

# Statistical Issues with LiDAR Applications to Support Large-scale Forest Inventory

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**Summary:**

Airborne laser instrumentation provides finely detailed data about the height of vegetation.

When linking a sample of laser data to data from field plots with a double sampling regression estimator, we are able to estimate aboveground forest biomass for large regions.

**Purpose of today's presentation:**

Provide an overview of what we did in Hedmark County, and then focus on some unresolved statistical issues.

I emphasize the latter over the results obtained in HC.

Since 2004, a core group has been working together:

**Erik Næsset & Terje Gobakken & Ole Martin Bolandsas**  
**Norwegian University of Life Sciences**  
**Ås Norway**

**Timothy G. Gregoire**  
**Yale University**  
**New Haven, CT, USA**

**Ross Nelson**  
**Goddard Space Flight Center, NASA**  
**Greenbelt, MD, USA**

**Göran Ståhl**  
**Swedish University of Agricultural Sciences**  
**Umeå, Sweden**

We meet once or twice a year, and customarily invite a few other scientists or statisticians to join our discussion.

Side note: For his work in the development of ALS for forest inventory, the 2011 Marcus Wallenberg Prize was awarded to Erik Næsset and presented by the King of Sweden in a ceremony held in Stockholm on 3 October 2011.



## **Light Detection and Ranging (LiDAR)**

There are an increasing number of folks around the globe actively investigating the potential of LiDAR for forest inventory, yet there are applications of this technology in many other fields, too.

Many folks are considering LiDAR as the principal tool to be used in the UN-IPCC REDD+ Monitoring, Reporting, and Verification process in the immense regions of tropical forest cover. FAO.

Some applications of LiDAR rely on the delineation of individual tree crowns, a process known generically as segmentation.

Not our's.

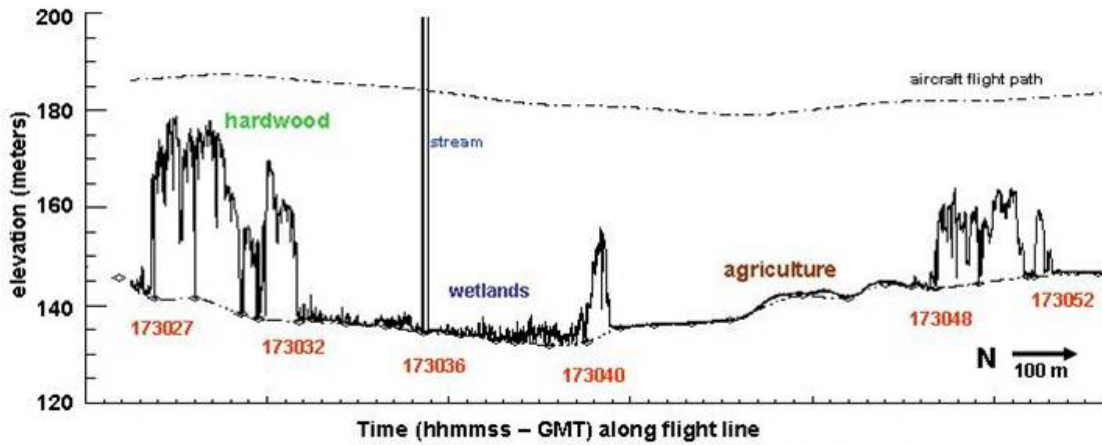
Two different approaches using LiDAR have been developed and demonstrated in operational projects.

