Using advanced airborne remote sensing as a sampling tool to support forest inventory in interior Alaska, USA

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1. Introduction

The USDA Forest Service Forest Inventory and Analysis (FIA) program is mandated by US Congress to implement a forest inventory and monitoring system in the boreal forests of interior Alaska, and extending the FIA inventory into this region has been identified as a strategic priority for the national program. Given the extreme logistical challenges and high costs associated with implementing a field inventory in this remote region – where there is virtually no transportation infrastructure and almost every plot requires a helicopter to access – there is a strong interest in leveraging state-of-the-art remote sensing technology to support the FIA inventory in interior Alaska. For this reason, FIA has partnered with NASA-Goddard to implement an innovative, multi-level sampling design in this region, where a sparse grid of field plots is supplemented with high-resolution airborne remote sensing data collected with the multi-sensor G-LiHT (Goddard Lidar-Hyperspectral-Thermal) system. Initial results from the first inventory unit (Tanana Valley) indicate that use of model-assisted estimation in a 2-stage design can increase the precision of estimates for key inventory attributes (biomass, carbon).

2. Data

2.1 Forest inventory data

The FIA program established 690 field inventory plots on forested conditions in the Tanana inventory unit during the period 2014-2018. Field plots were established on a regular hexagonal grid, with a spacing between plots of approximately 11 km, resulting in a field sampling intensity of 1 plot per 12000 ha. The standard FIA plot design was used, where each plot consists of a cluster of four 1/60th ha fixed-A large number of forest attributes were measured at each plot, including measurements of tree size, species and condition (live/dead), downed woody materials, lichens/moss, and soil properties (bulk density, carbon, etc.) (Cahoon et al., *in prep*), as well as condition-level attributes such as forest type, stand size, etc. In addition, high-precision GNSS receivers were used to obtain high-quality spatial coordinates for each FIA subplot (Andersen et al., *in prep*). Total aboveground biomass for individual trees (live and dead) was calculated using published biomass equations (Cahoon et al., *in prep*) and total biomass, by forest type, was calculated for each plot.

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2.1 G-LiHT airborne remote sensing data

High-resolution airborne remote sensing data was collected with the Goddard Lidar-Hyperspectral-Thermal (G-LiHT) system in a strip sampling mode over the entire Tanana unit in 2014 and 2018 (fig. 1). This multi-sensor instrument provides 1) detailed forest structure and terrain morphology using lidar scanning, 2) forest composition and health measurements using imaging spectrometry, and 3) surface temperature measurements using thermal scanning (Cook et al., 2013). G-LiHT data were acquired in nominal 350 meter side swaths along flight lines (spaced approx. 9,200 meters apart, oriented in a NE-SW direction) that were planned to cover every potentially-forested FIA field plot. In the end, G-liHT measurements were acquired over 906 out of 1,091 total FIA plots in the Tanana Unit (most of the plots missed by G-LiHT were in clearly unvegetated rock/ice areas of the Alaska Mountain Range, etc.).

3. Methods

3.1 Post-stratified, 2-stage model-assisted estimation framework

The standard estimation approach in the FIA program uses post-stratification (Bechtold and Patterson, 2005), where the stratification is usually based on a combination of spatial layers including satellite-derived land cover classification (e.g. National Land Cover Dataset (NLCD), Dewitz, 2019), and other environmental gradients such as precipitation, elevation, etc. In order to incorporate the additional information provided by the G-LiHT strip sample in interior Alaska, we utilize a post-stratified ratio estimator under a two-stage design, where the FIA plots and G-LiHT acquisition can be seen as a two-stage (cluster) sampling design, with the G-LiHT swaths (strips) treated as clusters (1st stage) and the FIA plots represent a subsample within the clusters (2nd stage). The efficiency of the estimation from this two-stage design can be further improved through post-stratification and by accounting for the length of the strips (via ratio estimation). The resulting estimator is a post-stratified, ratio estimator for model-assisted estimation in a two-stage design (Andersen et al., 2011; Ringvall et al., 2016; Strunk et al., 2014). Following Ringvall et al. (2016), the response variable is a forest inventory attribute (possibly for a specific domain, such as forest type) summarized at the FIA plot-level, and the predictor variables are G-liHT derived metrics extracted from the footprint of the FIA plot (average lidar-derived canopy height, hyperspectral-based forest type classification), and a linear regression model is developed relating the inventory attribute to lidar metrics.

