by coniferous species, tree architecture is constrained to the point where a unified relationship between lidar measurements and stand structure might exist for these forests generally. In existing studies of this type (Lefsky et al. 2002 and 2005 A) there has been an attempt to have a structural or temporal sequence of stands at one or more study locations.

Density is mass/volume.

PIPO fit comparison: Weaker RMSE than those that have were built on small data sets covering a limited lidar footprint.

\subsection{model fit}

The models perform best in the central range of the data and tend to underpredict regions with high biomass and over predict regions with low biomass.

Iid - linear issues: Over predicted low values (Li et al 2008, Kim et al 2009)

Power relationship –

* Log(biomass) Lim and Treitz 2004, Naesset 2011, Shao et al 2018
* Log, log – Gobakken 2012
* Stephens uses P30^2 (Stephens 2012)

Height shape, L-moments (Latifi, Hernandez 2014, Hernadnez 2015, Gonzalez 2014, li 2014, Valbuena 2016, vega 2016)

Separate models by productivity (Gobakken 2012); Naesset also did: Commonly used stratification criteria such as age class and site quality, which is correlated with at least the dominant conifer tree species in Norway, may therefore be useful for an efficient stratification of inventories. In the present study, stratification according to age class and site quality was efficient to represent distinct forest types in practical inventories (Naesset 2002).

‘Results

3.1. Regressions models for BA and AGB estimation

The 10 best models were selected for BA and AGB estimation from linear, multivariate linear and non-linear regressions based on their residual distribution, R2 and RMSE. The selected BA and AGB models had R2 of more than 0.70 and 0.85, respectively (see Tables 3 and 4). All return density and height percentiles metrics failed to fulfil good model requirements due to insignificant parameters, low R2, high RMSE and non-normal residual distribution. The best percentile parameters for the models were a + b × P40 and a + b × P25 + c × VAR (see Models No. 1 and 8 in Tables 3 and 4). (Manuri 2017)

Similar to Sheridan et al. (2014), this study also confirmed the heteroscedasticity of the residuals using these parameters. These models were thus excluded in the next step of the analysis. (Manuri 2017)

The power models using CRP variable explained 80.9% and 90.9% of the BA and AGB variations, respectively. These fits were similar or slightly better than those of squared CRP (QCRP) linear models. However, the regressions between predicted and observed values from all linear models had better-fitted lines than power models with slopes not significantly different from 1 and intercepts not significantly different from 0. A 10-fold cross-validation confirmed the lowest RMSE for all CRP-related models (Fig 5.). (Manuri 2017)

All models tended to have low precision in estimating small AGB. Only tree species were recorded on the plots (Manuri 2017). Thus, the biomass values of \*\* aspen groves\*\*\* did not completely represent the actual biomass in the plots. The consequence of excluding trees with a small dbh from plots is that the biomass estimate may not be representative of the distributions of laser canopy heights, especially those with few trees.

These models also tended to under-estimate higher biomass and over-estimate low biomass. The other reason could be due to the model form. Similar trend was found by Englhart et al. (2013) when applying power model. They further suggested to use 2 equations: i.e. power model for low AGB and linear for high AGB values. (Manuri 2017)’

[22] There were slight, nonlinear trends in the relationships between mean DBH and μlidar and σlidarand total basal area and μlidar for coniferous forests ([Figure 3](http://onlinelibrary.wiley.com/doi/10.1029/2008JG000870/full#jgrg498-fig-0003)). We tested various data transformations to improve linear model fits and found that natural log transformations improved models of basal area for both forest types and mean tree height for deciduous forests. More complicated, nonlinear models may have explained the data better; however, our sample sizes were small and there were few degrees of freedom available to fit nonlinear models well. Therefore, we continued the analysis with linear regression models. In spite of the slight nonlinear trends, the scatterplots show that the randomly sampled points did not capture the nonlinear patterns in the data as well as the stratified sample. Hawbaker 2009

[23] Our second goal was to evaluate the two sampling designs and their influence on prediction errors for vegetation structure and biomass. To accomplish this goal, we used the predictor variables selected in the countywide models but estimated regression coefficient values using only the data from each sample design. By using the previously established countywide model form, each sampling design could be evaluated as to how well it captured the trends. This resulted in four models for each tree measurement corresponding to the two sample designs and two forest types (coniferous random, coniferous stratified, deciduous random, and deciduous stratified). Hawbaker 2009

[24] For each model, we calculated the root mean squared error (RMSE) using the model predictions and observations from the data set used to construct the model, referred to as RMSEmodel. Then, we validated models by making predictions for the other sample design and calculated the RMSE from its predictions and observations, referred to as RMSEvalidate. Thus, models built with the stratified sample were validated with the random sample and vice versa. We expected that models built using the stratified sample would have RMSEmodel values similar to RMSEvalidate. Because the random samples may not have included values at the edges of the data distribution, which are more difficult to predict, we expected RMSEmodel for models built using the random sample would be less than RMSEvalidate. Hawbaker 2009

\subsection{differences in forest structure due to contrasting environmental conditions, site productivity, and species composition}.

Our other remotely sensed or measured variables--elevation, slope, and Region 3 Ecological Unit--all relate directly to factors that influence growth and forest composition. ERU influence vs. dominant species?

evergreen vs. deciduous:

no difference in our data? Due to small amount of deciduous trees in sample (0.5%)? – consider adding to diversity of species compositions within sample, then a combination of conventional optical remote sensing data and methods may result in significant estimation improvements.

Novelty of using an estimate of the magnitude of seasonal variation of greenness (NDVI) from a Landsat time-series analysis. Discuss differences in evergreen vs deciduous spp.

issues/differences \cite{ Maiersperger et al., 2001, Næsset, 1997a; Nelson, Oderwald, & Gregoire, 1997, Nelson, 1997}.

