# Chapter 15
# Modeling and Estimating Change

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**Abstract** Airborne laser scanning (ALS) data are a source of spatial information that can be used to assist in the efficient and precise estimation of forest attributes such as biomass and biomass change, particularly for remote and inaccessible forests. This chapter includes an introduction to the use of ALS data for estimating change and a detailed review with tabular summary of the small number of known published reports on the topic. The review proceeds chronologically, noting the progression from exploratory and correlation studies to modeling and mapping and finally to statistically rigorous inference for population parameters. Both direct and indirect approaches for constructing models and mapping change are summarized. Although maps can be used to assist in the estimation procedure, systematic model prediction errors as reflected in maps induce bias into estimators. Thus, if the objective is rigorous inference for population parameters such as mean biomass change per unit area, rather than just maps of the populations, then bias must be estimated and incorporated into the parameter estimates, and uncertainty must be estimated. The design-based, model-assisted estimators that are presented for both independent estimation samples and single samples with repeated observations satisfy these criteria and produce inferences in the form of confidence intervals.

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## 15.1 Introduction

Estimates of changes in the amounts and distributions of forest biomass are important for both general monitoring purposes and for assessment in the context of climate change. For example, countries that ratified the Kyoto protocol have also committed to reporting estimates of their emissions and removals of atmospheric carbon for land use, land use change and forestry (LULUCF) activities (Höhne et al. 2007) such as afforestation, reforestation, deforestation, and forest management. To be credible, the reported estimates must be based on objective data. The most common and comprehensive sources of objective forest data are national forest inventories (NFI) (e.g. Rypdal et al. 2005; Tomppo et al. 2010). The large range of variables observed and measured on the extensive and systematic NFI networks of field plots produce estimates of multiple parameters including many related to biomass and carbon. Change for NFI variables such as biomass between times $t_1$ and $t_2$ is typically estimated as the difference between the estimate for $t_2$ and the estimate for $t_1$. However, because the aggregate coverage of NFI plots is relatively small, even with intense sampling, the spatial resolution of pure NFI-based estimates is limited with the result that only large area estimates of current biomass and the change in biomass can be reported reliably.

The United Nations collaborative program on Reducing Emissions from Deforestation and forest Degradation in developing countries (UN REDD) relies on establishment of efficient monitoring systems for purposes of estimating, reporting, and verifying changes in carbon stocks. In addition to carbon stocks, great interest has been expressed in monitoring the possible effects of climate change on forests such as changes in growth rates, accumulation of biomass in existing forest, and the invasion of trees on previously treeless areas. Pure field based inventory and monitoring systems such as NFIs can be and are used to estimate change over large areas such as regions and nations. However, because change phenomena of interest such as the invasion of forest into mountainous areas are often relatively rare, areas subject to specific changes and the consequent number of field plots are both small with the result that the precision of plot-based estimates is also small.

Airborne laser scanning (ALS) is a source of auxiliary data that can improve the efficiency of efforts to estimate change and can contribute to improving the precision of change estimates. Multiple approaches for using ALS data to estimate change may be considered. First, for areas of limited size, full area ALS coverage can be obtained, but for larger areas cost factors may constrain ALS data acquisition to strips. Strip sampling approaches, while less costly, require more complex statistical estimators and, of necessity, lead to less precise estimates because sampling uncertainty in the form of the strip-to-strip variability must be incorporated into variance estimates.

Second, methods for modeling and estimating change using multi-temporal field observations and corresponding multi-temporal ALS-data are often characterized as either direct or indirect (Sect. 15.3). With the direct method, change in the variable of interest is estimated directly from multi-temporal auxiliary data such as ALS height and density metrics. With the indirect method, change is estimated as the difference between estimates of the variable at two points in time.

Third, change can be estimated and relationships between change and auxiliary variables can be modeled at different spatial scales. For example, segment-based modeling and estimation focus on spatial units such as individual trees, whereas change modeling for grid cells focuses on regular, fixed area spatial units larger than the crowns of individual trees. Thus, inventory methods that use ALS data are frequently characterized as either single-tree or area-based (Næsset 2002, 2004). The success of single-tree methods depends largely on successful segmentation of crowns for individual trees (Hyyppä and Inkinen 1999; Popescu and Wynne 2004; Solberg et al. 2006a), a challenging task because the algorithms can both fail to detect some trees (omission errors) and produce false trees (commission errors) (Kaartinen et al. 2012; Vauhkonen et al. 2012). The accuracy of segmentation is influenced by both forest conditions (Falkowski et al. 2008) and the point density of the ALS data (Tesfamichael et al. 2009). Because omission and commission errors often vary between measurement occasions, they are potentially more serious for change estimation than for inventories of current conditions.

Area-based methods focus on constructing models of relationships between ground plot observations and corresponding ALS metrics that describe the vertical and horizontal distributions of the ALS pulse echoes. For areas with no ground observations, the models may be used to predict biomass or biomass change for grid cells that are ideally the same size or larger than the ground plot, but not necessarily the same shape. Biomass or biomass change for an entire area is then estimated as the sum of the model predictions for all grid cells. Area-based inventories conducted at two points in time facilitate estimation of change as the difference in estimates for both grid cells and coarser units such as forest stands or forests.

