Filtering ground noise from LiDAR returns produces inferior models of forest aboveground biomass

A Preprint

Michael J Mahoney *
Graduate Program in Environmental Science
State University of New York College of Environmental Science and Forestry
1 Forestry Drive, Syracuse, New York, 13210
mjmahone@esf.edu

Lucas K Johnson
Graduate Program in Environmental Science
State University of New York College of Environmental Science and Forestry
1 Forestry Drive, Syracuse, New York, 13210
ljohns11@esf.edu

Eddie Bevilacqua
Department of Sustainable Resources Management
State University of New York College of Environmental Science and Forestry
1 Forestry Drive, Syracuse, New York, 13210
ebevilacqua@esf.edu

Colin M Beier
Department of Sustainable Resources Management
State University of New York College of Environmental Science and Forestry
1 Forestry Drive, Syracuse, New York, 13210
cbeier@esf.edu

December 11, 2021

*Corresponding author.

This paper is a non-peer reviewed preprint submitted to EarthArXiv prior to journal submission.

Abstract

Airborne LiDAR has become an essential data source for large-scale, high-resolution modeling of forest biomass and carbon stocks, enabling predictions with much higher resolution and accuracy than can be achieved using optical imagery alone. Ground noise filtering – that is, excluding returns from LiDAR point clouds based on simple height thresholds – is a common practice meant to improve the 'signal' content of LiDAR returns by preventing ground returns from masking useful information about tree size and condition contained within canopy returns. Although this procedure originated in LiDAR-based estimation of mean tree and canopy height, ground noise filtering has remained prevalent in LiDAR pre-processing, even as modelers have shifted focus to forest aboveground biomass (AGB) and related characteristics for which ground returns may actually contain useful information about stand density and openness. In particular, ground returns may be helpful for making accurate biomass predictions in heterogeneous landscapes that include a patchy mosaic of vegetation heights and land cover types.

In this paper, we applied several ground noise filtering thresholds while mapping two study areas in New York (USA), one a forest-dominated area and the other a mixed-use landscape. We observed that removing ground noise via any height threshold systematically biases many of the LiDAR-derived variables used in AGB modeling. By fitting random forest models to each of these predictor sets, we found that that ground noise filtering yields models of forest AGB with lower accuracy than models trained using predictors derived from unfiltered point clouds. The relative inferiority of AGB models based on filtered LiDAR returns was much greater for the mixed land-cover study area than for the contiguously forested study area. Our results suggest that ground filtering should be avoided when mapping biomass, particularly when mapping heterogeneous and highly patchy landscapes, as ground returns are more likely to represent useful 'signal' than extraneous 'noise' in these cases.

Keywords random forest · LiDAR · aboveground biomass · ground noise · machine learning

1 Introduction

Accurate assessment of forest carbon stocks for the purposes of greenhouse gas accounting and climate change mitigation requires high-resolution maps of above-ground biomass (AGB) across large spatial extents. The production of these maps has been aided in recent years by the proliferation of publicly available airborne LiDAR data, allowing researchers access to granular data on land cover heights at fine grained resolutions (Dubayah and Drake, 2000). By aggregating returns to a pixel or object level and computing descriptive statistics characterizing the distributions of heights of returns, modelers are able to convert these point clouds into tabular data formats which may then be used to fit regression models for predicting AGB (Hawbaker et al., 2010).

However, there exists some disagreement about precisely which returns to aggregate when computing these statistics. While some LiDAR-based AGB models include all returns when calculating summary statistics (Hudak et al., 2020), others first filter out returns below various height thresholds when calculating percentile heights (Ma et al., 2018), density percentiles (Huang et al., 2019), or their entire suite of predictors (García et al., 2010). Filtering is typically described as being done to remove ground noise from return data, in order to avoid having "ground" returns mask any signal contained in the remaining "canopy" returns. The height threshold used in this process varies across studies, with examples ranging from 0.3 m (García et al., 2010) to 1.3 m (Deo et al., 2017; Ma et al., 2018) to 2 m (Anderson and Bolstad, 2013) to 2.5 m (Huang et al., 2019).

This diversity of approaches demonstrates a lack of consensus about a data processing technique that results in systematically greater estimates of percentile heights and other computed predictors. The practice itself appears to have originated with Nilsson (1996), whose early work with airborne LiDAR focused on calculating tree heights based on the maximum heights of returns, as well as stand volume as a function of the mean height of all returns. Nilsson does not appear to filter returns based on a height threshold; rather, they set the height values of all points below 2 m to 0, in effect reducing the resulting mean height values. The following year, Næsset (1997) published what may be the earliest rationale for ground noise filtering in a study calculating mean stand height from LiDAR returns, excluding returns below 2m in order to avoid interference from shrubs, rocks, and other understory features. In concert, these two studies have provided the justification for filtering out ground returns in a multitude of forest modeling studies (Anderson and Bolstad, 2013; Magnussen and Boudewyn, 1998; Wasser et al., 2013), to the extent that it appears to now be such a commonly accepted practice as to not merit discussion or citation at all (Hawbaker et al., 2010; e.g. White et al., 2015).

Yet this practice, initially justified so as to not include the height of stones in calculating the mean heights of trees (Næsset, 1997), may not be necessary or desirable as modelers turn their attention to stand characteristics such as AGB. Increased density of ground returns may be associated with sparser stands, and as a result, the left-censoring of variables derived from LiDAR pulses by omitting ground noise may remove useful information about stand structure available for predictive models. This common practice may therefore result in inferior estimates of forest AGB. Filtering may particularly harm predictive accuracy in less contiguously forested and mixed-use landscapes, as we might expect filtering to exclude more returns in areas without tree canopies intercepting and reflecting pulses. As a result, these filtering procedures may adjust LiDAR-derived variables by greater amounts in these settings compared to contiguously forested regions, given their increased proportion of ground returns. It is likely that modeling such heterogeneous landscapes will be an increasing concern over time, as larger data sets and improved computing power enables modelers to map AGB over larger spatial scales; however, there has not been much discussion in the literature concerning any effects filtering may have on forest AGB predictions either in these landscapes or in more homogeneous settings.

In this paper, we use LiDAR data sets representing both continuously forested and mixed-use landscapes to investigate the impacts of ground noise filtering on predictive models of forest AGB. We set out to first identify how filtering ground noise impacts the distribution of commonly used LiDAR-derived predictors, using multiple height thresholds as found throughout the literature. We then fit models to each of these predictor sets using the random forest algorithm (Breiman, 2001), a popular tool used in modeling AGB, to assess how the different predictor distributions may impact model performance. Our results suggest ground filtering is actively detrimental to predictions of AGB, particularly in models that incorporate mixed-use landscapes and areas with only marginal forest cover. These results may help inform future work looking to accurately predict forest AGB using models incorporating predictors derived from airborne LiDAR data products.

2 Methods

2.1 LiDAR Data Sets and Site Characteristics

In order to identify the impacts of ground filtering on predictive models of AGB, we obtained leaf-off LiDAR data sets flown for two regions within New York State (Figure 1). The first of these data sets represents the majority of Cayuga and Oswego counties in Central New York (New York Office of Information Technology Services, 2018), a mixed agricultural and developed landscape with small regions of continuous forest and a large amount of marginal forestland composed of many small fragments of tree cover (Figure 2). LiDAR data for this region was acquired from flights between April and May of 2018 and spans an area of 4,455 square kilometers with a nominal pulse spacing of 0.7 meters.

