

REVIEW ARTICLE

Using remotely sensed data to construct and assess forest attribute maps and related spatial products

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Abstract

Tremendous advances in the construction and assessment of forest attribute maps and related spatial products have been realized in recent years, partly as a result of the use of remotely sensed data as an information source. This review focuses on the current state of techniques for the construction and assessment of remote sensing-based maps and addresses five topic areas: statistical classification and prediction techniques used to construct maps and related spatial products, accuracy assessment methods, map-based statistical inference, and two emerging topics, change detection and use of lidar data. Multiple general conclusions were drawn from the review: (1) remotely sensed data greatly contribute to the construction of forest attribute maps and related spatial products and to the reduction of inventory costs; (2) parametric prediction techniques, accuracy assessment methods and probability-based (design-based) inferential methods are generally familiar and mature, although inference is surprisingly seldom addressed; (3) non-parametric prediction techniques and model-based inferential methods lack maturity and merit additional research; (4) change detection methods, with their great potential for adding a spatial component to change estimates, will mature rapidly; and (5) lidar applications, although currently immature, add an entirely new dimension to remote sensing research and will also mature rapidly. Crucial forest sustainability and climate change applications will continue to push all aspects of remote sensing to the forefront of forest research and operations.

Keywords: *accuracy assessment, change detection, inference, lidar, prediction.*

Introduction

Recent decades have witnessed an explosion in the construction, distribution and use of forest attribute maps and related spatial products. This phenomenon may be attributed to four factors: (1) development of remote sensors of the Earth's surface; (2) availability of data from these sensors in usable formats and at operationally feasible costs; (3) access to fast personal computers; and (4) widespread availability of efficient data-processing algorithms and supporting computer software. Thus, a review of the current state of advances and emerging issues related to the construction and assessment of remote

sensing-based forest attribute maps and related spatial products merits attention.

The objective of this review, following a brief historical overview, is to describe commonly used methods for constructing and assessing remote sensing-based maps and spatial products and to discuss two related emerging topics, remote sensing-based forest change detection and the use of lidar data. Even for these few topics, a comprehensive review, whether technical or only descriptive, is impossible for a journal article. Therefore, this review focuses primarily on describing underlying concepts, principles and approaches, and on

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identifying key literature citations. Further, for the benefit of the general forestry reader, formulae and technical jargon and notation are minimized where possible. Related topics are addressed by Rautiainen et al. (2010), who review methods that use remote sensing-based reflectance models to assess forest vegetation, and McRoberts et al. (2010), who review uses of remotely sensed data to enhance estimation in the context of national forest inventories.

History

The term remote sensing refers to the observation and sensing of the Earth's surface from a distance. The term was first introduced by Evelyn L. Pruitt of the US Office of Naval Research in 1960, although remote sensing had been occurring since photographs were first taken from balloons in the 1850s and from kites in the 1880s. Many early applications of aerial photography were military in nature. By the end of World War I in 1918, both the British and the German armies were recording the entire front twice per day. By the end of World War II in 1945, aerial photography for military uses had advanced to the point that it was the primary source of intelligence in the Pacific theater.

During the 1950s, color-infrared photography became important for distinguishing vegetation types. In addition, multispectral imagery that captured data for different portions of the electromagnetic spectrum was tested. LaBau et al. (2007) address the use of aerial photography in support of forest inventories. In the late 1960s, space photography became prominent with the Gemini and Apollo missions.

In 1972, land-use maps were constructed using photography from Skylab, the American space station, and in the same year the first Earth Resources Technology Satellite (ERTS-1), later renamed Landsat 1, was launched. Six other Landsat satellites followed, each of which had multiple visible-light

and infrared bands. The Landsat series has been among the most successful remote sensing platforms and has led to more satellites (e.g. SPOT, IRS, MODIS; Table I) with improved capabilities. The sensors on these satellites are characterized as passive because the energy to which they respond, usually solar energy reflected from the Earth's surface, is external to the sensor system. Table I provides a brief description of the characteristics of common passive sources of remotely sensed data.

In contrast to passive sensors, active sensors are so characterized because the systems of which they are components emit energy and then detect and measure the energy that is reflected or backscattered from the target. Among active sensors, radar (radio detection and ranging) and lidar (light detection and ranging) have been the most commonly used for forestry applications. By the end of World War II in 1945, radar had come into civilian use, but it was not until 1978, when the Seasat satellite was launched, that radar was used to produce images of ocean currents and details of the Earth's surface. Radar data have also been obtained from the Space Shuttle to produce images of landforms below the vegetation cover. Lidar development began with the invention of the laser in the early 1960s, and modern laser-based remote sensing began in the 1970s with efforts by the US National Aeronautics and Space Administration (NASA) to measure properties of the atmosphere, ocean water, forest canopies and ice sheets. Lidar is the only active source considered for this review, and its characteristics are described in more detail in the lidar section.

