

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

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November 26, 2022

## 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. We applied several ground noise filtering thresholds while mapping two regions within New York State, 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.

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## Introduction

Airborne LiDAR has become an essential data source for large-scale modeling of forest aboveground biomass, enabling predictions with 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 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.

Originating from LiDAR-based estimation of mean tree and canopy height (Næsset, 1997), ground noise filtering has remained prevalent in LiDAR pre-processing across domains, including aboveground biomass estimation. In this new domain, ground returns may actually provide 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.

## Methods

We applied several height thresholds (no filtering, filtering points classified as “ground”, and filtering all points below 0.1, 1, and 2 meters above ground) to leaf-off LiDAR data flown for two regions within New York State (USA). The first area represents the majority of New York’s Cayuga and Oswego counties, a mixed agricultural and developed landscape with a large amount of marginal forestland with fragmented tree cover. The second area covers the northern sections of Warren and Washington counties and the southern section of Essex county, a predominantly forested region largely within New York’s Adirondack Park.

We fit random forests to predict forest aboveground biomass calculated from FIA plot measurements, using metrics derived from the filtered LiDAR data sets as predictors. Separate models were fit to each region, as well as to a combined data set. Model accuracy was assessed against a hold-out set made from 30% of available FIA plots.

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## Results

Predictors derived from filtered LiDAR had lower variance across plots and higher correlations between predictors. This combination results in lower amounts of information available to each model.

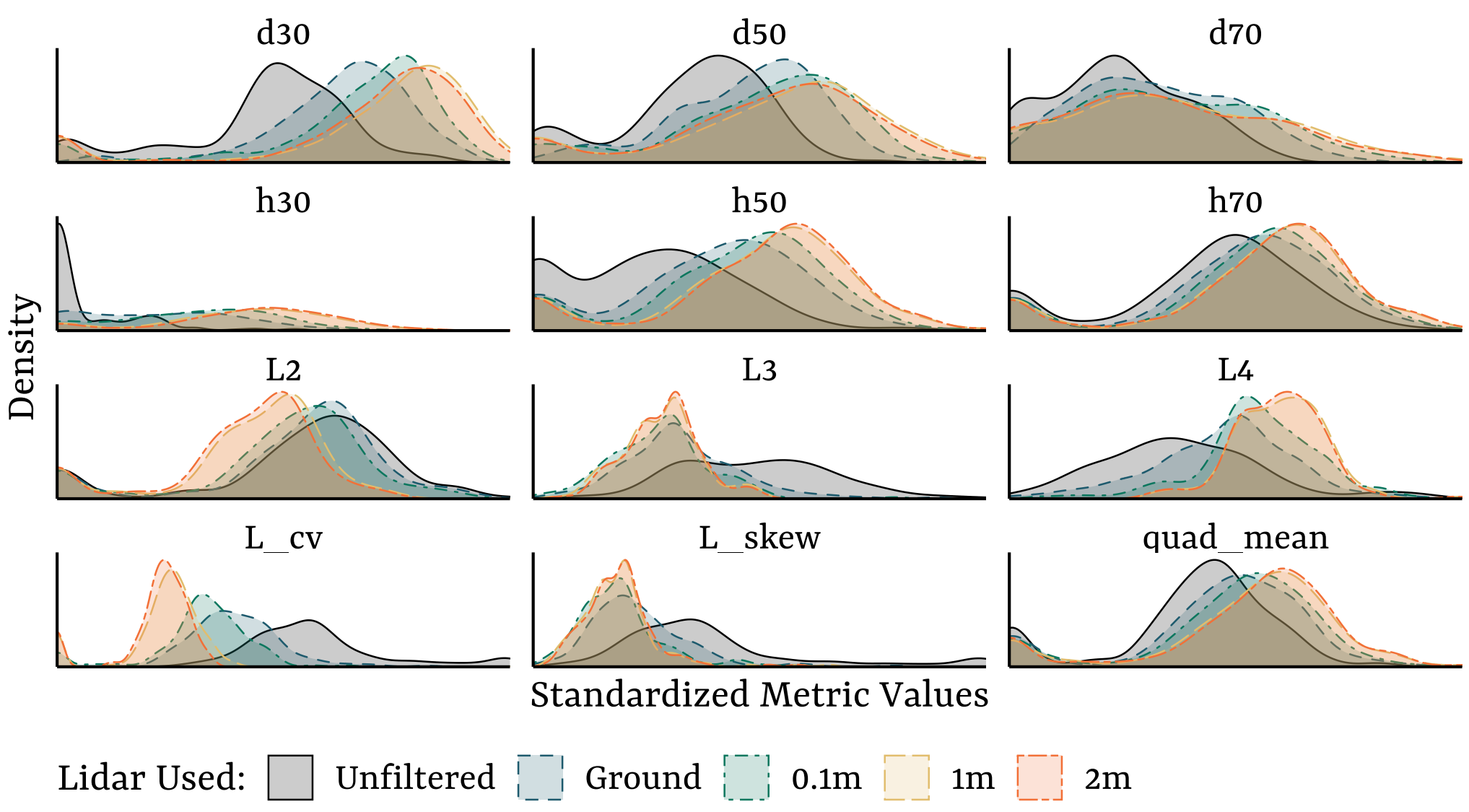


Figure 1: Distributions of common LiDAR-derived metrics (including density percentiles, decile heights, L-moments (from Hosking, 1990), and quadratic mean height) for the pooled dataset at various levels of ground noise filtering. Filtering reduces the variance in many metrics, reducing the total amount of information available to models.