The remainder of the chapter is organized into three main sections. Section 15.2 consists of a review of the literature in three parts: single tree studies, canopy gap studies, and area-based studies. Section 15.3 focuses on modeling and mapping, primarily as preliminary and background information for Sect. 15.4 which addresses estimation. Although a map is often a useful end product, in a broader context it is simply an intermediate product on the path to an inference in the form of a confidence interval for a parameter of the population that the map only inaccurately depicts. Finally, although the focus is estimation of biomass or biomass change using ALS metrics, the approaches documented are generally appropriate for estimation using any remotely sensed data.

## 15.2 Literature Review

In characterizing the scientific method, Reichenbach (1938) emphasized the distinction between the context of *Discovery* and the context of *Justification*. Discovery is characterized by exploratory studies that estimate correlations between response and predictor variables and develop empirical models that account for variation in observations of the response variables. Whereas Discovery is a creative enterprise and is subject to few constraints, Justification has a formal logic that leads to scientific inferences characterized by statistical rigor. Thus, the chronological maturation of a discipline would be expected to be characterized by early exploratory and feasibility studies but shifting toward greater statistical rigor with the passage of time. As the following review indicates, such is the case for the use of ALS data to estimate forest change.

ALS-based change studies are of two general kinds, single-tree studies and area-based studies. Single-tree studies are characterized by individual crown segmentation algorithms, primary use of ALS maximum heights, and single-tree attributes such as tree height growth. Area-based studies are characterized by estimation for grid cells of sizes on the order of 100s of $m^2$, greater focus on multi-tree, below canopy attributes such as change in biomass per unit area, and use of distributions of heights of ALS pulse echoes.

### *15.2.1 Single Tree Studies*

Because ALS data in their most basic form are height information, many early ALS change studies focused on exploring the relationships between ALS metrics and change in heights for single trees and aggregation of height changes for multiple trees. The first study using multi-temporal ALS data was conducted in Finland by Hyyppä et al. (2003) who estimated the height growth of single trees segmented from ALS data with pulse densities of 10 pulses/$m^2$. Single tree height growth was estimated as the difference between 1998 and 2000 maximum ALS heights within tree segments. Mean stand growth was estimated as the mean of single tree growth estimates within stand boundaries. Estimates of tree height growth based on differences in maximum ALS heights were within 15 cm of field observations of growth for approximately half the trees. At the stand-level, standard errors were less than 5 cm. Differences between field-based and ALS-based estimates of height growth were attributed to differences in the digital elevation models (DEM) between measurement occasions, failure to match trees between measurements, and suppressed trees that could not be identified. The important conclusion was that estimation of forest height growth is feasible using multi-temporal ALS data.

In a series of papers, Yu et al. (2003, 2004, 2005, 2006) used multi-temporal ALS data to estimate single-tree height change and related attributes for a study area in Finland. Yu et al. (2003, 2004) successfully detected 61 of 83 trees harvested between 1998 and 2000 using a tree matching algorithm, ALS data with pulse density of 10 pulses/$m^2$, and differences in maximum ALS heights. Trees that were not detected were generally below the dominant canopy. Means of single tree height growth estimates for plots and stands for the 2-year interval were estimated with accuracies of 5-cm and 10–15-cm, respectively. Yu et al. (2005) used an augmented dataset and an improved tree-to-tree matching algorithm to estimate height growth for 153 pine trees using differences in maximum ALS heights for

1998, 2000, and 2003. Statistically significant differences between field height growth and differences in maximum ALS heights were attributed to two causes. First, reception of an echo from the apex of a single coniferous tree is unlikely, even with dense ALS data, because the apex of a tree rarely has surface area sufficiently large to trigger an echo (Andersen et al. 2006). Second, differences can be partially attributed to the use of different sensors with different properties such as penetration rates at different times. Continuing rapid technological development diminishes the likelihood of using the same sensor at different times. Yu et al. (2006) estimated the correlation between observed height growth between 1998 and 2003 for segments corresponding to single trees and three ALS metrics: (i) differences between maximum ALS heights, (ii) mean and median of differences in digital surface models (DSM) corresponding to tree crowns, and (iii) differences in the 85th, 90th, and 95th ALS height percentiles. The single predictor variable that best explained the variation in observed growth was the difference between the maximum ALS heights. The two primary conclusions from this series of studies were that crown segmentation using ALS data is feasible, and that ALS metrics and changes in the metrics have potential for predicting individual tree and mean tree height growth.

### *15.2.2 Canopy Gap Studies*

In multiple respects, canopy gap studies are intermediate between single-tree and area-based studies. Similar to single-tree studies, they typically focus on tree height and canopy-level response variables. Some canopy gap studies (e.g., Vastaranta et al. 2012) use distributions of ALS height metrics to segment individual crowns, whereas other studies (e.g., Kellner et al. 2009; Hirata et al. 2008) use ALS maximum heights and grid cells, albeit small grid cells (0.25–25 $m^2$) that are closer in size to individual crowns than sizes used for more typical area-based studies.