Prediction and estimation

Prediction and estimation methods using remotely sensed data may be distinguished with respect to multiple factors including unsupervised versus supervised approaches, categorical versus continuous response variables, parametric versus non-parametric

Table I. Characteristics of passive sources of remotely sensed data.

Sensor	Spatial resolution (pixel side dimension at nadir)	Repeat cycle	Spectral coverage
AVHRR	1.1 km	Daily	Visible, near-infrared, thermal infrared
MODIS	0.25–1.00 km	Near daily	Visible, near-infrared, shortwave infrared, thermal infrared
VEGETATION	1.15 km	Near daily	Visible, near-infrared, shortwave infrared
Landsat: MSS, TM, ETM+	15–79 m	16 days	Visible, near-infrared, shortwave infrared, thermal infrared
IKONOS	0.8 m, 3.2 m	On demand	Visible, near-infrared
QuickBird	1 m, 4 m	On demand	Visible, near-infrared
SPOT 5-XS	2.5–25.0 m	2–3 days	Visible, near-infrared, shortwave infrared
IRS-1D LISS-III	23–70 m	5 days	Visible, near-infrared, shortwave infrared

Notes: AVHRR=Advanced Very High Resolution Radiometer; MODIS=Moderate Resolution Imaging Spectroradiometer; MSS=Multispectral Scanner; TM=Thematic Mapper; ETM+=Enhanced Thematic Mapper+.

techniques, and single pixel versus multi-pixel units. With unsupervised classification, image pixels are aggregated into classes based on similarity in values of independent or ancillary variables. Labels are assigned to the classes using reference or training data, expert opinion or other methods. With supervised classification, a model of the relationship between observations of the response variable and corresponding observations of the ancillary variables for a sample of pixels is used to predict the classes of pixels lacking observations of the response variable. Although unsupervised methods are useful and merit consideration, supervised methods are more common and are the focus of this review.

Parametric approaches to pixel-level classification for categorical response variables

Prediction methods that depend on the parameters of populations or probability distributions are characterized as parametric methods. With one such method, maximum likelihood, the means and covariances of the distributions of sample observations of the ancillary variables are first estimated (Lillesand et al., 2008). Then, for a pixel whose class is unknown, the probability of each class is calculated based on the observed values of its ancillary variables, the estimates of the class means and covariances, and the assumption that the distributions are Gaussian. The class with the greatest estimated probability is assigned to the pixel. Magnussen et al. (2004) used a maximum likelihood approach to classify Landsat pixels by forest type. Discriminant analysis, another parametric classification technique used for remote sensing applications, assigns a pixel to one of multiple classes based on the pixel's similarity in spectral space to the sample means for those classes (Richards & Xiuping, 2008). The similarity between the pixel and the k th class mean is expressed using squared Mahalanobis distance, calculated as:

$$D_k^2(\mathbf{X}) = (\mathbf{X} - \hat{\mu}_k)' \hat{\mathbf{V}}^{-1} (\mathbf{X} - \hat{\mu}_k), \quad (1)$$

where $\mathbf{X}$ is a vector of spectral variables, $\hat{\mu}_k$ is the sample mean vector for the k th class, and $\hat{\mathbf{V}}$ is the common covariance matrix for all the classes. The pixel is assigned to the class for which D^2 is smallest, which is equivalent to similarity being the greatest. Variations address cases for which the class covariance matrices are not the same and for which prior information on class membership is available. Tomppo (1992) used discriminant analysis to predict classes of site fertility for forest income taxation purposes in Finland; Thessler et al. (2005) used canonical discriminant analysis to differentiate three forest categories in Costa Rican lowland rain forests;

and McRoberts (2009a) compared discriminant analysis and two other methods for estimating forest cover classes. Logistic regression is a third approach for predicting the classes of a categorical variable from the spectral values of satellite imagery. For a dichotomous response variable such as forest ($Y=1$) and non-forest ($Y=0$), the parameters of a binomial logistic regression model of the form:

$$q_i = \frac{\exp(\beta_0 + \beta_1 X_{1i} + \dots + \beta_p X_{pi})}{1 + \exp(\beta_0 + \beta_1 X_{1i} + \dots + \beta_p X_{pi})}, \quad (2)$$

are estimated, where q_i denotes the probability of forest, the X s are spectral variables, and the β s are parameters to be estimated. Pixels are classified as forest if $q_i \geq 0.5$ and non-forest if $q_i < 0.5$. Multinomial logistic regression predicts classes of a polychotomous response variable using a series of binomial logistic regressions. Tomppo (1992) compared multinomial logistic regression and discriminant analysis for predicting the site fertility classes of forest stands and found that discriminant analysis performed better than logistic regression.