The second data set covers the northern sections of Warren and Washington counties and the southern section of Essex County, with smaller inclusions of Hamilton and Franklin Counties (New York Office of Information Technology Services, 2015). This region (which we refer to as the "Warren, Washington and Essex" region) in the northeastern part of the state is largely situated within New York's Adirondack State Park, the largest protected area within the contiguous United States (Thorndike, 1999). As a result, this area is predominantly forest land, with less developed and agricultural land than Cayuga and Oswego counties (Figure 2). LiDAR data was acquired from flights between April and May of 2015 and spans an area of 6,278 square kilometers with a nominal pulse spacing of 0.556 meters.

2.2 Field Data

Field measurements of AGB for all trees measuring $\geq$ 12.7 cm diameter at breast height were taken as part of the United States Department of Agriculture (USDA) Forest Inventory and Analysis (FIA) program (Gray

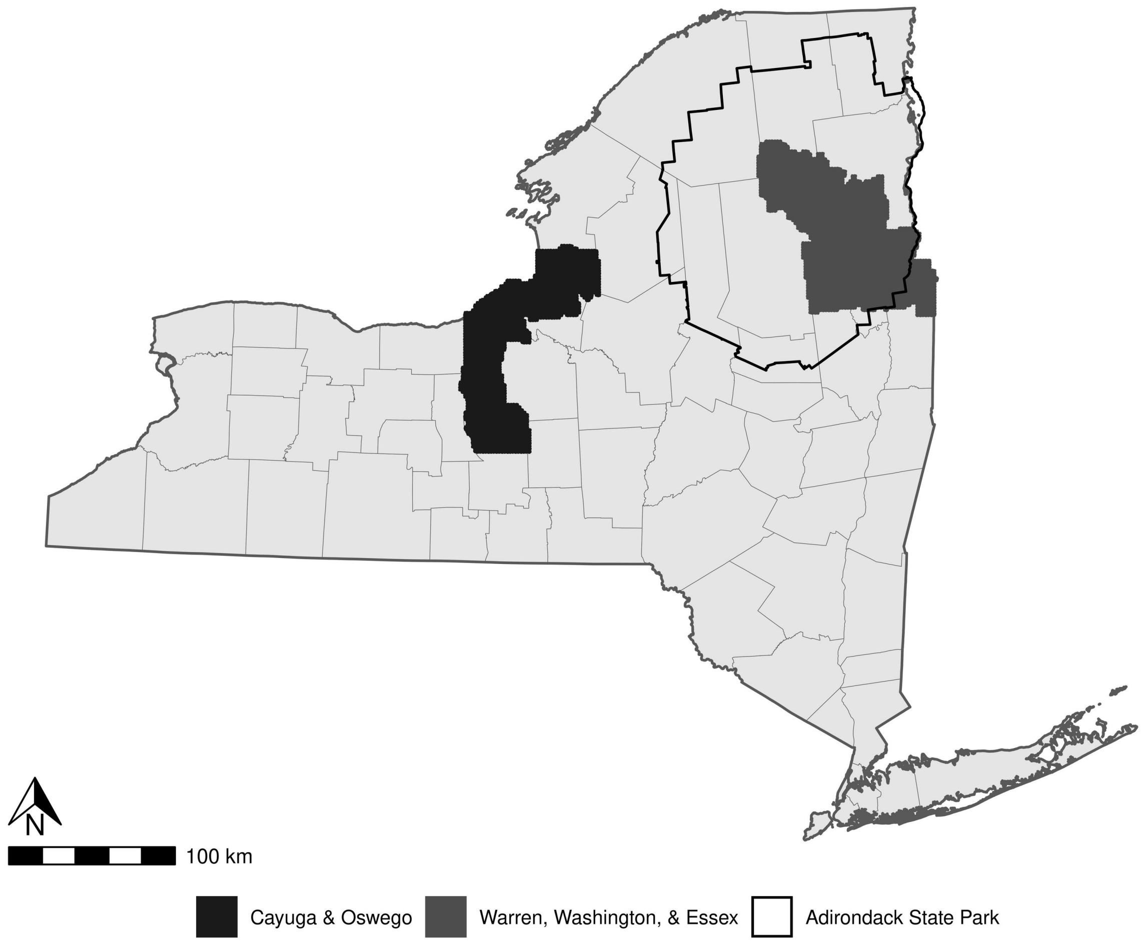

Figure 1: Location of the "Cayuga and Oswego" and "Warren, Washington, and Essex" LiDAR data sets within New York State. The border of the Adirondack State Park is included to show the portion of the Warren, Washington, and Essex data set located within protected lands.

et al., 2012), with true plot centroid locations obtained under agreement with the USDA. Measurements were recorded in pounds, then converted and area-normalized to units of megagrams per hectare (Mg ha^{-1}). Only FIA plots sampled the same year as LiDAR flights, or FIA plots with samples from before and after the LiDAR acquisition year with a difference in AGB within [-5%, ∞) were used for training and evaluating models. In situations where FIA year did not match LiDAR acquisition year, AGB was calculated by linearly interpolating between the values measured in the temporally closest FIA samples. Plots were additionally excluded if any subplots were marked as nonsampled, if FIA measurements indicated 0 Mg ha^{-1} of AGB but maximum LiDAR return heights at the plot exceeded 10 meters, or if the convex hull of all LiDAR returns for a subplot contained less than 90% of the subplot's area. In total, 33 suitable FIA plots were identified within the Cayuga and Oswego region and 129 within the Warren, Washington and Essex region, for a total of 162 plots in the combined data set.