St. Onge and Vepakomma (2004) used a region growing algorithm to assess differences in canopy height model predictions between 1998 and 2003 for 50-cm $\times$ 50-cm grid cells in Quebec, Canada. First echo ALS pulse densities were 0.3 for 1998 and 3.0 for 2003. Overall accuracy of the gap detection was 96 % based on comparisons with high resolution imagery. Vepakomma et al. (2008, 2010) used the same dataset for more detailed studies of gap and forest dynamics and concluded that gap sizes of 5 $m^2$ or greater could be reliably detected. Kellner et al. (2009) used 1997 and 2006 ALS data to characterize the dynamics and distribution of canopy gap sizes in Costa Rica. For each 5-m $\times$ 5-m grid cell, they calculated mean ALS height and estimated change in canopy height as differences in the means between 1997 and 2006. They then constructed a transition matrix for 1-m height classes for the 5-m $\times$ 5-m grid cells and reported three primary results: (i) ALS-based estimates of forest structure and dynamics were similar to ground-based estimates; (ii) most canopy gaps were produced by loss of vegetation below the canopy level; and (iii) the distribution of canopy heights was close to a steady-state equilibrium. Hirata et al. (2008) assessed canopy gap dynamics in Japan using ALS data acquired in 2001 and 2005 with densities in the range 32–50 pulses/m$^2$. Gaps were defined as areas for which canopy height was less than a specified threshold, and for each year gap areas were estimated. Based on changes in gap area estimates between 2001 and 2005, individual gaps were assigned to one of five change classes: appearance, enlargement, reduction, disappearance, and no change. For the reduction and disappearance classes, absolute values of estimates of area changes were positively correlated with initial gap sizes. The general conclusion from these canopy gap studies was that ALS data have considerable potential for quantitative evaluation of gaps and gap dynamics. More discussion on use of ALS data to assess canopy gaps can be found in Chap. 21.

### *15.2.3 Area-Based Studies*

Whereas single tree studies focus on the use of ALS height data to segment individual trees, to predict attributes for single trees, and to predict means over single trees for larger areas, by contrast, area-based studies focus on estimation of plot and stand-level attributes using distributions of ALS heights without regard to individual trees.

Gobakken and Næsset (2004) compared height and density metrics obtained from 1999 to 2001 ALS first-pulse point clouds with densities of approximately 1 pulse/m$^2$ for 87 plots of size 300–400 m$^2$ in Norway. The plots were assigned to two categories, young forest and mature forest with poor site quality. Mean differences between 1999 and 2001 for all ALS metrics, except maximum ALS height in the mature stratum, were statistically significantly different from zero. Næsset and Gobakken (2005) used an extended dataset from the same study area and predicted change in mean stand tree height, stand basal area, and timber volume for selected stands in southeastern Norway using 1999 and 2001 ALS data with mean pulse densities of 0.87 and1.18 pulses/m$^2$, respectively. For each year and each of three strata related to age class and site quality, regression models were constructed to represent relationships between the three response variables and ALS height percentiles. The models were used to predict the response variables for 350-m$^2$ grid cells that tessellated 56 stands, and change was estimated for each variable as the difference between the model predictions. Estimates of correlations between the response variables and nearly all ALS-based variables derived from the first-echo point cloud were statistically significantly greater than zero. However, estimates of correlations with last-echo variables were much smaller. Systematic deviations between growth predictions and field observations and large uncertainties were attributed to the short 2-year period between measurements. Nevertheless, the large correlations for both studies indicated that ALS metrics have the potential for predicting forest growth.

Solberg et al. (2006b) used multi-temporal ALS metrics to construct a map of change in leaf area index (LAI) as a measure of defoliation resulting from a pine-sawfly attack. ALS data with pulse densities in the range 3–10 pulses/m$^2$ were acquired in May, July, and September 2005 for a 21-km$^2$ area in southeastern Norway. For each date, a regression model was constructed to represent the relationship between field measured LAI and gap fraction calculated as the ratio of below canopy echoes and the total number of echoes. The models were then used to predict LAI for each 10-m × 10-m grid cell in the study area, and a defoliation map was constructed by geographically depicting differences in model LAI predictions for each grid cell. As expected, the maps indicated a decrease in LAI between May and July and a slight increase between July and September. The primary conclusion is that changes in gap fraction calculated from ALS data can be used to predict LAI change and to construct maps for identifying areas of defoliation.

Yu et al. (2008) used linear regression models to estimate relationships between plot-level mean canopy height and volume growth and three sets of ALS metrics. For ALS data acquired in 1998, 2000, and 2003 with pulse densities of 10 pulses/m$^2$, the metrics included differences between maximum ALS heights, mean and median of differences in DSMs corresponding to tree crowns, and differences in ALS height percentiles. Mean canopy height growth was best predicted by maximum ALS heights, and volume growth was best predicted by DSM differences. The primary conclusion was that multi-temporal ALS data can be used to estimate mean height and volume growth for spatial areas larger than individual trees.

Hopkinson et al. (2008) used ALS data to estimate plot-level height growth for a red pine plantation in Ontario, Canada. Their data consisted of field measurements of tree heights for 19 plots of 121-m$^2$ and ALS data with pulse densities in the range 2.5–3.6 pulses/m$^2$ acquired four times between 2000 and 2005. Differences in maximum ALS heights for 2000–2002, 2002–2004, and 2004–2005 were compared to corresponding observed mean plot-level height growth. The ALS-based height growth estimates correlated well with observed mean height growth for both methods, although changes in maximum ALS heights were, on average, smaller than observed changes. The reason is the same as for single tree studies, i.e., maximum ALS heights rarely capture canopy apices. The authors concluded that although uncertainties associated with annual estimates of plot-level change are unacceptably large, uncertainties on the order of 10 % for 3-year estimates of change are operationally acceptable.