(1) the use of an airborne profiling laser (PALS) designed for sampling-based inventories, which collects height information along a narrow line on the ground. When flying at 150m aboveground, the divergence of the profiling laser beam is approximately 44cm

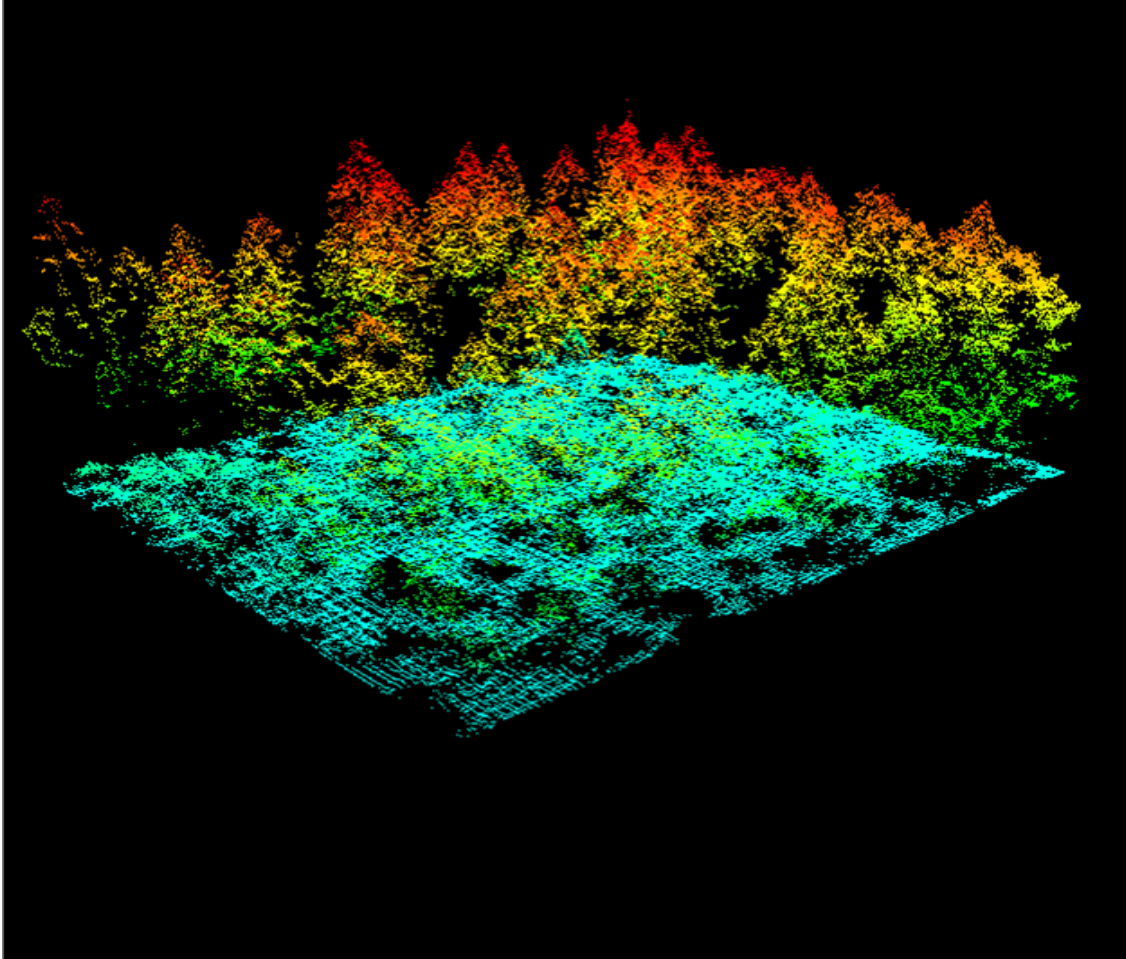
(2) the use of an airborne laser scanner (ALS), which typically has a swath width of up to several hundred meters. Scanning is roughly perpendicular to flight line.

The profiling system developed at NASA (Nelson et al. 2003a), labeled "Portable Airborne Laser System" (PALS), is a simple device with low development- and operation costs.

Data, after processing, enables construction of a linear height profile as show below.



In contrast, instrumentation for airborne laser scanning (ALS) costs nearly \$1,000,000US, and collects data for a continuous area. After processing, the "point cloud" of height measurements from ALS might look like this:





For the application of LiDAR for forest inventory which I describe today, the study area is Hedmark County (HC) in southeastern Norway on the Swedish border.



The total area is approximately 27,390 km<sup>2</sup> and the altitude varies from 119 to 2178 m a.s.l. The county has the largest productive forest area in Norway.