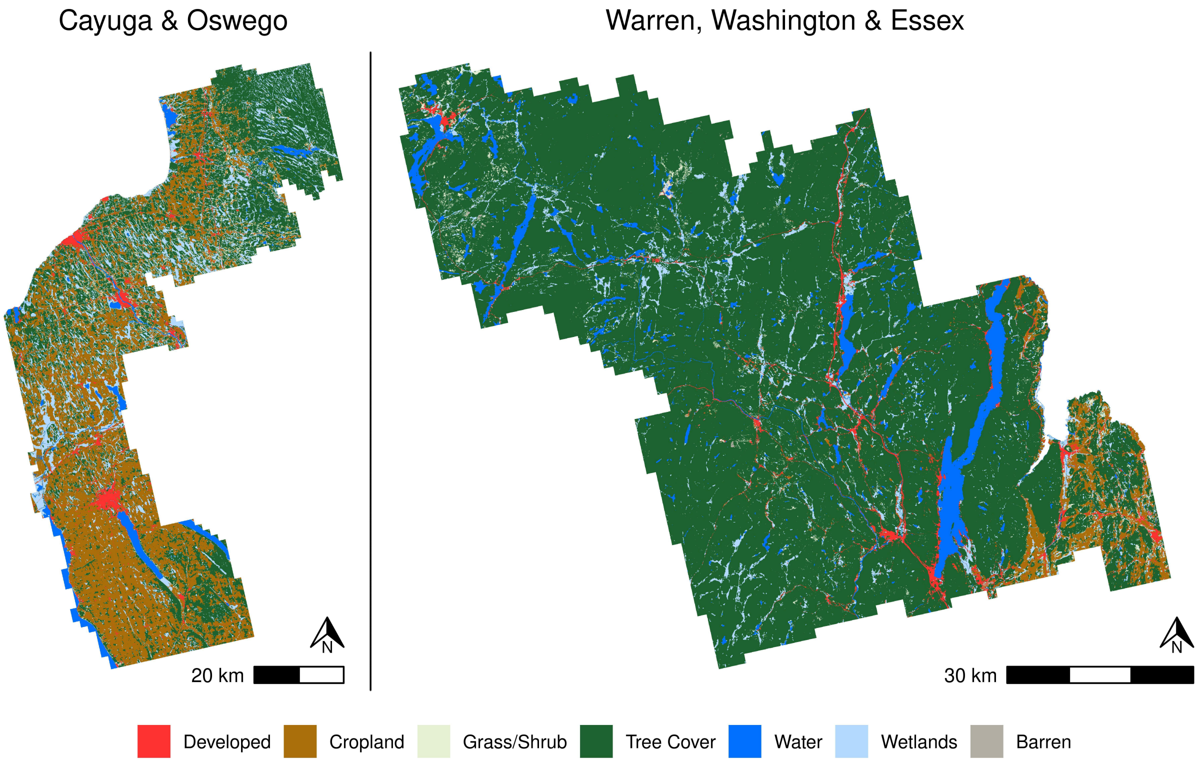

Figure 2: A comparison of land cover across the "Cayuga and Oswego" (left) and "Warren, Washington, and Essex" (right) regions, using land cover classifications from LCMAP (Brown et al., 2020). Colors represent the same land cover categories across both regions, while scale bars differ between regional maps.

2.3 LiDAR Pre-Processing

A digital terrain model (DTM) was calculated for both sites using a k-nearest-neighbors inverse-distance weighting imputation algorithm (using k = 5) as implemented in the lidR R package (Roussel et al., 2020), fit using the points classified as "ground" within the raw LiDAR point cloud data set. The calculated terrain at each point was then subtracted from the point's z value to create a height-normalized point cloud. Ground noise filtering rules were then applied to create five separate points clouds for each site, each representing a different ground noise filtering approach: one point cloud containing all points in the original file (hereafter referred to as "unfiltered"), one removing all points classified as "ground" in the original metadata ("ground"), and three removing all points with normalized z values below a 0.1, 1, or 2 meter threshold ("0.1m," "1m," and "2m," respectively).

Separate sets of 40 predictors, chosen due to their prevalence in published models of AGB and forest structure, were derived from each of these point clouds using the lidR R package (Table 1) (Hawbaker et al., 2010;

Table 1: Definitions of LiDAR-derived predictors used for model fitting.

Predictor	Definition
H0, H10, ... H100, H95, H99	Decile heights of returns, in meters, as well as 95th and 99th percentile return heights.
D10, D20... D90	Density of returns above a certain height, as a proportion. After return height is divided into 10 equal bins ranging from 0 to the maximum height of returns, this value reflects the proportion of returns at or above each breakpoint.
N	Number of returns at a given plot or pixel
ZMEAN, ZMEAN_C	Mean height of all returns (ZMEAN) and all returns above 2.5m (ZMEAN_C)
Z_KURT, Z_SKEW	Kurtosis and skewness of height of all returns
QUAD_MEAN, QUAD_MEAN_C	Quadratic mean height of all returns (QUAD_MEAN) and all returns above 2.5m (QUAD_MEAN_C)
CV, CV_C	Coefficient of variation for heights of all returns (CV) and all returns above 2.5m (CV_C)
L2, L3, L4, L_CV, L_SKEW, L_KURT	L-moments and their ratios as defined by Hosking (1990), calculated for heights of all returns
CANCOV	Ratio of returns above 2.5m to all returns (Pflugmacher et al. 2012)
HVOL	CANCOV * ZMEAN (Pflugmacher et al. 2012)
RPC1	Ratio of first returns to all returns (Pflugmacher et al. 2012)

Huang et al., 2019; Pflugmacher et al., 2014, 2012; Roussel et al., 2020). Predictors computed for FIA plot locations were derived from only the pooled returns coincident with the sampled subplot locations, so as to not include any returns from the unsampled regions of the macroplot. For plots where ground noise filtering resulted in the removal of all points, variables were set to a default value of 0. As highly correlated predictor variables may provide the random forest model less information for AGB predictions, relationships between predictors were assessed using Pearson's linear correlation coefficient. Changes in predictor distributions under different filtering methodologies were assessed using Kolmogorov-Smirnov statistics (Massey, 1951).

2.4 Model Fitting

AGB models were fit using the ranger R package's implementation of the random forest algorithm (Breiman, 2001; Wright and Ziegler, 2017), a popular machine learning technique for predicting forest biomass across landscapes (see for instance Huang et al., 2019; Hudak et al., 2020). Separate models were fit on predictors calculated using each level of ground noise filtering ("unfiltered," "ground," "0.1m," "1m," and "2m" thresholds) for each LiDAR data set (Cayuga and Oswego, Warren, Washington and Essex, and a combination of the two regions), for a total of fifteen separate models. Models were fit solely on LiDAR derived predictors to ensure differences in model performance resulting from ground noise filtering were not mediated by the introduction of variables which might be highly correlated with the unfiltered predictors.

Each of these were tuned separately using a standard uniform grid search, with each model evaluated using the same 17,784 combinations of hyperparameters detailed in Supplementary Materials S1. The top 100 sets of hyperparameters for each model, as determined via mean root-mean-squared error (RMSE) from 5-fold cross validation (Stone, 1974) (Equation (1)), were then evaluated using leave-one-out cross validation (Lachenbruch and Mickey, 1968), with the set of hyperparameters associated with the lowest RMSE used to fit the final model reported in the text. This method ensured that each random forest compared is the best version of the model that could be fit to these predictors, with the result that any difference in model performance will be due to ground noise filtering and not stochastic differences between models or effort spent in tuning hyperparameters. Recent work has suggested cross validation assessments of model accuracy are likely overoptimistic compared to actual predictive accuracy (Bates et al., 2021), which does not impact our aim of comparing ground noise filtering approaches within a single study, but should be kept in mind when assessing these models as AGB estimators in their own right.

All modeling work was done using R version 4.0.5 (R Core Team, 2021).

2.5 Model Assessment

Models were evaluated using multiple metrics calculated via leave-one-out cross validation (Lachenbruch and Mickey, 1968). Performance metrics calculated included root-mean-squared error both as a value in Mg ha^{-1} (RMSE, equation (1)) and as a percentage of mean plot AGB (RMSE %, equation (2)), mean absolute error (MAE, equation (3)), and the coefficient of determination (R^2, equation (4)).

$$\text{RMSE} = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

$$\text{RMSE \%} = 100 \cdot \frac{\text{RMSE}}{\bar{y}} \tag{2}$$

$$\text{MAE} = (\frac{1}{n})\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$\text{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

Where n is the number of FIA plots included in the data set, $\hat{y}_i$ is the predicted value of AGB, y_i the AGB value measured at the corresponding location, and $\bar{y}$ the mean AGB value from FIA field measurements.

Table 2: Mean (with standard deviation in parentheses) Pearson correlation coefficients of LiDAR-derived variables calculated from point clouds processed with five different ground noise filtering methodologies across two separate regions and a combined data set. Variables with standard deviations of 0 after filtering (such as when minimum return height at all plots became 0 due to ground noise filtering) were excluded from calculations.