Vastaranta et al. (2011) constructed a logistic regression model using ALS change data to predict the probability of snow damage for 85 grid cells of size 25-m$^2$ in Finland. Predictor variables were changes in height percentiles for ALS data acquired in 2007 with pulse density of 7 pulses/m$^2$ and in 2010 with pulse density of nearly 12 pulses/m$^2$. Overall accuracy with respect to predictions of the damage/no-damage class was 78.6 % when assessed using leave-one-out cross validation. Vastaranta et al. (2012) segmented damaged canopy areas using differences in canopy height model predictions between 2006/2007 and 2010. Detection of changes in all canopy layers due to causes such as storm damage or insect defoliation using full ALS height distributions and an area-based approach was judged to be superior to single-tree methods, particularly if the pulse density is small or if geometric alignment is a problem. These two studies demonstrated that abrupt structural changes to canopies can be detected using ALS-based height percentiles.

Nyström et al. (2013) used discriminant analysis with ALS metrics to classify field plots in the forest-tundra ecotone of northern Sweden with respect to three categories of harvest: (i) no harvest, (ii) harvest of 50 % of trees with heights greater than 1.5-m, (iii) harvest of all trees with height greater than 1.5-m. ALS data acquisitions were deliberately different to mimic the small likelihood of identical flight parameters over time. In 2008 ALS data were collected with a TopEye scanner with average pulse density of 12 pulses/m$^2$, and in 2010 data were acquired using an Optech scanner with average pulse density of 1.2 pulses/m$^2$. Histogram matching was used to calibrate the two sets of ALS variables. Classification accuracy was 0.88 using relative differences in ALS height percentiles and density metrics as predictor variables. The study demonstrated that histogram matching can alleviate difficulties associated with classification using ALS data acquired with different sensors with different flight parameters.

Bollandsås et al. (2013) evaluated three approaches for using ALS data to model and predict biomass change between 2005 and 2008 for a mountain forest in southeastern Norway. For each approach, the model predictor variables were either height percentiles or differences in height percentiles between 2005 and 2008 for ALS data with pulse densities of 3.4–4.7 pulses/m$^2$. The first approach was indirect and entailed constructing a model of the relationship between biomass observations and height percentiles aggregated for both years. Biomass change was then estimated as the difference between the model predictions for the 2 years. The second approach was direct and entailed constructing a model of the relationship between biomass change and differences in ALS height percentiles. The third approach consisted of constructing a model of the relationship between the average annual relative growth rate between 2005 and 2008 and corresponding average annual relative change in ALS height percentiles. Models based on the second and third approach that directly predicted growth variables were superior to the first approach that only indirectly predicted growth, and models based on the second approach that predicted actual growth were slightly superior to models based on the third approach that predicted relative growth. This study was among the very first to demonstrate that change in an important climate change variable, biomass, can be predicted using change in ALS metrics.

Næsset et al. (2013a) demonstrated that categories of biomass changes between 1999 and 2010 associated with different management activities in Norway could be distinguished, and that population estimates of biomass change could be calculated using observations for a sample of field plots and wall-to-wall ALS data with pulse densities of 1.2 and 7.3 pulses/m$^2$. The analyses consisted of four steps. First, non-forest areas and stands younger than 20 years were excluded, and aerial photography was then used to classify forest stands into four forest pre-strata based on stand age and species dominance in 1999. Second, based on changes between 1999 and 2010, three post-strata were defined: (i) recent clear cut representing deforestation, (ii) thinned representing forest degradation, and (iii) untouched representing natural growth with no harvest. Each of 176 plots was then assigned to a single post-stratum. A multinomial logistic regression model was constructed using the plot post-stratum assignments and corresponding ALS metrics from 1999 to 2010 and used to assign each 200-$m^2$ grid cell to a post-stratum. Third, for each post-stratum, three models were constructed: models of the relationship between biomass and ALS metrics for each of 1999 and 2010, and a model of the relationship between biomass change and change in ALS metrics. For each grid cell, biomass change was predicted both as the difference between the 2010 and 1999 biomass model predictions and from the biomass change model. Fourth, the design-based, model-assisted regression estimator was used to estimate the area of each post-stratum, biomass change for each post-stratum, and corresponding standard errors. The results were compared to corresponding estimates obtained using only field data. The standard errors for the post-strata area estimates obtained using the model-assisted estimator were 18–84 % smaller than standard errors obtained using only the field plot data. Similarly, standard errors for the post-strata mean biomass change estimates were 43–75 % smaller when obtained using the model-assisted estimator. The study demonstrated that deforested, thinned and degraded, and unchanged forest areas can be discriminated and that change in biomass for those areas can be precisely estimated using ALS metrics. Of more importance, the study was the first to use statistically rigorous methods to estimate and quantify bias, to estimate precision, and to quantify the utility of auxiliary ALS data for increasing the precision of estimates for areas consisting of multiple grid cells.

### *15.2.4 Summary*

This brief review has illustrated general trends in the development of a discipline (Table 15.1). Initial studies focused on exploratory and feasibility investigations, estimation of correlations, and simple empirical models of relationships between response variables such as tree height and predictor variables such as ALS maximum heights. Greater maturity was reflected in construction of models for more complex response variables such as canopy gaps, snow damage, and classes of harvest. Enhancement and optimization of the models and their use for constructing maps represents a succeeding step. However, whereas map accuracy assessments focus on describing maps, mature disciplines focus on estimating parameters of the populations that maps only inaccurately depict. The latter studies emphasize estimating and adjusting for bias and estimating and maximizing precision.