McRoberts et al. (2006) constructed a map of the probability of forest cover using a logistic regression model with forest inventory and Landsat data and used the map to construct strata for use with a stratified estimator. A similar map was constructed using the same methods and served as the basis for a model-based approach to estimating forest area (McRoberts, 2006, 2010a, b). McRoberts (2009a) compared multinomial logistic regression to two other methods for constructing non-forest, coniferous forest and deciduous forest maps, and found the logistic regression approach to be slightly superior.

Parametric approaches to pixel-level estimation for continuous response variables

Regression analysis is an obvious method for predicting the values of continuous variables when ground truth or training data are available. Many different regression approaches have been used for a variety of international applications: volume, volume by tree species, basal area, mean stand diameter, mean stand volume in Finland (Tomppo, 1987; Koistinen et al., 2008); proportions of hardwood and conifer cover in Oregon, USA (Maidersperger et al., 2001); stand height and basal area in Scotland (Puhr & Donoghue, 2000); biomass in Brazil (Steininger, 2000); volume in British Columbia, Canada (Gemmell, 1995); age and a structural index based on stand properties in the Pacific Northwest of the USA (Cohen et al., 1995); age in Estonia (Nilson & Peterson, 1994); age in Colorado,

USA (Nel et al., 1994); biomass in England (Danson & Curran, 1993); and volume in New Brunswick, Canada (Ahern et al., 1991).

Non-parametric approaches to pixel-level classification and estimation

Among non-parametric approaches to classification and estimation for use with remotely sensed data, nearest neighbors techniques have become exceedingly popular, particularly for use with forest inventory data. Nearest neighbors techniques are non-parametric approaches to either univariate or multivariate prediction that have been used widely with satellite image data for mapping, small area estimation and statistical inference. With nearest neighbors terminology, the set of population units or pixels for which observations of both response variables (Y) and ancillary variables (X) are available is designated the reference set; the set of population units for which predictions of response variables are desired is designated the target set; and the space defined by the ancillary variables, X , is designated the feature space. All elements of both the reference and target sets are assumed to have a complete set of observations for all feature space variables.

For continuous response variables, the prediction for the i th target set element obtained using the k -nearest neighbors (k NN) technique is:

$$\tilde{y} = \frac{1}{W_i} \sum_{j=1}^k w_{ij} y_j^i, \quad (3)$$

where $\{y_j^i, j = 1, 2, \dots, k\}$ is the set of response variable observations for the k reference set elements that are nearest to the i th target set element in feature space with respect to a distance metric, d , and w_{ij} is the weight assigned to the j th nearest neighbor with $W_i = \sum_{j=1}^k w_{ij}$. Common choices for the weights are $w_{ij} = d_{ij}^t$, where $t \in [-2, 0]$. For categorical variables, the predicted class of the i th target set element is the most heavily weighted class among the k nearest neighbors, a weighted median or mode in case of ordinal scale variables, and a mode in the case of nominal scale variables.

Popular choices for the distance metric include Euclidean distance, weighted Euclidean distance, Mahalanobis distance, and metrics based on canonical correlation analysis (Moeur & Stage, 1995) and canonical correspondence analysis (Ohmann & Gregory, 2002). Tomppo and Halme (2004) and Tomppo et al. (2009) developed a distance metric based on a weighted sum of spectral components and coarse-scale predictions of forest attributes. This metric features near-optimal weights obtained using

a genetic algorithm and is now used operationally by the Finnish multisource national forest inventory.

Considerable research effort has been committed in recent years to increasing the efficiency of techniques for searching for nearest neighbors, optimizing the distance metric, deriving variance estimators and investigating inferential methods. McRoberts et al. (2010) provides a more comprehensive review of nearest neighbors techniques, particularly as they are used with Landsat and forest inventory data. A comprehensive bibliography of peer-reviewed nearest neighbors publications is available at <http://blue.for.msu.edu/NAFIS/biblio.html>

The popularity of nearest neighbors techniques should not be construed to suggest the absence of other non-parametric techniques. Of these other techniques, Random Forests is an ensemble classifier that constructs large numbers of decision trees and then, for each mapping unit, predicts the class that is the mode of the distribution of predicted classes from the individual decision trees (Breiman, 2001; Breiman & Cutler, 2010). Decision tree approaches to classification use rules to recursively partition the space of ancillary variables into classes using specified criteria where the class boundaries are determined empirically from the training data.

Hudak et al. (2008) compared a Random Forests approach and several nearest neighbors approaches for estimating basal area and tree density using lidar data. McInerney and Nieuwenhuis (2010) compared Random Forests and k NN techniques for estimating volume and basal area in Ireland.