	Cayuga & Oswego	Warren, Washington & Essex	Combined
Unfiltered	0.262 (0.768)	0.191 (0.571)	0.212 (0.618)
Ground	0.236 (0.590)	0.192 (0.541)	0.200 (0.538)
0.1m	0.553 (0.479)	0.257 (0.538)	0.397 (0.472)
1m	0.611 (0.497)	0.418 (0.463)	0.507 (0.465)
2m	0.574 (0.534)	0.430 (0.463)	0.510 (0.464)

3 Results

3.1 Variable Distribution

Filtering out ground noise resulted in notable shifts in predictor distributions (Figure 3). Mean predictor values for each ground noise filtering method, alongside Kolmogorov-Smirnov test statistic values comparing the distributions of filtered predictors to that of the unfiltered predictors, are presented in Supplementary Materials S2. Filtering returns based upon z-thresholds or ground classifications resulted in systematically elevated height percentile and return density predictors (the H and D prefixed predictors in Table 1; Figure 3), with differences persisting into the highest percentiles calculated. Notable differences in distributions also existed for all L-moment based predictors, with increasing height thresholds associated with increased magnitude of difference.

Changing variable distributions resulted in changes to correlation between variables, as measured via Pearson correlation coefficients. More aggressive filtering approaches were generally associated with stronger positive correlations between all variables (Figure 4; Table 2).

3.2 Model Performance

Models fit on the unfiltered set of predictors were consistently more accurate than those fit to predictors derived from ground noise filtered point clouds, both for each region separately as well as in the combined data set (Table 3). While differences in model accuracy between the ground noise filtered sets were slight, treatments with less aggressive filtering (the ground point removal and 0.1 meter threshold groups) were generally more accurate than the more aggressively filtered predictor sets (1 meter and 2 meter thresholds; Table 3).

Models trained on unfiltered predictors tended to perform better at predicting all but the highest AGB plots when compared against those trained on predictors calculated after ground noise filtering (Figure 5).

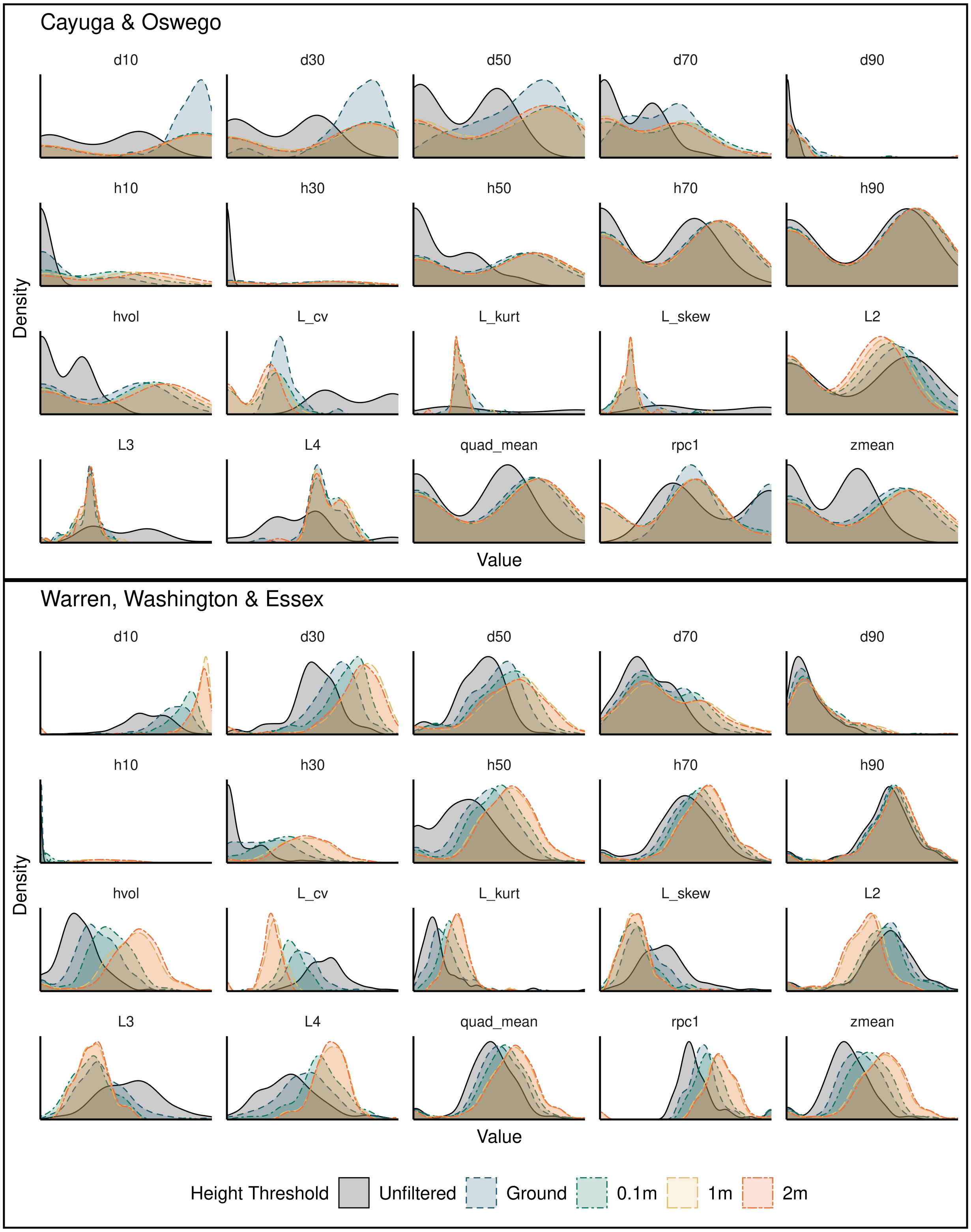

Figure 3: Selected LiDAR-derived predictor distributions for five ground noise filtering approaches. Each subplot is scaled independently so that the X-axis represents the full range of that predictor and the Y-axis represents the full range of the kernel density estimate of that predictor.