## 15.3 Modeling and Mapping

Two categories of approaches for estimating forest attribute change from remotely sensed data are prominent. Trajectory methods use time series of three or more sets of remotely sensed data to assess the type, extent, and temporal patterns of change

**Table 15.1** Literature review

| Data years (Point density) | Reference | Approach | Response variable |
|---|---|---|---|
| 1998, 2000 (10) | Hyyppä et al. (2003) | Indirect (object) | Growth of trees, mean mean height-growth stands |
| 1998, 2000 (10) | Yu et al. (2003) | Indirect (object) | Harvested trees, growth of trees |
| 1999, 2001 (1.1, 0.9) | Gobakken and Næsset (2004) | Indirect (grid cell) | Effect of growth on ALS-variables |
| 1998, 2003 (0.3, 3.0) | St-Onge and Vepakomma (2004) | Indirect (grid cell, object) | Gap detection, growth of trees, mean growth on plots |
| 1998, 2000 (10) | Yu et al. (2004) | Indirect (object) | Harvested trees, growth of trees |
| 1998, 2000, 2003 (10) | Yu et al. (2005) | Indirect (object) | Growth of trees |
| 1999, 2001 (1.1, 0.9) | Næsset and Gobakken (2005) | Indirect (grid cell) | Change of mean height, basal area, and volume |
| 1998, 2003 (10) | Yu et al. (2006) | Indirect (object) | Growth of trees |
| 2005 (4.4, 4.9, 4.6) | Solberg et al. (2006a, b) | Indirect (grid cell) | Leaf area index |
| 2001, 2005 (32, 51) | Hirata et al. (2008) | Indirect (object) | Detection and classification of gaps |
| 1998, 2000, 2003 (10) | Yu et al. (2008) | Direct (object, grid cell) | Mean height growth, volume growth |
| 2000, 2005 (2.5, 3.6, 2.8, 3.2) | Hopkinson et al. (2008) | Direct (grid cell) | Mean height growth |
| 1998, 2003 (0.3, 3.0) | Vepakomma et al. (2008, 2010) | Indirect (grid cell) | Gap dynamics |
| 1997, 2006 | Kellner et al. (2009) | Indirect (grid cell) | Detection of gaps |
| 2007, 2010 (7.0, 11.9) | Vastaranta et al. (2011) | Direct (grid cell) | Classification of plots with snow-damage trees |
| 2006/2007, 2010 (9.8/7.0, 11.9) | Vastaranta et al. (2012) | Direct (object) | Segmentation of damaged crown area |
| 2008, 2010 (1.2, 12.0) | Nyström et al. (2013) | Direct (grid cell) | Classification of change type |
| 2005, 2008 (3.4, 4.7) | Bollandsås et al. (2013) | Indirect, direct (grid cell) | Change of biomass |
| 1999, 2010 (1.2, 7.3) | Næsset et al. (2013a) | Direct (grid cell) | Change of biomass |

over time (Kennedy et al. 2007, 2010; Cohen et al. 2010; Zhu et al. 2012). Although trajectory methods have the potential to provide crucial details on the nature and exact time of change for individual grid cells, these methods are both data and computationally intensive. In addition, statistically rigorous methods for assessing uncertainty have not been developed. Bi-temporal methods are more common and entail analyses of separate sets of ground and remotely sensed data for two times and can further be separated into two subcategories, direct and indirect methods.

Direct bi-temporal methods use models to represent the relationship between change for a response variable and auxiliary data. Of necessity, models used with direct methods require training data consisting of two observations of the response and auxiliary variables for the same sample units. ALS auxiliary variables are often formulated as differences between corresponding metrics for the two time points; this approach is often characterized as *differencing*. However, using each metric separately is not prohibited.

For continuous response variables such as biomass change, models must produce both negative and positive predictions. Regardless of the mathematical forms of models and the ALS auxiliary variables, caution must be exercised when extrapolating beyond the range of the values of ALS independent variables in the training sample. Often, the ranges of values of the ALS independent variables may be greater in the population than in the training data used to construct the models. If so, extrapolating the models beyond the range of the sample data may produce both unrealistic negative and/or unrealistic positive predictions. Linear models have been popular, presumably because of their familiarity and their ease of use, but they are particularly susceptible to extrapolation errors. For example, Næsset et al. (2013a) found that linear model predictions of 11-year biomass change for some grid cells in the population were as large as 19,500 Mg/ha, whereas the maximum observed change for the field plot observations used as training data was only 462.3 Mg/ha. To compensate, they truncated the model predictions and used a design-based model-assisted estimator that includes a bias adjustment to obtain an estimate for the entire study area. Although construction of nonlinear models, particularly models with asymptotes, may be more difficult, judicious selection of such models may alleviate extrapolation errors.

For categorical response variables with classes such as deforestation, degradation, and no change, model procedures that produce continuous probabilities for each of the different possible classes are often used. Examples of such procedures include binomial or multinomial logistic regression models, discriminant analysis, and maximum likelihood methods. Nearest neighbor techniques can be used to produce either probabilities for classes or class predictions (Tomppo et al. 2009; McRoberts 2012).

Indirect bi-temporal methods use models to represent the relationship between the response and auxiliary variables for each of two separate times. Models for use with indirect methods can use training data consisting of either repeated observations of the same sample units at different times or observations of different sample units at different times. If the relationship between the response variable and the ALS metrics is stable over time, a single model may be constructed using data that has been aggregated for the two times. Change maps may be constructed by calculating the difference in model predictions for each grid cell.

For continuous response variables such as biomass, the same cautions regarding extrapolation errors must be exercised as for direct methods. McRoberts et al. (2013b) used a variation of a logistic model whose predictions cannot be negative and whose largest predictions are constrained by an asymptote to circumvent extrapolation errors. For categorical response variables, the same kinds of models used with direct methods may be used with indirect methods.