Neural networks is a general purpose, non-parametric prediction technique that mimics some functions of the human brain. Neural networks typically consist of large numbers of simple processing units that are linked by weighted connections, are often massively parallel, can learn by example and then generalize and, as such, are useful for complex and non-linear problems. Foody et al. (2001, 2003) report the use of neural networks for predicting and mapping biomass in Borneo, Brazil, Malaysia and Thailand, and Ingram et al. (2005) used neural networks for predicting forest structure in Madagascar.

Postprocessing methods to enhance pixel-level predictions

The similarity and spatial correlation among observations of ground units corresponding to image pixels can be used to enhance pixel-level predictions, both in the selection of ancillary variables and during and after prediction. Segmentation algorithms have been used and tailored for many forest-related estimation and mapping studies. A commonly used approach is to delineate the image pixels of an area of

interest (AOI) into spectrally homogeneous and connected segments. The segment averages of spectral and other ancillary variables are used to predict the classes of categorical variables or estimate the values of continuous variables for the segment. With segmentation approaches, multiple advantages accrue: the number of segments is considerably smaller than the number of pixels, thereby reducing the magnitude of the classification or estimation effort; segmentation decreases the effects of noise and prediction errors and at least partially ensures that similar pixels in close geographical proximity are classified in a similar manner; and segmentation makes the representation of the image more meaningful by depicting features such as forest stands. The disadvantages are that boundaries between segments are often transitional rather than discrete; classification or estimation is based on segment averages for ancillary variables for which corresponding variances could be large, thereby causing quite dissimilar pixels to receive the same classification or estimated value; and segmentation necessarily reduces the information content of the image.

Tomppo (1987) used a modification of the segmentation method of Narendra and Goldberg (1980) for delineating forest stands and for predicting growing stock volume, mean diameter, basal area and age of trees with regression analysis, as well as site fertility categories using logistic regression analysis. Pekkarinen (2002) proposed a two-phase segmentation method for use with high-resolution spectrometer data to facilitate prediction of growing stock volume. The first phase consisted of a detailed segmentation in spectral space, and the second phase consisted of merging similar segments.

Selecting the image features

Multiple transformations of spectral bands have been derived for use as ancillary variables for classification and estimation. Although the original spectral bands include all the information, band ratios have also performed well, particularly for distinguishing tree species and site fertility categories (Tomppo, 1987, 1992; Tomppo & Halme, 2004; Tomppo et al., 2009). Because satellite image bands are highly correlated, transformations usually contribute to more efficient analyses. The normalized difference vegetation index (NDVI) (Rouse et al., 1973) and the tasseled cap (TC) transformations (brightness, greenness and wetness) (Kauth & Thomas, 1976; Crist & Ciccone, 1984) are commonly used transformations. Canonical and principal components transformations may be useful for reducing large numbers of ancillary variables into a smaller number of relevant components. However,

these transformations assume multivariate Gaussian distributions of the ancillary variables which is not necessarily the case for remotely sensed data. Weighted combinations of spectral band variables and band ratios, where the weights are obtained using a genetic algorithm optimization, have worked better than principal components or canonical variables and are used operationally in the Finnish multisource national forest inventory (Tomppo et al., 2008). Textural features such as those of Haralick et al. (1973) have often been used, although medium resolution satellite imagery such as Landsat TM and ETM+, SPOT 5-XS and IRS-1D LIS-III are somewhat coarse for derivation of textural features for forest applications (Table I). However, Tomppo (1992) derived these features from co-occurrence matrices and used them for site fertility classification. McInerney and Nieuwenhuis (2010) used textural features for forest/non-forest classification with the forest class further subdivided into two subcategories.

Accuracy assessment

Types of maps and products

The goal of map accuracy assessment is to evaluate the quality of a map by comparing the mapped or predicted value to the observed or true condition. Methodologies for assessing accuracy depend on whether the variable mapped is categorical or continuous. The most common mapped categorical variables are land cover-related variables. For example, forest cover is a key constituent of global and continental land-cover maps (Mayaux et al., 2006; Pekkarinen et al., 2009), and the categorical variable may be simply forest/non-forest or a more detailed classification of forest-cover types such as deciduous, coniferous and mixed forest. Change in forest cover as a result of deforestation, reforestation and afforestation is another example of a categorical cover variable. The crucial importance of understanding temporal dynamics of forest cover has resulted in a large number of forest change maps (e.g. Hansen & DeFries, 2004). Maps of forest disturbances such as fire (Tansey et al., 2004; Roy et al., 2005) and insect defoliation (Wulder et al., 2006) represent special cases of forest change categorical variables. Percentage or proportion of forest cover (Häme et al., 2001; Hansen et al., 2003; McRoberts, 2006, 2009b, 2010a) and biomass (Dong et al., 2003; Blackard et al., 2008) are examples of continuous variables.