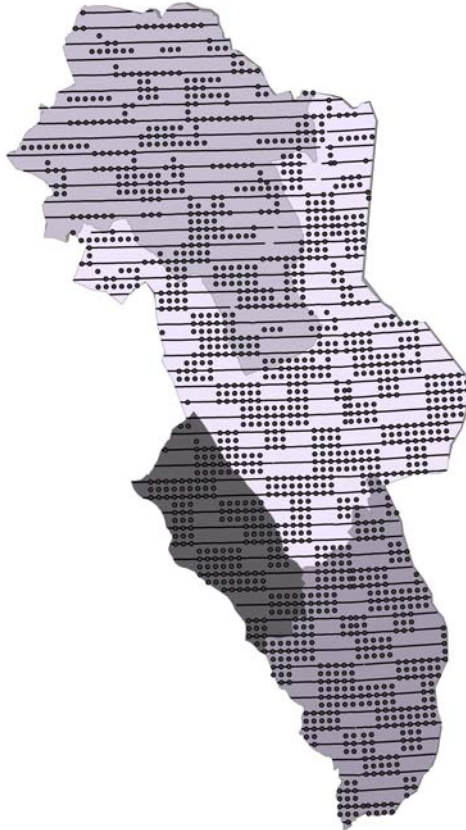
The dominant tree species are Norway spruce (*Picea abies* (L.) Karst.) and Scots pine (*Pinus sylvestris* L.).



## NFI sample plots

There are 2309 NFI sample plots in HC, distributed systematically on a 3x3 km grid.

Of the 2309 plots in HC, 1483 had been measured in 2005-2007, and were used in our study.



Each circular plot has a size of 250 m<sup>2</sup>.

Above the coniferous tree line in the mountain areas plots were located on a 3x9 km grid. Because of this we established additional plots in these areas.

Additional plots were also established in developed areas, outside the forests, where the number of regular NFI plots is limited.

## **Post-stratification**

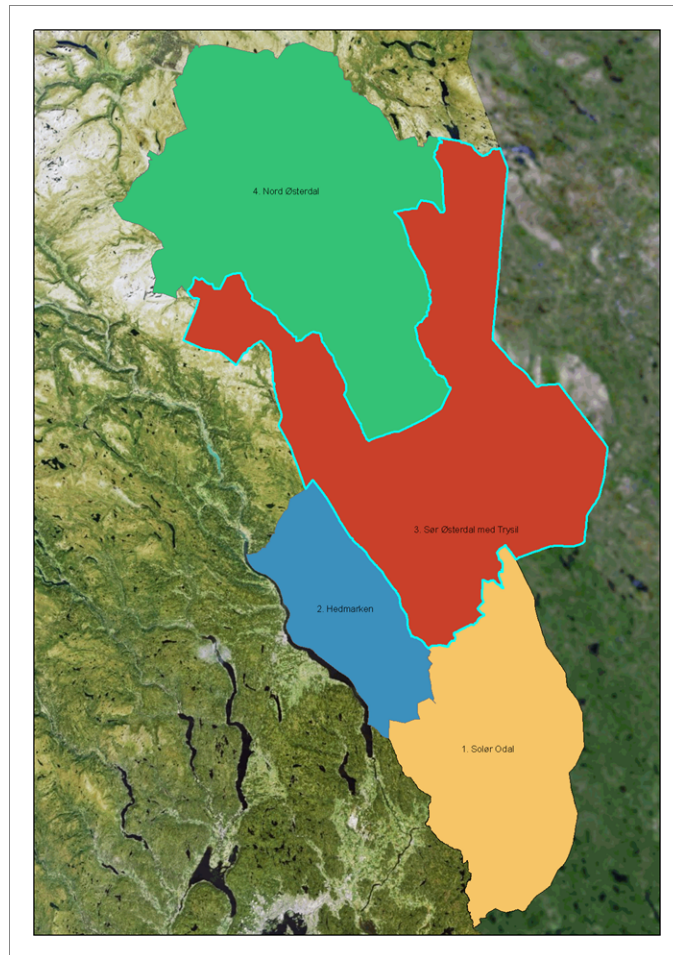
Existing land use maps, digital terrain models (DTM) derived from official Norwegian topographic map series and Landsat 5 TM satellite images were used to classify the area of HC into eight land cover classes:

Four productive forest classes:

1) High, 2) Medium, 3) Low productivity forests, and 4) young forest.