Change maps can be constructed using either direct or indirect methods. With direct methods, the model can be used to predict change in the response variable for each grid cell. With indirect methods, land cover class is predicted for each grid cell at each time, and the difference between the predictions constitutes the prediction of change. For many applications, the change map may be regarded as an end product such as when the location of change is as important as the overall estimate of change. In addition, a change map can be used as the basis for stratified sampling to produce precise estimates of attributes for each category of change. However, as per Sect. 15.4, the map may serve only as an intermediate product, albeit an important product, on the path toward an inference for a change parameter.

## 15.4 Inference and Estimation

### *15.4.1 Inference*

The Oxford English Dictionary definition of infer is "to accept from evidence or premises" (Simpson and Weiner 1989). Because evidence in the form of complete enumerations of spatial populations is prohibitively expensive, if not logistically impossible, statistical procedures have been developed to infer values for population parameters from estimates based on observations from a sample of population units. In a sampling framework, inference requires expression of the relationship between a population parameter $\mu$ and its estimate $\widehat{\mu}$ in probabilistic terms (Dawid 1983). For estimation problems, the probabilistic relationship is most often expressed as a confidence interval in the form,

$$\widehat{\mu} \pm t \cdot \sqrt{\widehat{\mathrm{Var}}\left(\widehat{\mu}\right)},$$

where $t$ reflects the probability that confidence intervals constructed using data for all possible samples will include $\mu$. Thus, inference for estimation problems mostly reduces to the problem of using sample data to estimate both $\mu$ and $\mathrm{Var}\left(\widehat{\mu}\right)$.

### *15.4.2 Estimation*

Both design-based and model-based inferential methods are appropriate for use with ALS data to estimate population parameters such as mean biomass per unit area or mean change in biomass per unit area. Both approaches require definition of the population of interest. For ALS studies, finite populations of interest are usually defined as consisting of N population units in the form of equal-size grid cells. The size of the cells is typically similar, if not the same, as the size of the ground plots. Similarity in sizes ensures consistency in ALS metrics based on scale-dependent height and density distributions calculated separately for plots and cells.

Design-based inference, also characterized as probability-based inference (Hansen et al. 1983; McRoberts 2011), is based on three assumptions: (1) units are selected for the sample using a randomization scheme; (2) the probability of inclusion into the sample for any unit is positive and known; and (3) the value of the response variable for each unit is a fixed value as opposed to a random variable. The validity of design-based estimators is based on random variation resulting from the probabilities of inclusion of units into the sample. Of importance for ALS studies, the sample units do not necessarily conform to the population units as previously defined. Whereas the plots that serve as sample units are typically circular to facilitate ground sampling, the grid cells that serve as population units are typically square to ensure mutual exclusivity. Further, because plot centers do not necessarily correspond to grid cell centers, plot area may partially extend into multiple grid cells. Nevertheless, if the relationship between the response variable and the ALS metrics is the same for both plots and grid cells, estimation and inference are not affected.

Design-based, model-assisted estimators use models to predict the response variable for each grid cell but rely on probability samples for validity. Multiple forms of these estimators have been reported for land cover applications using satellite data (McRoberts 2010, 2011, 2014; McRoberts and Walters 2012; Vibrans et al. 2013; Sannier et al. 2014) and for estimating volume and biomass using ALS and InSAR data (D'Oliveira et al. 2012; Gregoire et al. 2011; Gobakken et al. 2012; Næsset et al. 2011, 2013a, b; McRoberts et al. 2013a, b; Strunk et al. 2012).

The assumptions underlying model-based inference differ considerably from the assumptions underlying design-based inference. First, the observation for a population unit is a random variable whose value is considered a realization from a distribution of possible values, rather than a fixed value as is the case for design-based inference. Second, the basis for a model-based inference is the model, not the probabilistic nature of the sample as is the case for design-based inference. Third, randomization for model-based inference enters through the random realizations from the distributions for population units, whereas randomization for probability-based inference enters through the random selection of units into the sample. Several advantages accrue to model-based inference: (i) inference is possible for regions without probability samples; examples include tropical countries with no probability-based inventories but with data from management or other focused inventories; (ii) inference is possible for small areas for which sample sizes are too small to support design-based inference; and (iii) uncertainty can be estimated for each population unit which is not possible with design-based inference. The disadvantages are reliance on correct model specification, estimators with greater mathematical complexity, and greater computational intensity. Although model-based inference is not discussed further in this chapter, references include McRoberts (2006, 2010), and particularly Ståhl et al. (2011) and McRoberts et al. (2013a) who used ALS auxiliary data.

Regardless of whether a change is predicted and a map is constructed using direct or indirect methods, model prediction errors produce bias in estimators based on adding map unit predictions and uncertainty in estimates for areas consisting of multiple grid cells. Design-based methods for estimating and compensating for the bias and for estimating uncertainty require an estimation sample whose observations are of equal or greater quality with respect to factors such as resolution and accuracy than the training observations used to construct the models. This estimation sample may also be used as an accuracy assessment sample for estimating map accuracy measures, but when the emphasis is estimation rather than map assessment, the term estimation sample is more appropriate. If necessary, the sample used to acquire training data can also be used as the estimation sample (Næsset et al. 2011, 2013a), but the practice is discouraged because it may lead to underestimates of both bias and uncertainty. Finally, of importance for estimation purposes, the form of the design-based statistical estimators used to calculate estimates of bias and uncertainty must conform to the design of the estimation sample, not the design of the training sample.