The fundamental basis of an accuracy assessment is a location-specific comparison of a map prediction and a ground observation. Accuracy

assessment requires specifying three primary components (Stehman & Czaplewski, 1998): (1) the sampling design, which is the protocol for choosing which locations are visited; (2) the response design, which is the protocol for deciding the observed or ground condition at each location along with the definition of agreement used to decide whether the map predicted and observed condition match; and (3) an analysis protocol for estimating accuracy parameters and summarizing the results of the assessment. Multiple overview articles provide details of the range of options available for each of these components (Stehman & Czaplewski, 1998; Foody, 2002; Czaplewski, 2003; Strahler et al., 2006; Stehman & Foody, 2009).

Each of the three accuracy assessment components has crucial measurement and statistical requirements. The response design is largely a measurement problem. Methods for obtaining the true value or condition of the target variable at each location require subject matter expertise pertaining to the measurement or observation of that variable. As such, the response design requires strong input from scientists constructing the map to develop a protocol for properly determining the true condition. Protocols for the sampling and analysis components are inherently statistical. The accuracy assessment results must be supported by rigorous statistical inference, because the fundamental basis of the assessment is the ability to generalize from the sample data to a population of interest. If the sampling design and analysis protocols do not meet the criteria required for rigorous statistical inference, then the entire basis of the assessment is undermined and the results are of limited value.

Accuracy assessments are conducted to accommodate a variety of objectives and uses. Traditionally the primary objective is to provide descriptive

information about map quality such as the proportion of the area mapped as coniferous forest that actually is coniferous forest, or the mean absolute deviation of mapped biomass values relative to the observed biomass. These descriptive accuracy objectives address the need to provide key meta-data documenting map quality. The descriptive accuracy information may be used in a variety of ways. For example, the prevalence of different classification errors may be used as input into error or uncertainty analyses evaluating applications using the map data. Information provided on the types and prevalence of classification errors obtained from a descriptive accuracy assessment can also be used to improve the classifier or model. The sample of the observed condition that is used for an accuracy assessment also serves as a basis for estimating area (Czaplewski & Catts, 1992; Stehman, 2005, 2009a; McRoberts, 2009b), one of the primary applications of cover-type categorical variables.

Analysis

The analysis protocol includes defining the parameters used to summarize accuracy, and specifying the statistical estimators (formulae) used to estimate these parameters from the sample data. A common format for organizing and reporting the results of an accuracy assessment of a categorical map is an error or confusion matrix (Table II). The rows of an error matrix represent observed conditions, and the columns represent map predictions, although this convention may be reversed. Each cell of the error matrix, p_{ij} , is the proportion of area with observed class i and map class j . The diagonal cells of the matrix, therefore, represent correct classifications, and the off-diagonal cells represent classification errors. The most common parameters used to

Table II. Population error matrix for four-class map of forest cover.

Reference classification	Map classification				Total	Omission error
	Deciduous	Coniferous	Mixed	Non-forest		
Deciduous	p_{11}	p_{12}	p_{13}	p_{14}	p_{1+}	$1 - \frac{p_{11}}{p_{1+}}$
Coniferous	p_{21}	p_{22}	p_{23}	p_{24}	p_{2+}	$1 - \frac{p_{22}}{p_{2+}}$
Mixed	p_{31}	p_{32}	p_{33}	p_{34}	p_{3+}	$1 - \frac{p_{33}}{p_{3+}}$
Non-forest	p_{41}	p_{42}	p_{43}	p_{44}	p_{4+}	$1 - \frac{p_{44}}{p_{4+}}$
Total	p_{+1}	p_{+2}	p_{+3}	p_{+4}	1.00	
Commission error	$1 - \frac{p_{11}}{p_{+1}}$	$1 - \frac{p_{22}}{p_{+2}}$	$1 - \frac{p_{33}}{p_{+3}}$	$1 - \frac{p_{44}}{p_{+4}}$		

Notes: p denotes a proportion.

summarize a population error matrix (Table II) are overall accuracy, which is the sum of the diagonal entries, and two class-specific parameters based on different conditioning perspectives. Omission error, defined as $1 - \frac{p_{ii}}{p_{i+}}$, represents the proportion of observed area of class i that is not predicted as class i , and is the complement of producer's accuracy; commission error, defined as $1 - \frac{p_{ii}}{p_{+i}}$, represents the proportion of predicted area of class i that is not observed as class i , and is the complement of user's accuracy. In practice, the population error matrix and associated parameters must be estimated from a sample, and the parameter estimates should be accompanied by standard errors to quantify the variability of the estimates. Stehman and Foody (2009) provide estimators for the basic simple random, systematic, stratified random and cluster sampling designs, and Stehman (2000) presents a general estimation approach applicable to any probability sampling design.