Perhaps as a result, models consistently performed better when using predictors derived from less-filtered data sets. This trend was most noticeable in the mixed-use landscape, likely due to the higher proportion of near-ground returns in the region.

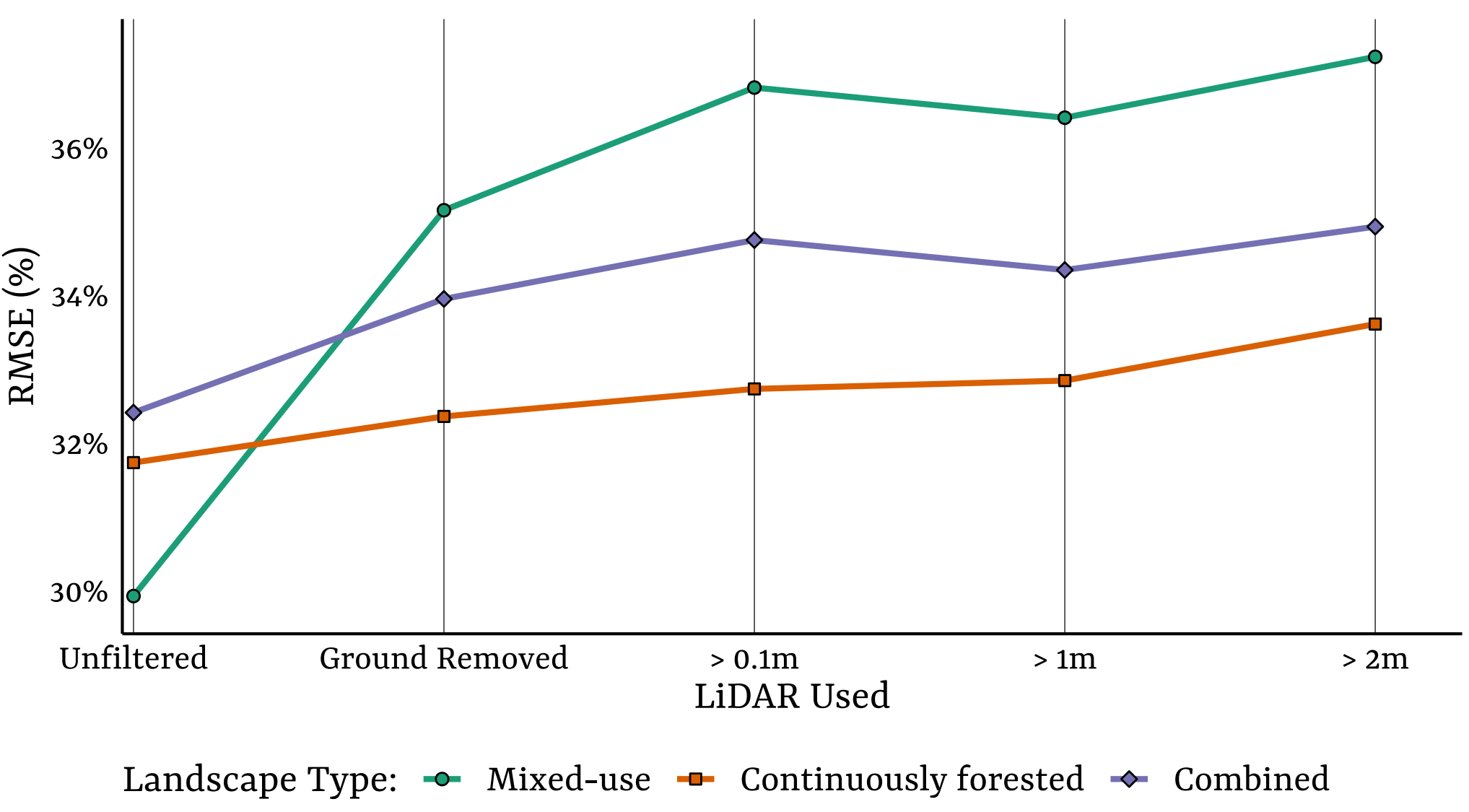


Figure 2: Height threshold-based filtering of LiDAR returns produces inferior models across all landscape types, with more notable impacts in mixed-use landscapes

Although well-justified in its original context of modeling mean stand heights, ground noise filtering for LiDAR-based AGB modeling appears to produce less accurate predictions than could be achieved using currently available data.

## References

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Næsset, E. (1997). *ISPRS J. Photogramm. Remote Sens* 52: 49-56.