The design-based estimators that follow are sufficient to produce the estimates of population parameters and their variances that are necessary for inference and are based on several assumptions. First, the ALS auxiliary data are assumed to represent wall-to-wall coverage of the population. Examples of estimators for ALS data acquired in strips are described in Ene et al. (2012). Second, estimation samples are assumed to have been acquired using simple random or systematic sampling designs. If simple random or systematic samples do not produce enough observations of change, then stratified sampling may be necessary. In the latter case, the estimators below may be used for within-strata estimation. Third, a continuous response variable such as biomass or biomass change is assumed as opposed to a categorical response variable such as snow damage or no snow damage (Vastaranta et al. 2011), harvest class (Nyström et al. 2013), or disturbance class (Næsset et al. 2013a). Fourth, change estimators are provided for two estimation sampling designs, a single sample with repeated observations and two independent samples. Finally, design-based estimators are provided only for full coverage ALS; Chap. 14 addresses estimation for partial coverage, such as acquisition of ALS data in strips.

### *15.4.3 Estimators for Single Estimation Sample with Repeated Observations*

Generally, estimation is simplified if the estimation sample data can be acquired by observing the same population units at different times. The primary example is repeated observation of permanent NFI or other inventory plots whose locations are selected using a probability sampling design.

Denote a simple random sample of the population as $S = \{p_i : i = 1, \cdots, n\}$, where p denotes a population unit in the form of a grid cell, i indexes the sample, and n is the sample size. Further, let $y_i^k$ denote the observation of biomass for $p_i$ where $k = 1$ and $k = 2$ correspond to the two repeated observations. In addition, let $w_i = y_i^2 - y_i^1$ denote the observation of change in biomass for $p_i$ with model prediction, $\widehat{w}_i$. An initial estimator of $\Delta$, change in biomass per unit area, is,

$$\widehat{\Delta}_{\text{initial}} = \frac{1}{N}\sum_{i=1}^{N} \widehat{w}_i, \tag{15.1}$$

where N is the population size. However, this estimator may be biased as a result of systematic model prediction error. The bias of this estimator is estimated as,

$$\widehat{\text{Bias}}\left(\widehat{\Delta}_{\text{initial}}\right) = \frac{1}{n}\sum_{p_i \in S} \left(\widehat{w}_i - w_i\right). \tag{15.2}$$

One form of the model-assisted regression estimator (Section 6.5 in Särndal et al. 1992) for $\Delta$ is defined as the difference between the initial estimator and the expectation of its bias estimate which, under the assumptions that $N$ is both large and much larger than n, is,

$$\widehat{\Delta} = \widehat{\Delta}_{\text{initial}} - \widehat{\text{Bias}}\left(\widehat{\Delta}_{\text{initial}}\right) = \frac{1}{N}\sum_{i=1}^{N} \widehat{w}_i - \frac{1}{n}\sum_{p_i \in S} \left(\widehat{w}_i - w_i\right) \tag{15.3}$$

with variance estimator,

$$\widehat{\text{Var}}\left(\widehat{\Delta}\right) = \frac{1}{n\,(n-1)}\sum_{p_i \in S} \left(\varepsilon_i - \overline{\varepsilon}\right)^2, \tag{15.4}$$

where $\varepsilon_i = \widehat{w}_i - w_i$ is the model prediction error and $\overline{\varepsilon} = \frac{1}{n}\sum_{p_i \in S} \varepsilon_i$.

### 15.4.4 Estimators for Two Independent Estimation Samples

Two conditions may necessitate use of independent estimation samples. A first condition is when repeated observation of the same sample units is not possible. A first example is use of observations from temporary NFI plots; a second example is use of different sources for different dates. A second condition is when repeated observation of the same sample units fails to produce sufficient numbers of observations for some classes of a categorical response variable.

Denote the k-th estimation sample as $\mathrm{S}^{\mathrm{k}} = \{\mathrm{p}_i^k : \mathrm{i} = 1, \cdots, \mathrm{n}\}$, where $p$ denotes a population unit in the form of a grid cell, $i$ indexes the sample, and $n$ is the sample size. Further, let $\mathrm{y}_i^k$ denote the observation of biomass for $\mathrm{p}_i^k$ with model prediction, $\widehat{\mathrm{y}}_{\mathrm{i}}^{\mathrm{k}}$. With independent estimation samples, mean biomass per unit area is estimated separately for each of $\mathrm{k} = 1$ and $\mathrm{k} = 2$, and mean biomass change per unit area is estimated as the difference between the two estimates. An initial estimator of mean biomass per unit area for the k-th time, denoted $\mu^{\mathrm{k}}$, is,

$$\widehat{\mu}_{\text{initial}}^{\mathrm{k}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \widehat{\mathrm{y}}_{\mathrm{i}}^{\mathrm{k}}, \tag{15.5}$$

where N is the population size. However, systematic model prediction errors induce bias into this estimator which, for equal probability samples, can be estimated as,

$$\widehat{\mathrm{Bias}}\left(\widehat{\mu}_{\text{initial}}^{\mathrm{k}}\right) = \frac{1}{\mathrm{n}} \sum_{\mathrm{p}_{\mathrm{i}}^{\mathrm{k}} \in \mathrm{S}^{\mathrm{k}}} \left(\widehat{\mathrm{y}}_{\mathrm{i}}^{\mathrm{k}} - \mathrm{y}_{\mathrm{i}}^{\mathrm{k}}\right). \tag{15.6}$$