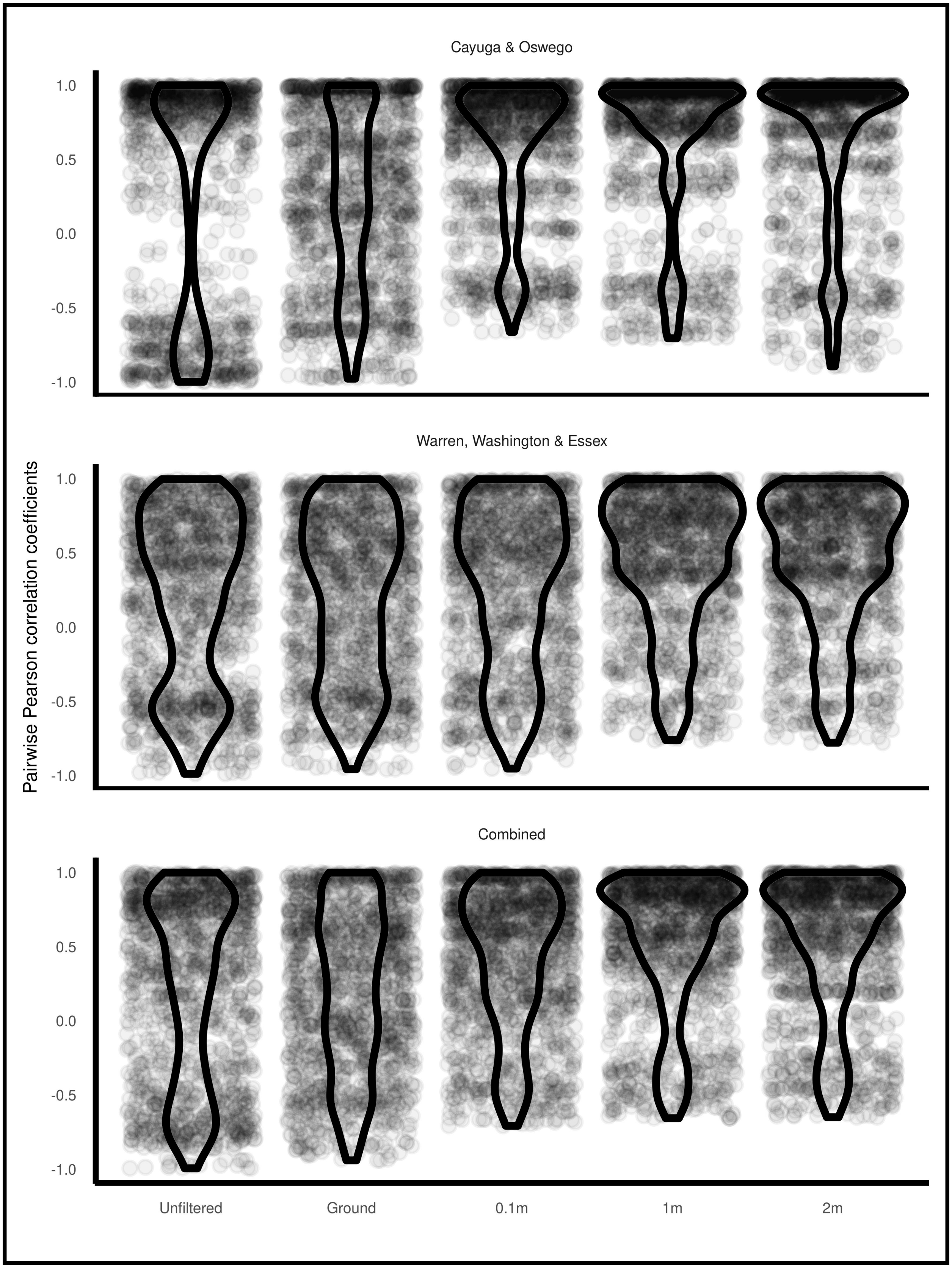

Figure 4: A comparison of the distributions of pairwise Pearson correlation coefficients for each permutation of LiDAR-derived variables examined in this study. Variables with standard deviations of 0 after filtering (such as when minimum return height at all plots became 0 due to filtering) were excluded. Points represent individual correlation coefficients and are slightly transparent, such that darker regions correspond larger densities of correlation coefficients.

Table 3: Model accuracy and agreement metrics as assessed by leave-one-out cross validation.

	Unfiltered	Ground	0.1m	1m	2m
Cayuga & Oswego					
RMSE	23.195	27.243	28.530	28.214	28.853
RMSE (%)	29.934	35.159	36.820	36.412	37.236
MAE	14.698	18.454	20.493	18.566	20.019
R2	0.899	0.863	0.849	0.858	0.846
Warren, Washington & Essex					
RMSE	40.605	41.406	41.882	42.026	43.005
RMSE (%)	31.741	32.367	32.739	32.852	33.617
MAE	30.396	31.749	32.049	31.890	32.587
R2	0.576	0.559	0.544	0.541	0.517
Combined Data					
RMSE	38.140	39.952	40.890	40.412	41.103
RMSE (%)	32.418	33.958	34.755	34.349	34.936
MAE	28.037	29.188	29.567	29.203	30.098
R2	0.681	0.653	0.632	0.641	0.629

Most predictor sets were similarly inaccurate when predicting plots with the highest AGB values, a known limitation of AGB models built using solely LiDAR-derived predictors (St-Onge et al., 2008). An exception to this pattern was in the Cayuga and Oswego region, where models fit using ground noise filtered predictors were particularly poor at predicting plots with more than 100 Mg ha^{-1} AGB, instead predicting values near the mean AGB value for the higher-AGB subgroup (Figure 6). The model fit on unfiltered predictors for this region did not exhibit this behavior.

4 Discussion

This study set out to identify an empirical justification for threshold-based ground noise filtering for models of forest AGB, given that there exists no clear inductive justification for the practice. Instead we found that this common practice results in worse models of AGB, with lower predictive accuracy and agreement when fit on multiple sets of measured AGB values derived from separate LiDAR projects representing both continually forested and mixed-use landscapes. These results should encourage future modeling studies to use unfiltered point clouds when deriving variables for AGB models.

4.1 Ground noise filtering produces inferior predictive models

Our study demonstrates that the ground noise filtering approaches commonly used in preprocessing data for models of AGB systematically biases LiDAR-derived variables, with an end result being inferior models that produce less accurate predictions than models fit on unfiltered data sets (Figure 3, Table 3). These models fit on filtered data are generally inferior at predicting all but the highest AGB values relative to their unfiltered counterparts while exhibiting similar inaccuracy on the higher end of AGB values (Figure 5), likely due to