* crown shape differs between species and translates to differences in lidar metrics [(Nelson, 1997)](http://www.sciencedirect.com/science/article/pii/S0034425701002905#BIB28).
* Relationships of stand characteristics to lidar metrics vary between tree species [(Næsset, 1997a; Nelson, Oderwald, & Gregoire, 1997)](http://www.sciencedirect.com/science/article/pii/S0034425701002905" \l "BIB23).
* For the boreal coniferous site, the product of cover and several of the height indices performed better than the height indices alone; at the temperate deciduous site, the reverse was true, again due probably to the low range of canopy cover, and the resulting non-significant correlation between cover and biomass (Lefksy 2002).

solutions: \cite{Sherrill 2008,Li et al 2008, Sarrazin 2012, Ediriweera 2014, Laurin 2014, Strunk 2014}.

\subsection{inconsistent sample design}

Sample frame, descriptive stats post-stratification weights

Coconino/Tonto: spatial autocorrelation, cluster design, stand weights?

--> smaller biomass plots in Kaibab - compare res errors to other plots

\subsection{plot size}

References: [Magnussen & Boudewyn, 1998](http://www.sciencedirect.com/science/article/pii/S0034425701002905#BIB17), Naesset 2002, Gobakken and Naesset 2009, Frazer 2011, Mascaro et al. [2011b](https://link.springer.com/article/10.1007/s00442-011-2165-z#CR40), Zolkos, Sheridan, Knapp et al 2018

Small plot size increases model error (RMSE). Above ~0.1 ha there is little influence (Mascaro et al. ?). Small areas are subject to substantial inherent variation around canopy height quantiles leading to highly variable predictions (cf. [Magnussen & Boudewyn, 1998](http://www.sciencedirect.com/science/article/pii/S0034425701002905" \l "BIB17), Naesset 2002, Zolkos \*\*).

Edge effects 1) because lidar data includes crown returns from nearby trees – if the bole isn’t in the plot it isn’t measured in the field, but lidar includes recordings from nearby trees canopy returns. A larger plot radius reduces edge effects in relation to total area (perimeter to area ratio) – mitigates edge effect by reduces effects of discrepancies between field/laser measurement protocols at edge \cite{Gobakken and Naesset 2009, Frazer 2011}. GPS positional errors – large plots have higher degree of spatial overlap. larger plot sizes increase inventory costs - balance costs and precision benefits.

--> discuss biomass by plot size interactions in this sample design strategy. interactions and implications on model fit assumptions/requirements (iid)

\subsection{transferability}

The final biomass and volume models performed reasonably well when they were used to predict observed values in the 4FRI phase 3 and 2 lidar datasets (independent dataset acquired later in the analysis). The difference between the model-predicted and observed biomass and volume values were used to calculate the RMSPE. For aboveground biomass, the RMSPE in the 4FRI phase 3 data was very similar to that obtained from the data withheld from the initial model fit.

%The combined single model we produced had predictive performance equivalent to, or slightly better than, that of Bayesian Model Averaging ensemble prediction produced using the top 10,000 models.

\subsection{management implications, monitoring}

implications for underpredicting biomass -- in terms of carbon accounting and identifying fuels.

\subsection{other applications of methods}

We present a cost effective approach to use previous data collection efforts to assist in updating lidar-derived forest inventories. Extrapolation pitfalls still need to be considered - \*\*overfitting (Hawkins?)\*. But a framework to make use of the plethora of data already collected that represents a diversity of stand structures should help improve estimates. Bayesian updating approaches – but more complicated. Validation field work – smaller data set, less costly to validate compared to costs collecting enough data and diverse enough data to train new models. As long as domain of new study matches these forests.

Suggest the generality, approach can be used to monitor other forest structure attributes that are well predicted by lidar. Examples of characteristics of particular important in these forests that have the potential to be well estimated with lidar include ?timber volume \cite{}, canopy fuels \cite{ Anderson et al 2005, Erdody and Moskal 2010, Gonzalez 2014}, and with the integration of other data and lidar intensity values - detect dead biomass \cite{Kim 2009}.

\section{conclusion}

Lidar availability increasing. Agencies and (large) jurisdictions, such as states (WA), are forming lidar consortiums to acquire lidar covering a large spatial extent (frequently). Recognizing multi-purposes of lidar (hazards, terrain mapping, etc, etc) and the decreased unit cost as scanned surface increases (especially when multiple agencies jointly fund data collection. Fuels relationship is a function of how fuels are vertically distributed within the tree crown (Anderson et al 2005). Reconstructing characteristics of canopy interior depends on laser pulse penetration into canopy (function of point density) (Hyyppa et al 2008?). But good results reconstructing biomass and other elements closely related to the canopy topography from low density lidar data \cite{}.

\subsection{sensitivity to sensor specifications and sensory evolution considerations}

How the models will perform as lidar systems change? References - manuri paper, and gobakken?

Bob: exploration of data from different scanners flown over the same area and found that most of the metrics didn’t change much. However, if things like Geiger-mode data or photon-counting data start to become more common, some of the metrics may change. Linear scanners are still evolving/improving as well so their performance may change over time. Things like 95th percentile probably won’t change much but Elev MAD median or mode may change pretty significantly. Moving forward with the goal of having a model that can be applied to new acquisitions may make the selection of variables more important. Sensitivity to changes in lidar technology might be a good thing to add to the discussion.

… an indicator of the canopy height distribution (median of absolute deviations from the overall median) %here per Bob's recc, we can suggest an alternative metric that isn't as sensitive to sensor specifications. The other two metrics that are common to the literature and highly correlated with MAD median are standard deviation and the 2nd L-moment.

next steps -- think about applying to phodar, FIA data?

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