The same form of the model-assisted regression estimator may be used with independent samples to estimate $\mu^{\mathrm{k}}$, mean biomass per unit area, as was used with repeated observations of the same sample to estimate $\Delta$, mean change in biomass per unit area (Section 6.5 in Särndal et al. 1992),

$$\begin{aligned} \widehat{\mu}^{\mathrm{k}} &= \widehat{\mu}_{\text{initial}}^{\mathrm{k}} - \widehat{\mathrm{Bias}}\left(\widehat{\mu}_{\text{initial}}^{\mathrm{k}}\right). \\ &= \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \widehat{\mathrm{y}}_{\mathrm{i}}^{\mathrm{k}} - \frac{1}{\mathrm{n}} \sum_{\mathrm{p}_{\mathrm{i}}^{\mathrm{k}} \in \mathrm{S}^{\mathrm{k}}} \left(\widehat{\mathrm{y}}_{\mathrm{i}}^{\mathrm{k}} - \mathrm{y}_{\mathrm{i}}^{\mathrm{k}}\right). \end{aligned} \tag{15.7}$$

Under the assumptions that N is both large and much larger than $n$, that the prediction errors for a particular year are independent, and that simple random sampling was used, the variance of $\widehat{\mu}^{\mathrm{k}}$ can be estimated as,

$$\widehat{\mathrm{Var}}\left(\widehat{\mu}^{\mathrm{k}}\right) = \frac{1}{\mathrm{n}(\mathrm{n}-1)} \sum_{\mathrm{p}_{\mathrm{i}}^{\mathrm{k}} \in \mathrm{S}^{\mathrm{k}}} \left(\varepsilon_{\mathrm{i}}^{\mathrm{k}} - \bar{\varepsilon}^{\mathrm{k}}\right)^2, \tag{15.8}$$

where $\varepsilon_i^k = \widehat{y}_i^k - y_i^k$ is the model prediction error, and $\bar{\varepsilon}^k$ is the mean of the errors. When systematic sampling rather than simple random sampling is used, variances may be overestimated (Särndal et al. 1992, p. 83).

The estimator of mean change in biomass per unit area is,

$$\widehat{\Delta} = \widehat{\mu}^2 - \widehat{\mu}^1, \tag{15.9}$$

and the estimator of $\mathrm{Var}\left(\widehat{\Delta}\right)$ is,

$$\begin{aligned} \widehat{\mathrm{Var}}\left(\widehat{\Delta}\right) &= \widehat{\mathrm{Var}}\left(\widehat{\mu}^2 - \widehat{\mu}^1\right) \\ &= \widehat{\mathrm{Var}}\left(\widehat{\mu}^2\right) - 2 \cdot \widehat{\mathrm{Cov}}\left(\widehat{\mu}^2, \widehat{\mu}^1\right) + \widehat{\mathrm{Var}}\left(\widehat{\mu}^1\right). \end{aligned} \tag{15.10}$$

Estimates $\widehat{\mu}^1$ and $\widehat{\mu}^2$ obtained using Eq. 15.7 are used with Eq. 15.9 to estimate mean biomass change per unit area, and estimates $\widehat{\mathrm{Var}}\left(\widehat{\mu}^1\right)$ and $\widehat{\mathrm{Var}}\left(\widehat{\mu}^2\right)$ obtained using Eq. 15.8 are used with Eq. 15.10 to estimate the variance of the forest change estimate. Of importance, Eq. 15.10 includes an estimate of $\mathrm{Cov}\left(\widehat{\mu}^2, \widehat{\mu}^1\right)$. For independent estimation samples, $\mathrm{Cov}\left(\widehat{\mu}^2, \widehat{\mu}^1\right) = 0$ may be assumed.

Although the estimators formulated as Eqs. 15.7, 15.8, 15.9, and 15.10 have been developed under the assumption of independent estimation samples, they may also be used with repeated observations for the same sample. For the latter case, the sample observations for $k = 1$ and $k = 2$ are considered separate samples. However, because the two sets of observations are for the same sample units, $\widehat{\mathrm{Cov}}\left(\widehat{\mu}^2, \widehat{\mu}^1\right) = 0$ cannot be assumed. Nevertheless, it can be estimated using the sample data as,

$$\widehat{\mathrm{Cov}}\left(\widehat{\mu}^2, \widehat{\mu}^1\right) = \frac{1}{n\,(n-1)} \sum_{p_i \in S} \left(\varepsilon_i^2 - \bar{\varepsilon}^2\right)\left(\varepsilon_i^1 - \bar{\varepsilon}^1\right). \tag{15.11}$$

## 15.5 Conclusions

Although the number of published studies that report use of ALS data to estimate change in forest attributes is small, chronologically they represent a maturing process leading from early exploratory studies of correlations and simple relationships to construction of statistically rigorous inference. Of crucial importance, maturity requires distinguishing between modeling and mapping procedures and estimation and inferential procedures. Of importance, estimators that simply aggregate map values are inherently biased because of map errors resulting from prediction errors. When the objective is estimation and inference, this bias must be acknowledged, estimated, and incorporated into the final population estimates. In addition, the uncertainty that accrues as a result of map errors must be estimated. Design-based, model-assisted estimators for biomass change are intuitive and computationally easy and rely only on probability samples. Further, the samples may be in the form of independent samples for two different times or a single sample that is observed on two different occasions.

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