The marginal proportions of the error matrix contain relevant information about the AOI. The row margin, p_{i+} , is the sum of all proportions in row i and represents the proportion of area observed for class i , and the column margin, p_{+i} is the sum of all proportions in column i and represents the predicted or mapped proportion of area for class i . The difference between the column proportion and its corresponding row proportion, $p_{+i} - p_{i+}$, is called non-site-specific accuracy and is an estimate of the bias of the predicted proportion of area for each class. Because the row and column margins of an error matrix should reflect the reality of the AOI mapped, the practice of normalizing an error matrix should be avoided. Congalton and Green (1999) suggest normalizing an error matrix by applying an iterative proportional fitting algorithm that adjusts row and column margins of the error matrix to be equal. In reality, neither the predicted nor the observed classes will be equally represented, so parameters estimated from a normalized error matrix will be biased because the normalized matrix has no correspondence with the actual marginal proportions associated with the AOI (Stehman, 2004).

Chance-corrected measures of accuracy, kappa being the most popular (Cohen, 1960), are commonly used to adjust accuracies for agreement that would occur simply by random chance. Despite their popularity, these chance-corrected measures do not characterize an observable accuracy feature of the map, because chance agreement is a hypothetical construct. In particular, actual locations where correct map predictions can be attributed to chance agreement or simply good luck cannot be distin-

guished from other locations where the correct map predictions can be attributed to good cause. Stehman (1997, 2000) and Foody (2004) discuss additional conceptual and technical difficulties associated with the use of kappa for map accuracy assessment. The concept of chance-corrected agreement takes on a reasonable meaning when used in the context of evaluating the model or classification algorithm used to generate the map predictions. However, even in this context, kappa does not provide a measure of the model's predictive ability, and alternatives to kappa should be considered for this purpose (DeMast, 2007). Liu et al. (2007) provide a comprehensive review and analysis of other proposed accuracy measures.

For a continuous map variable, a predicted value, $\hat{y}_i$, and an observed value, y_i , are obtained for an assessment unit; for example, $\hat{y}_i$ and y_i may be the predicted and observed proportions of forest area. Simple measures characterizing the degree to which $\hat{y}_i$ and y_i agree include mean deviation, mean absolute deviation and root mean square error. The correlation between $\hat{y}_i$ and y_i is another potentially useful descriptive measure, and a scatterplot of y_i versus $\hat{y}_i$ can be examined to assess the degree to which the predicted and observed values fall along a 1:1 line through the origin. These parameters must be estimated from the sample and, as stated for assessment of categorical variables, the standard error for each estimate should be reported as a means of quantifying the variability of the estimate.

Response design

The response design encompasses the collection and interpretation of information leading to the determination of the true or observed value of the variable. The first step in the response design protocol is to specify the assessment unit that will serve as the basis for the location-specific comparison between the predicted and observed conditions. Pixels and map polygons are the two most common choices. Janssen and van der Wel (1994) and Strahler et al. (2006) recommend a pixel as the basic spatial unit of the assessment. Pixel-based assessments evaluate accuracy at the smallest spatial unit of the classification. Moreover, a pixel is a practical and well-defined sampling unit on which to base a rigorous probability sampling design, and the uniformity of pixel size and shape contribute to consistency in the response design protocol. Polygon assessment units are typically homogeneous map objects, but a polygon-based assessment should take into account that polygons may not be homogeneous with respect to the actual ground condition. Even for pixel-based assessments, mixed pixels complicate the response

design and analysis protocols, and polygon assessment units exacerbate these problems. Because polygons vary in size, the sampling and response designs must accommodate both very small and very large polygons.

Location error is a potential problem whether the assessment unit is a pixel or a polygon. The inability to co-locate the map and ground information introduces the possibility of confounding location error and thematic error (McRoberts, 2010*b*). The problem is acute for polygon edges, where a registration error of one or two pixels would matter, whereas the interior of a polygon would be largely immune from location error effects. Polygon edges do not disappear and should not be ignored if a polygon assessment unit is used. Because location error cannot be completely eliminated, analyses that account for location errors may be used (Hagen, 2003). Alternatively, reporting accuracy separately for the subset of edge locations and the subset of interior locations provides information for gauging the potential impact of location error on the results.

The observed or ground condition of an assessment unit may be determined from an actual ground visit or interpreted from remote imagery. Ground visits may produce the highest quality information for assessing ground condition, but high cost and access difficulties often make this approach impractical. Use of national forest inventory plot data reduces costs by taking advantage of an existing data collection effort, and the probability sampling designs underlying most national forest inventories provide a rigorous basis for inference. Data quality is typically high because well-trained personnel collect the data. Barriers to using existing inventory data include temporal or spatial mismatches between the ground plot and map locations, insufficient information to distinguish the classes mapped, and proprietary and confidentiality constraints associated with the data (Stehman et al., 2000).