The remaining four cover classes were either nonproductive forest or nonforest, i.e., (5) Nonproductive forest, (6) Mountain areas >850 m a.s.l., (7) Developed areas, e.g., residential areas and infrastructure, and (8) open Water.

Post-stratified by the four Administrative Units (AU) for which post-stratified estimates of biomass were eventually derived.



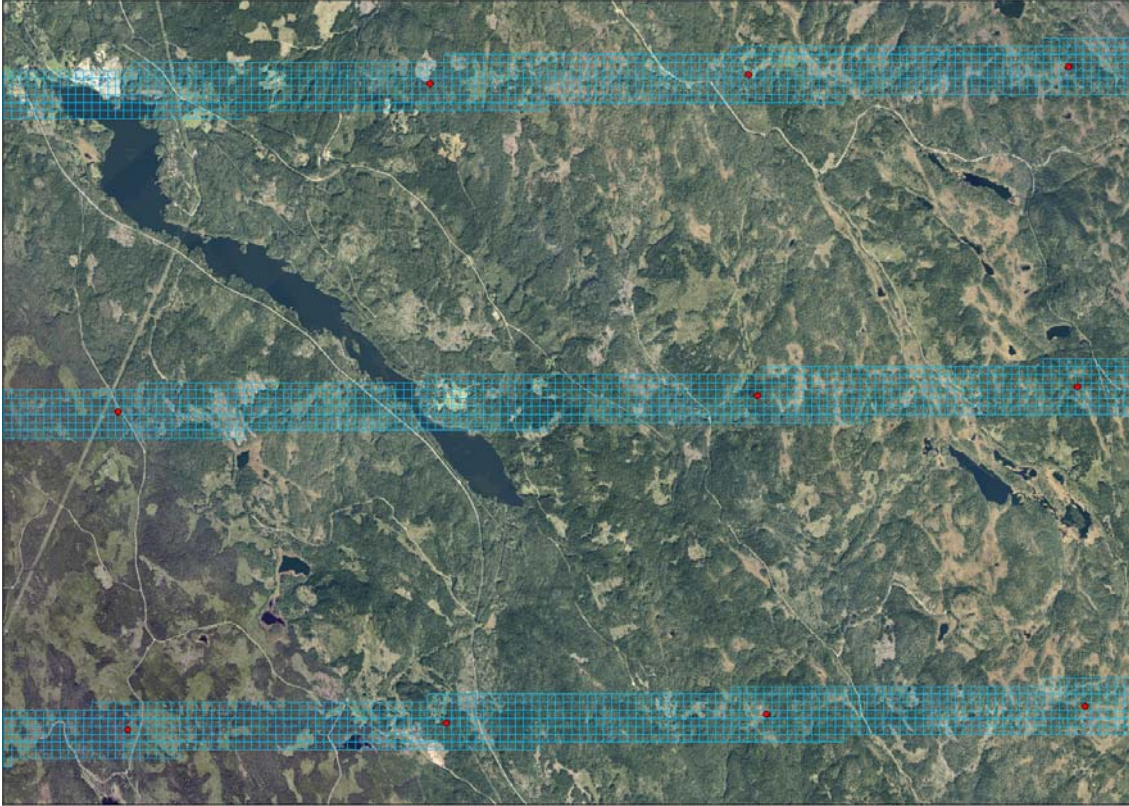
### **Laser scanner data**

The ALS data were acquired under leaf-on conditions from 22 July to 16 September 2006.

Fifty-three flight lines were flown with the scanning laser with an inter-line distance of 6 km. Therefore approximately 50% of the available NFI plots were covered by ALS data.