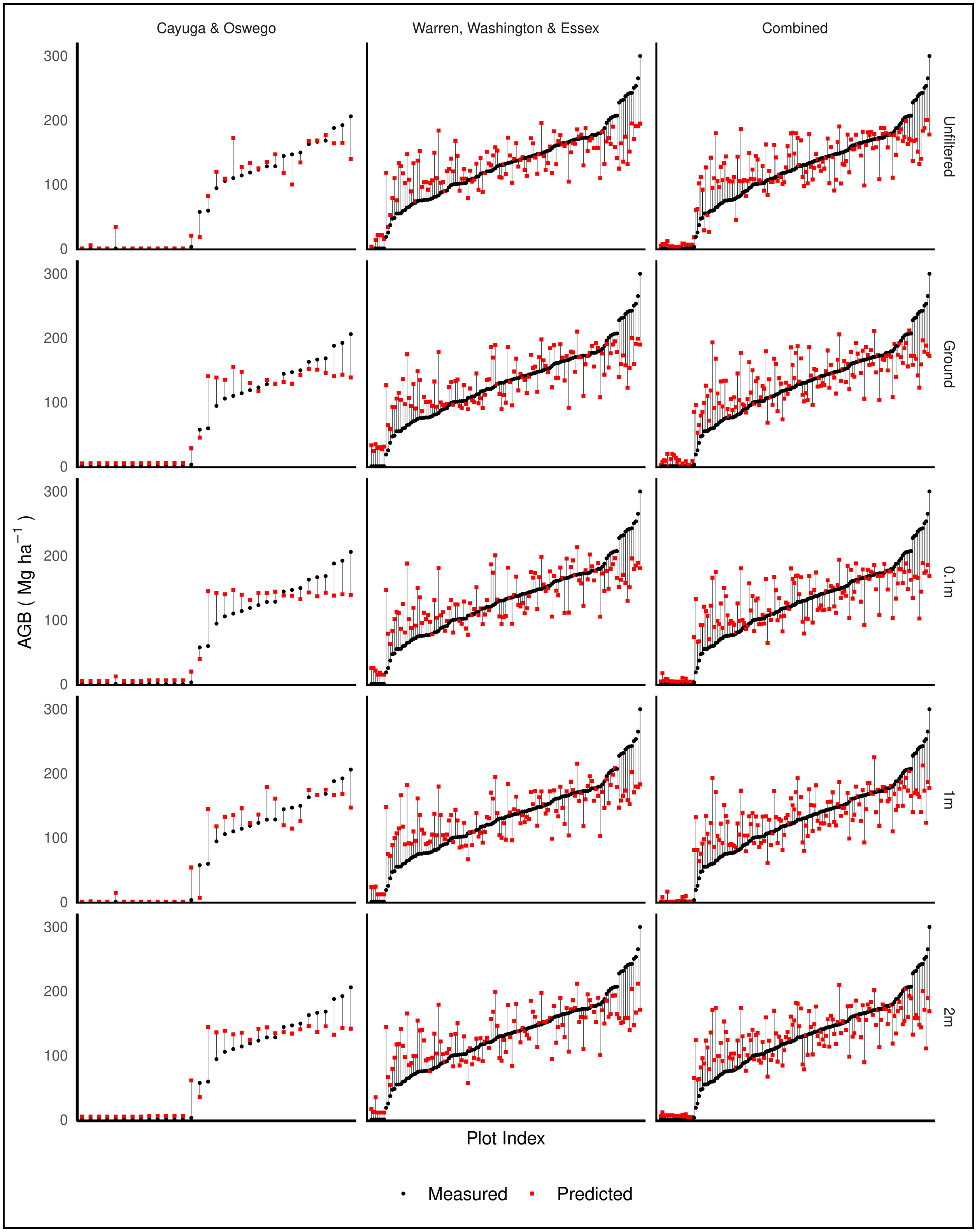

Figure 5: Measured and predicted AGB at each FIA plot for each combination of ground noise filtering approach (rows) and regional data set (columns). Plots are arranged along the X axis by AGB, so that plots with the lowest AGB value in a data set are on the left extreme and those with the highest AGB are on the right, with each plot evenly spaced from its neighbors. The distance between measured AGB (black circles) and predicted AGB (red squares) represents prediction error (black line).

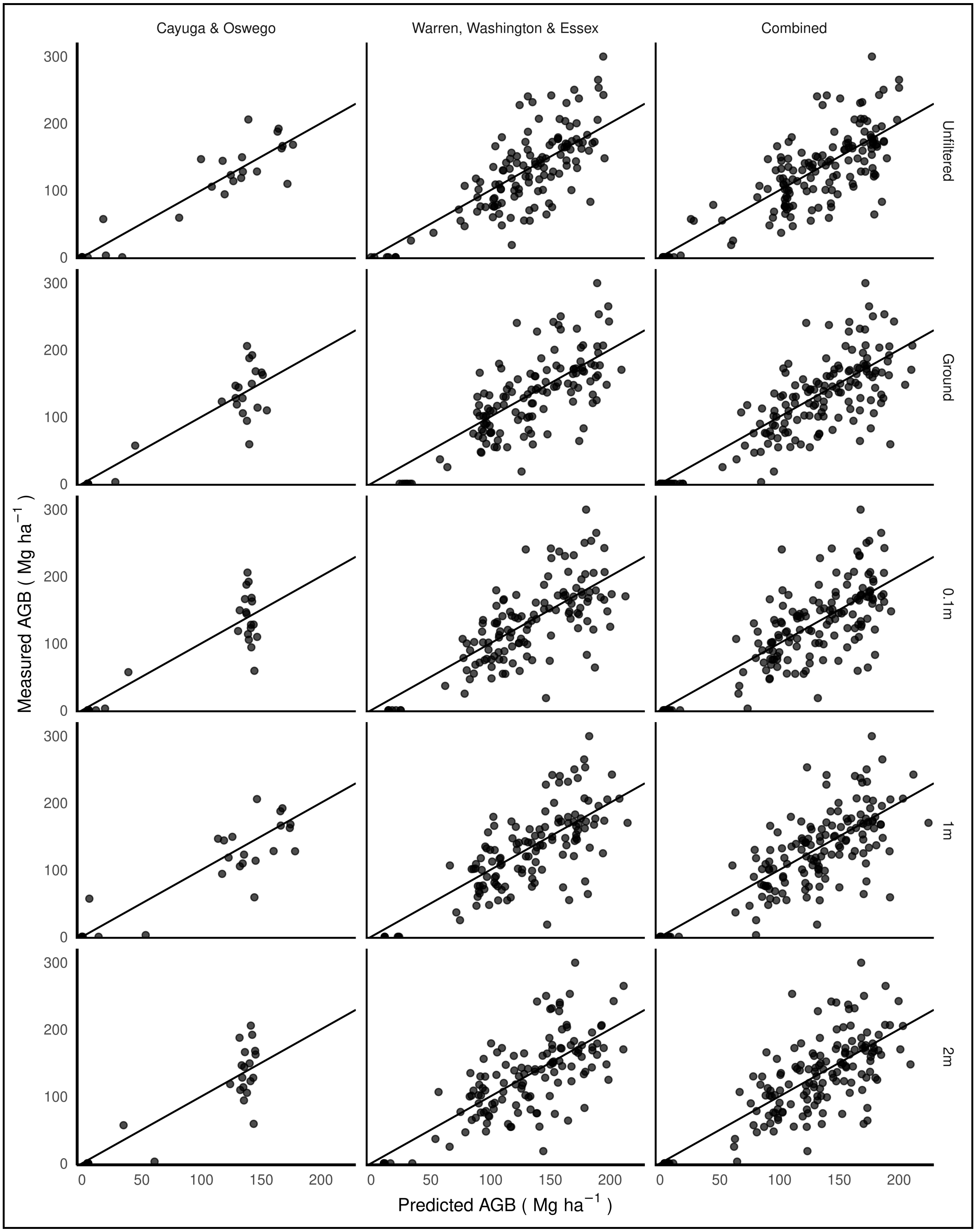

Figure 6: Scatter plots of predicted and measured AGB for five different ground noise filtering approaches (rows) across two regions and a combined data set (columns). A 1:1 relationship is included on each panel as a solid black line.

signal saturation (St-Onge et al., 2008). Increasing intensity of ground noise filtering was generally, but not universally, associated with worse model performance (Table 3). Overall, these patterns were strongest in models fit using only data from a single region.

These results are intuitive when thinking about the actual stand characteristics that may lead to an abundance or lack of ground returns. Dense forest stands making full use of the available light should be expected to have fewer returns reaching below the uppermost branches, while landscapes with many gaps in the canopy will have more such returns. If we conceive of our returns as providing information about the height structure of the stand as a whole, rather than about individual trees, it stands to reason that variables calculated using all returns are more informative about stand metrics such as AGB than those using filtered point clouds which may sacrifice information about stand openness. This could explain the impact of ground noise filtering seen in this study using leaf-off LiDAR; we might expect this impact to be even more pronounced were we to use leaf-on LiDAR in its place.

Our results also make sense mechanistically given the properties of the random forest algorithm used to construct AGB models in this study. Random forests excel at predicting outcomes based upon the consensus of weak learners (Breiman, 2001), individual decision trees which themselves rely upon small and ephemeral correlations between predictor variables and the outcome of interest. As shown (in Figure 4 and Table 2), ground noise filtering approaches increase positive correlations between predictor variables, with the resulting increased collinearities shrinking the number and magnitude of possible weak correlations between individual variables and AGB (Langford et al., 2001). While the decision trees comprising the random forest may be able to take advantage of the correlations between predictor variables and the outcome to achieve similar accuracy as when trained on unfiltered data sets, we would not expect that a process that uniformly increases the positive linear correlation between variables would be associated with improved predictions.