In lieu of ground visits, assessments are often based on determining the observed variables using a data source that is of greater quality than the source used to produce the map. As examples, aerial photography is commonly used because it offers a cost-effective option for covering extensive areas; videography can be used to determine the observed class or quantity (Powell et al., 2004; Wulder et al., 2007); and interpretation of very fine-resolution imagery such as IKONOS and QuickBird offers another, albeit expensive, option. Finally, airborne lidar data have been used to evaluate insect defoliation maps derived from spaceborne optical MODIS data (Eklundh et al., 2009), biomass estimated from spaceborne radar data (Solberg et al., 2010), and

canopy height estimated from spaceborne lidar data (Duncanson et al., 2009).

Regardless of the data source, the observed condition for a sampled assessment unit may be determined by visual judgment, such as by an interpreter, or by rules based on quantitative measurements, such as percentage forest cover estimated from ground plots. In addition to providing a primary reference label for the assessment unit, the response design may permit an alternate label to be specified in cases where a single label does not adequately represent the site. Examples include assessment units with areas of multiple classes, or units for which neither of two classes is entirely appropriate for an assessment unit because the classes are defined with respect to a boundary value for a continuous variable. Fuzzy labeling protocols may also be used. In contrast to crisp or hard classification protocols for which an assessment unit is classified as exactly one of the possible categories, a fuzzy labeling protocol permits assignment of a gradient or continuum of membership to the possible categories. For example, each assessment unit could be labeled with a fuzzy membership value in the continuous interval $[0, 1]$ as a means of representing the degree to which the unit matches each possible category. As particular examples, a pixel could be forest = 0.8 and non-forest = 0.2 for a two-category classification, or the ground condition could be characterized using a linguistic scale (Gopal & Woodcock, 1994; Franklin et al., 2001).

The last step of the reference data protocol is to specify a definition of agreement. In the simplest case of categorical variables, agreement is defined as a match between the predicted class and the observed primary label. The definition of agreement may be extended to include a match between the map class and either the primary or alternate label. Other definitions of agreement exist for the case in which the map is a hard classification but the reference data follow a fuzzy classification approach (Gopal & Woodcock, 1994) and when both the map and reference classifications are fuzzy (Binaghi et al., 1999). Continuous variables are assessed by quantifying the degree of agreement using measures such as mean absolute deviation or root mean square error.

Sampling design

Sampling designs for accuracy assessments are selected based on the objectives and guided by desirable design criteria (Stehman, 2009*b*). The primary descriptive objectives are estimates of overall and class-specific accuracies, possibly spatially disaggregated to a few important geographical subregions. If

the assessment relies on probability-based or equivalently design-based inference, the foremost desirable design criterion is that a probability sampling design must be used (Stehman, 2000). Other desirable design criteria are cost-effectiveness of the sample, ease of implementation and analysis, adequate spatial distribution, and flexibility to accommodate changes in sample size once the assessment is in progress, such as the draw sequential procedure described by Särndal *et al.* (1992, p. 26). The nearly omnipresent interest in estimating per-class accuracies motivates stratifying by the map classes to ensure that rare classes receive sample allocation sufficient to yield accuracy estimates with small standard errors. Typically, the sample is allocated equally to all classes (strata), although it is possible to adjust the per-stratum sample size to accommodate standard sample size recommendations for estimating a proportion (Cochran, 1977, Section 4.4).

Cluster sampling often merits consideration because of the potential for cost savings. Cluster sampling spatially constrains the sampling units so that if ground visits are used, travel costs can be reduced, or if aerial photography or very fine-resolution satellite images are interpreted, time and costs associated with obtaining and processing the photographs or images are reduced because fewer are needed. In general, a two-stage cluster sampling design would be used because a sample of assessment units within each cluster would be more efficient than using the entire cluster. A sampling design with both strata and clusters often satisfies the objectives and desirable design criteria. Such designs are inherently more complex, although various options have been used in practice (Stehman, 2009b). Systematic sampling is a viable design option because of its ease of implementation and generally better precision than simple random sampling (Stehman, 1992; Moisen *et al.*, 1994). Many forest inventories use systematic sampling grids, and if the inventory data can be used for accuracy assessment, the results are based on an underlying rigorous design.

Sampling design considerations and options for assessing accuracy of forest change differ little from those for any categorical variable. Because change is typically rare, stratification by predicted change is often recommended (Biging *et al.*, 1998) to ensure an adequate sample size for assessing the accuracy of predicted change. If many types of change are mapped, stratification by individual change types may be feasible. In addition, strata may need to be defined with respect to more general change groupings such as forest to any other land-cover class or any other land-cover class to forest. For sampling a continuous variable, the same approach of choosing

a sampling design based on objectives and desirable sampling design criteria is still applicable. Stratification may be necessary to increase the sample size representing relatively rare values of the continuous variable, and cluster sampling still retains a potential advantage for decreasing costs.