In total, 4570 km were flown, and with a swath width of approximately 500 m, the ALS data covered 2297 km<sup>2</sup> or 8.4% of the total county area.

Flights paths were in E-W direction, centered on the NFI ground plot. Each swath was further subdivided into square cells of 250 m<sup>2</sup>, in exact correspondence to the area of the NFI circular plots.





Nonetheless, the same model for each cover class was used in all AUs.

After having fitted the regression, a prediction of biomass per plot is obtained and corrected for the back-transformation bias.

Each cell was designated as belonging to a single cover class. The assignment of an ALS cell into an AU was based on only its location within HC.

## Estimation

The objective is to estimate total AGB for HC, as well as for each AU post-stratum and each cover class. Also, a credible estimate of standard error

I viewed the sampling as a two-stage design, with each flight line (PALS) or swath (ALS) serving as a primary sampling unit (PSU) and segments (cells) within a line (swath) as a secondary sampling unit.

My colleague Göran Ståhl chose to view it as a two-phase design, wherein the large first phase sample was constituted as all the cells or line segments for which we had LiDAR information.

In truth, it is neither a 2-stage nor a 2-phase sample, at least not in the classical sense.

Detailed results are presented in the two *Canadian Journal of Forest Research* papers from 2011.

## Results from Hedmark County

For all productive forest classes combined, the PALS (59.5 t/ha) and ALS estimates (59.9 t/ha) were quite close to the 64.0 t/ha estimated solely from the 975 NFI ground plots.

For all classes of nonproductive forest and nonforest combined, biomass estimates from PALS and ALS are quite close to the ground NFI estimate of 9.0 t/ha. Both PALS and ALS did least well in estimating the biomass of the nonproductive forest class.

The differences between the ground NFI and PALS and ALS estimates are more striking when assessed in terms of the estimates of standard error.

The NFI estimates are apparently more precise, in part because they are based on more plots than are used in the second stage of the PALS and ALS sampling that was conducted in Hedmark.

Even after accounting for this by multiplying the ground NFI standard error values by the factor (number of NFI plots/ number of LiDAR plots)<sup>0.5</sup>, the PALS and ALS estimated standard errors exceeded those of the NFI ground estimates, sometimes quite substantially.

Given the fundamental difference in the sampling designs, this adjustment based on number of plots can best be regarded as but a crude attempt to put the methods on a comparable basis.

In our case, this is complicated by the fact that the LiDAR sampling has a two-stage structure, whereas the NFI does not. In both cases, a systematic sampling design was used and a conservative estimate of standard error was employed.

Follow up work by Ene et al (2012) and Næsset et al (2013) indicate expected gains in precision by using the lidar data as auxiliary information, as well as the poor performance of usual estimators of standard error following systematic sampling.

## Design & Estimation issues

How apt is it to treat the systematic arrangement of flight lines and the systematic arrangement of NFI plots on a flight line as a two-stage sampling design?

Some post-strata had so few SSUs that precision of estimation was poor. Perversely, some variance estimates were negative. Yet the post-strata remain of inherent interest. A dilemma.

Post-strata estimates within a flight line have a design-based covariance, which complicates the assessment of precision when combining biomass estimates across post-strata.

Variance estimation following systematic sampling is astonishingly poor. (Ene et al, 2012, simulation)

Variance estimation following two-stage systematic sampling has never been addressed.

Ought first-stage flight lines be chosen with unequal probability (importance sampling) so as to give more informative lines a greater chance of being selected?

Ought a different estimator of biomass be used to deal with unequal length flight lines?

Do estimators that perform well for AGB work similarly as well to estimate change in biomass between two sampling occasions? Bollandas et al (2012, *Statistical Modelling and Applications*) took a model-based approach to estimating 4-year change.

Fuller use of auxiliary information: in addition to LiDAR metrics on the flight lines, we may have complete population (wall-to-wall) coverage based on satellite information, and other data from the field (2nd-stage) plots. Three-phase sampling, perhaps.

Recent indications (Philip Mundheng, Göttingen) that the effect of variable selection on accurate estimation of stand errors can be huge: false indication of precision.