Insights drawn from these results may not be limited to only machine learning based models. Anderson and Bolstad (2013) note that, when fitting linear models to predict AGB, models based on unfiltered point clouds always provided better results than those fit to predictors calculated using only returns above 2 meters. However, few other AGB modeling studies have performed similar investigations, necessitating our current study. Our conclusions may not apply to AGB models of non-forest systems; investigations of ground noise filtering as a preprocessing step for models of corn AGB found improvements in predictive accuracy with relatively low height thresholds (Luo et al., 2016), emphasizing that commonly accepted data processing practices cannot be assumed to transfer across systems or domains to new questions of interest.

4.2 Differences between regional models

Although we found that models fit using predictors derived from unfiltered point clouds to be the most accurate across both regions and the combined data set, the degree to which ground noise filtering damaged predictive accuracy and the relationship between filtering intensity and accuracy varied between regions. Of particular interest is the degree to which models performed worse when fit using predictors derived from filtered point clouds within the Cayuga and Oswego region (Figure 6, Table 3). This region is characterized by large amounts of marginal forestland spread across a mixed-use landscape, resulting in a notably higher proportion of plots with no or low AGB and much lower mean AGB values compared to the Warren, Washington and Essex region. As a result, the models appear to not have sufficient numbers of observations about these relatively higher AGB plots to reliably differentiate them once any information on stand structure conveyed by ground returns is removed. As a result, the random forest algorithm produces relatively few nodes dedicated to separating out these observations and instead predicts near the subgroup mean for all plots with more than 100 Mg ha^{-1} AGB.

Therefore, ground noise filtering may be more detrimental to models trained in regions dominated by low-AGB forestlands. While models fit using predictors derived from filtered point clouds were consistently inferior to those using unfiltered data, the filtering procedures were less detrimental within the contiguously forested Warren, Washington and Essex region than within the mixed-use Cayuga and Oswego region. We therefore suggest that our results in Cayuga and Oswego, where ground noise filtering produced a model with an RMSE up to 24% greater than that of the unfiltered model, represent close to the maximum impact ground noise filtering may have on model performance. Our combined data set – fit on many more points representing much more contiguous forestland – is likely more similar to a typical AGB mapping project, and as such we believe the approximately 5-7% increase in RMSE introduced via ground noise filtering is closer to the impact that would be seen in multi-region models of AGB.

4.3 Limitations as AGB models

The models discussed in this study were purposefully designed so as to maximize the potential effect of ground noise filtering on model performance. For this reason, models were fit using only LiDAR-derived predictors, as predictors obtained from additional data sources may be correlated with unfiltered predictors and as such used in their place by the random forest algorithm (Efron, 2020), thus mediating the impact of the filtering approaches. Additionally, these models were fit using relatively few field measurements (a total of 162 FIA plots) located across two spatially disparate regions with varying cover types, with hyperparameter tuning performed via an automated process so as to avoid unintentionally biasing results by giving different models differing levels of attention or time in tuning. Further, model assessment was done using leave-one-out cross validation, which is sufficient for comparison between individual models but lacking as a way to characterize model AGB predictions spatially and across multiple scales (Riemann et al., 2010). While none of these limitations impact the comparison of ground noise filtering approaches at the center of this study, in combination they prevent us from using these models to make fine-scale estimates about AGB stocks across these regions and how model predictions compare to regional FIA estimates.

4.4 Recommendations for future models

Our results and examination of the literature suggest that ground noise filtering procedures are not well justified for studies modeling AGB, given both the potential information lost about stand density and structure, and the empirical inferiority of models fit using predictors derived from filtered point clouds. We make no such claim about researchers modeling other variables using LiDAR-derived predictors; for instance, when modeling mean tree heights similar to Næsset's (1997) study which originated the practice of ground noise filtering. The best data preprocessing procedure will necessarily depend on the purpose of the model (Sambasivan et al., 2021).

More generally, we recommend our approach to any researcher considering a new (or reviewing an old) data preprocessing step to include in their model. While tracing methodological details to their origins in the literature may not always be fruitful, researchers should ideally have the ability to separate out small sections of their data to evaluate model performance with and without the proposed procedure. The results of these small tests may justify including the procedure in the data preprocessing workflow for the full data set, or alternately lead a team to remove a processing step to save data cleaning time without damaging predictive accuracy. In these early days of big data in environmental science, we remain wanting for a cohesive theory of optimal prediction (Efron, 2020); as a result, beliefs about methodological improvements are still best tested by experiment.

5 Conclusion

Our study demonstrates that preprocessing LiDAR point clouds to filter out ground noise may be detrimental when making predictions of above-ground biomass using machine learning methods. By removing signal of stand density and structure from LiDAR-derived predictors, ground noise filtering produces models that are systematically worse at predicting low AGB plots while impairing the ability of models to accurately capture the variance present in higher AGB regions. This impact is particularly notable within mixed-use and otherwise heterogeneous landscapes, given the increased proportion of ground returns recorded when mapping these areas compared to contiguously forested regions. Although well-justified in its original context of modeling mean stand heights, the persistence of ground noise filtering in LiDAR-based AGB modeling appears to produce less accurate predictions than could be achieved using currently available data.

More broadly, this study serves as a reminder that commonly accepted data preprocessing workflows do not necessarily transcend domains and methodologies. Noise which may mask information in one modeling application may provide useful signal when modeling other outcomes, requiring modelers to reevaluate data transformations when moving between problems and contexts. Whether such an evaluation is done empirically through comparisons of model performance or by examining the logical basis for the manipulation (or as presented here, both), critically assessing data preprocessing pipelines remains an essential task in the production of accurate and useful models from remotely sensed data sources.

6 Acknowledgements

We would like to thank the US Forest Service Forest Inventory & Analysis program for their data sharing and cooperation, the New York State GIS Program Office for compiling LIDAR data, and the New York State Department of Environmental Conservation, Office of Climate Change, for funding support.

References

Anderson, R.S., Bolstad, P.V., 2013. Estimating Aboveground Biomass and Average Annual Wood Biomass Increment with Airborne Leaf-on and Leaf-off LiDAR in Great Lakes Forest Types. Northern Journal of Applied Forestry 30, 16–22. https://doi.org/10.5849/njaf.12-015

Bates, S., Hastie, T., Tibshirani, R., 2021. Cross-validation: What does it estimate and how well does it do it? arXiv:2104.00673v2 [stat.ME].