FIA plots are distributed about 9 km apart along each G-LiHT strip (1,091 total FIA plots), and remote sensing (RS) plots (with the same spatial configuration and size as a FIA plot) were distributed at 200 meter intervals along the center of each G-LiHT strip (fig 3; 73,509 total RS plots). At each of these RS plots, the regression model is used to predict the inventory parameter. In addition, if the population is post-stratified, where the number of remote sensing plots within each stratum is assumed to be known without error, the model-assisted regression estimate for the specified inventory attribute in a given strip and stratum can be calculated. In cases where a RS plot is missing (mountainous areas, low clouds, etc.), the value for the RS plot measurement (lidar and/or forest type classification) was imputed as the mean lidar height or most commonly occurring forest type class within the stratum. A ratio-to-size estimator at the stratum level and the post-stratified ratio estimator can be calculated. The variance estimator of the post-stratified ratio estimator takes into account 1) the variance of the model-assisted estimator within strips, 2) variance between strips, and 3) the dependency between stratum-level estimates within strips. A variance estimator can be applied in cases where only a small portion of the strips may cover individual strata (Ringvall et al., 2016). However, with very small strip- and stratum-level plot sample sizes the variance estimator is likely highly variable or even impossible to calculate. Therefore the variance estimator is modified to replace stratum- and strip-level residual variance with the stratum-level residual variance calculated across all strips, which we assume will be more stable and, if anything, will be a conservative estimate because residuals within strips are likely to be spatially-autocorrelated). It should be noted that this variance estimator assumes that the G-LiHT strips, RS, and FIA plot subsamples are collected as a simple random sample in both stages. In reality, both the FIA data (regular hexagonal grid) and the G-LiHT strips (evenly-spaced strip sample) represent a systematic sample, not a simple random sample. This likely leads to an overestimation of variance, although it should be noted that small samples at the strip level can also lead to unreliable variance estimators (Ringvall et al., 2016). Further research on optimal field sampling intensity, stratification, and use of hyperspectral-based forest type classification within this 2-stage design and model-assisted inferential framework is needed and ongoing.

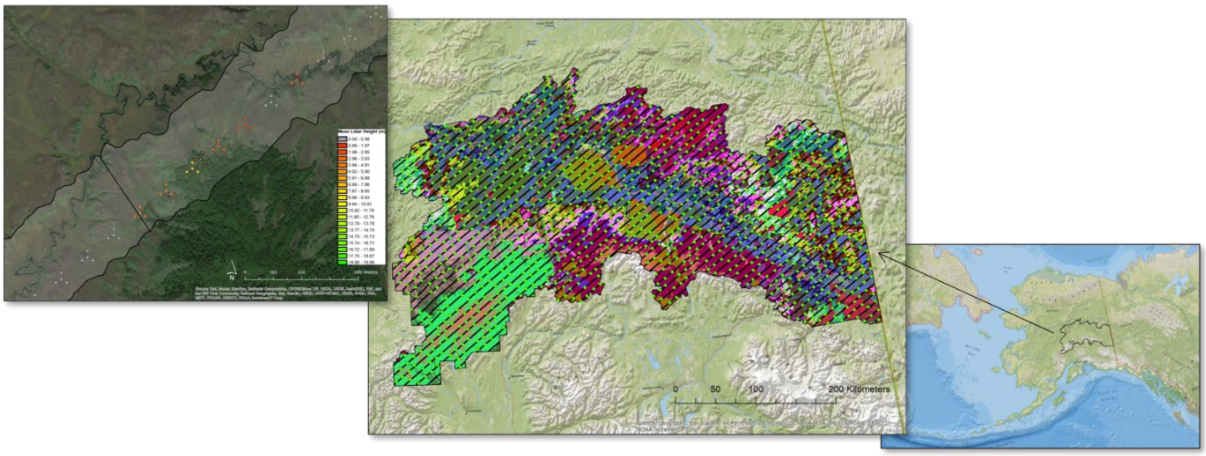

Figure 1: Alaska, USA (right), Tanana inventory unit (center) with FIA plots (green dots), G-LiHT flight lines (black) and post-strata (various colors). Left inset image shows G-liHT swath covering RS plots and FIA plot (dark outline), colored by lidar canopy height.

4. Results

A comparison of the tabular estimates for aboveground tree biomass, by forest type, provided by the standard post-stratified and post-stratified ratio estimator is shown in Table 1. These results indicate that incorporating the G-LiHT lidar height measurements in the estimator through a ratio estimator can significantly improve the precision of the inventory estimates. The standard errors (SE) of the post-stratified ratio estimators are generally lower than the post-stratified estimator, with the most significant reduction in the more aggregated estimators (i.e. total biomass, all softwood, all hardwood) and less improvement in the precision of biomass estimates for specific domains (i.e. forest types).

Table 1 - Comparison of standard FIA post-stratified and post-stratified ratio estimates under a two-stage design of aboveground biomass by forest type, Tanana Unit, Alaska, 2018

Forest type	Post-stratified		Post-stratified Ratio	
	Total	**SE**	**Total**	**SE**
Softwoods		*thousand tons*		
White Spruce	71,113	9,151	68,807	7,767
Black Spruce	101,820	6,368	99,948	5,761
Tamarack	527	309	522	399
Total Softwoods	173,460	9,811	169,277	7,654
Hardwoods				
Paper Birch	74,553	8,370	70,140	5,667
Aspen	22,114	4,631	20,375	4,711
Balsam Poplar	5,118	2,323	4,850	1,503
Total Hardwoods	101,786	9,244	95,390	6,769
Nonstocked				
< 10% live trees	25	16	25	360

Total	275,271	12,008	264,667	7,407

5. Discussion and conclusions

The results of this study indicate that incorporating airborne lidar sampling in the FIA sampling design in interior Alaska – through model-assisted estimation – can improve the precision of key inventory estimates, such as aboveground biomass and carbon. The gains are precision are most pronounced for aggregate estimates, such as total biomass or total biomass for hardwoods/softwoods. The gains in precision for more specific domains (forest type) are much less pronounced, indicating that more informative predictor variables, or perhaps more sophisticated modelling approach, should be used to leverage the information provided by G-LiHT measurements to improve domain-level estimation. Going forward, FIA and NASA are proceeding with data collection in other regions of interior Alaska and it is expected that FIA will continue to leverage the detailed information provided by this airborne data to increase the reliability and value of the scientific products from this inventory and monitoring program.

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