Breiman, L., 2001. Random Forests. Machine Learning 45, 5–32. https://doi.org/10.1023/A:1010933404324

Brown, J.F., Tollerud, H.J., Barber, C.P., Zhou, Q., Dwyer, J.L., Vogelmann, J.E., Loveland, T.R., Woodcock, C.E., Stehman, S.V., Zhu, Z., Pengra, B.W., Smith, K., Horton, J.A., Xian, G., Auch, R.F., Sohl, T.L., Sayler, K.L., Gallant, A.L., Zelenak, D., Reker, R.R., Rover, J., 2020. Lessons learned implementing an operational continuous united states national land change monitoring capability: The land change monitoring, assessment, and projection (LCMAP) approach. Remote Sensing of Environment 238, 111356. https://doi.org/10.1016/j.rse.2019.111356

Deo, R.K., Russell, M.B., Domke, G.M., Andersen, H.-E., Cohen, W.B., Woodall, C.W., 2017. Evaluating site-specific and generic spatial models of aboveground forest biomass based on landsat time-series and LiDAR strip samples in the eastern USA. Remote Sensing 9. https://doi.org/10.3390/rs9060598

Dubayah, R.O., Drake, J.B., 2000. Lidar Remote Sensing for Forestry. Journal of Forestry 98, 44–46. https://doi.org/10.1093/jof/98.6.44

Efron, B., 2020. Prediction, estimation, and attribution. Journal of the American Statistical Association 115, 636–655. https://doi.org/10.1080/01621459.2020.1762613

García, M., Riaño, D., Chuvieco, E., Danson, F.M., 2010. Estimating biomass carbon stocks for a mediterranean forest in central spain using LiDAR height and intensity data. Remote Sensing of Environment 114, 816–830. https://doi.org/10.1016/j.rse.2009.11.021

Gray, A.N., Brandeis, T.J., Shaw, J.D., McWilliams, W.H., Miles, P., 2012. Forest inventory and analysis database of the united states of america (FIA). Biodiversity and Ecology 4, 225–231. https://doi.org/10.7809/b-e.00079

Hawbaker, T.J., Gobakken, T., Lesak, A., Trømborg, E., Contrucci, K., Radeloff, V., 2010. Light Detection and Ranging-Based Measures of Mixed Hardwood Forest Structure. Forest Science 56, 313–326. https://doi.org/10.1093/forestscience/56.3.313

Hosking, J.R.M., 1990. L-moments: Analysis and estimation of distributions using linear combinations of order statistics. Journal of the Royal Statistical Society. Series B (Methodological) 52, 105–124.

Huang, W., Dolan, K., Swatantran, A., Johnson, K., Tang, H., O'Neil-Dunne, J., Dubayah, R., Hurtt, G., 2019. High-resolution mapping of aboveground biomass for forest carbon monitoring system in the tri-state region of maryland, pennsylvania and delaware, USA. Environmental Research Letters 14, 095002. https://doi.org/10.1088/1748-9326/ab2917

Hudak, A.T., Fekety, P.A., Kane, V.R., Kennedy, R.E., Filippelli, S.K., Falkowski, M.J., Tinkham, W.T., Smith, A.M.S., Crookston, N.L., Domke, G.M., Corrao, M.V., Bright, B.C., Churchill, D.J., Gould, P.J., McGaughey, R.J., Kane, J.T., Dong, J., 2020. A carbon monitoring system for mapping regional, annual aboveground biomass across the northwestern USA. Environmental Research Letters 15, 095003. https://doi.org/10.1088/1748-9326/ab93f9

Lachenbruch, P.A., Mickey, M.R., 1968. Estimation of error rates in discriminant analysis. Technometrics 10, 1–11. https://doi.org/10.2307/1266219

Langford, E., Schwertman, N., Owens, M., 2001. Is the property of being positively correlated transitive? The American Statistician 55, 322–325. https://doi.org/10.1198/000313001753272286

Luo, S., Chen, J.M., Wang, C., Xi, X., Zeng, H., Peng, D., Li, D., 2016. Effects of LiDAR point density, sampling size and height threshold on estimation accuracy of crop biophysical parameters. Opt. Express 24, 11578–11593. https://doi.org/10.1364/OE.24.011578

Ma, W., Domke, G.M., D'Amato, A.W., Woodall, C.W., Walters, B.F., Deo, R.K., 2018. Using matrix models to estimate aboveground forest biomass dynamics in the eastern USA through various combinations of LiDAR, landsat, and forest inventory data. Environmental Research Letters 13, 125004. https://doi.org/10.1088/1748-9326/aaeaa3

Magnussen, S., Boudewyn, P., 1998. Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. Canadian Journal of Forest Research 28, 1016–1031. https://doi.org/10.1139/x98-078

Massey, F.J., 1951. The kolmogorov-smirnov test for goodness of fit. Journal of the American Statistical Association 46, 68–78. https://doi.org/10.1080/01621459.1951.10500769

Næsset, E., 1997. Determination of mean tree height of forest stands using airborne laser scanner data. ISPRS Journal of Photogrammetry and Remote Sensing 52, 49–56. https://doi.org/10.1016/S0924-2716(97)83000-6

New York Office of Information Technology Services, 2018. LIDAR collection (QL2) for Cayuga County and most of Oswego County, New York Lidar; Classified Point Cloud [Data file].

New York Office of Information Technology Services, 2015. NY WarrenWashingtonEssex Spring 2015; Classified Point Cloud [Data file].

Nilsson, M., 1996. Estimation of tree heights and stand volume using an airborne lidar system. Remote Sensing of Environment 56, 1–7. https://doi.org/10.1016/0034-4257(95)00224-3

Pflugmacher, D., Cohen, W.B., Kennedy, R.E., 2012. Using landsat-derived disturbance history (1972–2010) to predict current forest structure. Remote Sensing of Environment 122, 146–165. https://doi.org/10.1016/j.rse.2011.09.025

Pflugmacher, D., Cohen, W.B., Kennedy, R.E., Yang, Z., 2014. Using landsat-derived disturbance and recovery history and lidar to map forest biomass dynamics. Remote Sensing of Environment 151, 124–137. https://doi.org/10.1016/j.rse.2013.05.033

R Core Team, 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Riemann, R., Wilson, B.T., Lister, A., Parks, S., 2010. An effective assessment protocol for continuous geospatial datasets of forest characteristics using USFS forest inventory and analysis (FIA) data. Remote Sensing of Environment 114, 2337–2352. https://doi.org/10.1016/j.rse.2010.05.010

Roussel, J.-R., Auty, D., Coops, N.C., Tompalski, P., Goodbody, T.R.H., Meador, A.S., Bourdon, J.-F., de Boissieu, F., Achim, A., 2020. lidR: An r package for analysis of airborne laser scanning (ALS) data. Remote Sensing of Environment 251, 112061. https://doi.org/10.1016/j.rse.2020.112061

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., Aroyo, L., 2021. "Everyone wants to do the model work, not the data work": Data cascades in high-stakes AI, in: Proceedings of CHI 2021.

Stone, M., 1974. Cross-validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society. Series B (Methodological) 36, 111–147.

St-Onge, B., Hu, Y., Vega, C., 2008. Mapping the height and above-ground biomass of a mixed forest using lidar and stereo ikonos images. International Journal of Remote Sensing 29, 1277–1294. https://doi.org/10.1080/01431160701736505

Thorndike, E., 1999. New York's Adirondack Park: Where U.S. Wilderness preservation began. International Journal of Wilderness 5, 9–14.

Wasser, L., Day, R., Chasmer, L., Taylor, A., 2013. Influence of vegetation structure on lidar-derived canopy height and fractional cover in forested riparian buffers during leaf-off and leaf-on conditions. PLOS ONE 8, 1–13. https://doi.org/10.1371/journal.pone.0054776

White, J.C., Arnett, J.T.T.R., Wulder, M.A., Tompalski, P., Coops, N.C., 2015. Evaluating the impact of leaf-on and leaf-off airborne laser scanning data on the estimation of forest inventory attributes with the area-based approach. Canadian Journal of Forest Research 45, 1498–1513. https://doi.org/10.1139/cjfr-2015-0192

Wright, M.N., Ziegler, A., 2017. ranger: A fast implementation of random forests for high dimensional data in C++ and R. Journal of Statistical Software 77, 1–17. https://doi.org/10.18637/jss.v077.i01