In the future, it is likely that accuracy assessments will be called upon to address a broader set of objectives beyond the descriptive objectives emphasized to date. Accuracies of additional features related to map applications will need to be assessed. For example, the forest area within spatial units of a partition of the AOI is a common application of a land-cover map such as when an AOI is partitioned into 10×10 km cells and forest cover is estimated for each cell. A general description of the accuracy of this spatially aggregated map output would be useful (Strahler *et al.*, 2006; Stehman *et al.*, 2009). Net change is another potential objective of interest (Stehman & Wickham, 2006). Landscape pattern metrics that quantify forest fragmentation, patch size and shape metrics, and the adjacency of different land-cover classes are increasingly used (Heilman *et al.*, 2002) and represent another potential objective to be addressed by accuracy assessment. Assessing the accuracies of proportion of area, net change and landscape pattern may be better addressed by spatially contiguous sample data, thus motivating the use of one-stage cluster sampling for which a cluster of contiguous pixels is the sampling unit (Stehman, 2009b).

Inference

The utility of maps is greatly enhanced when they form an appropriate basis for inferring values of parameters describing the populations represented by the maps. Unless the maps consist of observations for all mapping units, inference requires expression of the relationship between a population parameter, μ , and its estimate, $\hat{\mu}$, in probabilistic terms (Dawid, 1983), usually in the form of $1-\alpha$ confidence intervals. In the context of map-based inference, two items are important to note: first, an error or confusion matrix does not constitute an inference, even though it may provide data to inform an inference, and second, construction of confidence intervals, $\hat{\mu} \pm t\sqrt{\text{Var}(\hat{\mu})}$, requires estimates, $\hat{\mu}$ and $\text{Var}(\hat{\mu})$. Two general approaches to inference are common: probability-based inference and model-based inference. Regarding terminology, the term design-based inference is often used in lieu of probability-based inference, and in the discussion that follows, the terms population unit, pixel and mapping unit are used interchangeably.

Probability-based inference

Properties of statistical estimators associated with probability-based inference derive from the probabilities of selection of population units into the sample, hence the characterization of these estimators as probability based (Hansen et al., 1983). Probability-based inference is based on three assumptions: (1) population units are selected for the sample using a probability-based randomization scheme; (2) the probability of selection for each population unit is positive and is either known or can be estimated; and (3) the observation of the response variable for each population unit is a constant as opposed to a random variable. Estimators are derived to correspond to sampling designs and typically are unbiased, meaning that the statistical expectation of the estimator, $\hat{\mu}$, over all samples that could be obtained with the sampling design, is the population parameter, i.e. $E(\hat{\mu}) = \mu$. However, the estimate obtained with any particular sample may deviate considerably from the true value of the population parameter.

The simplest approach to probability-based inference is to use the familiar simple random sampling (SRS) estimators (Cochran, 1977). However, use of SRS estimators with mapping unit predictions instead of observations is inappropriate for map-based inferences because no accommodation is made for the uncertainty of the predictions. Nevertheless, estimates obtained using the unbiased SRS estimators with mapping unit observations may be useful for producing standards for assessing model-based estimators which cannot be assumed to be unbiased.

Model-assisted estimators use mapping unit predictions obtained from models and ancillary data to enhance inferences, but rely on observations for population units selected from a probability sample for validity. Examples of model-assisted estimators include the familiar ratio and regression estimators (Cochran, 1977). Opsomer et al. (2007) report a model-assisted approach to estimation of forest resources using generalized models, and Gregoire et al. (in press) report a model-assisted approach to inference for biomass using lidar data.

Among model-assisted estimators, the difference estimator (Särndal et al., 1992) is likely to be the most generic because it is generally applicable for a wide range of problems for which mapping unit predictions are obtained using ancillary data regardless of the approach to prediction. The model-assisted difference (Dif) estimator of a population mean is based on observations where they are available, predictions where observations are not available, and a bias correction, and can be approximated as:

$$\hat{\mu}_{\text{Dif}} = \frac{1}{N} \sum_{i=1}^N \hat{y}_i - \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i). \quad (4)$$

Variance estimators are reported by Särndal et al. (1992), Baffetta et al. (2009), and McRoberts (2009b, 2010b). The model-assisted difference estimator is of particular utility because it can be used with any prediction technique to obtain the estimates, $\hat{\mu}_{\text{Dif}}$ and $\text{Var}(\hat{\mu}_{\text{Dif}})$, necessary for inference. Baffetta et al. (2009) used the model-assisted difference estimator with the k NN prediction technique and Landsat data to infer population values for timber volume. McRoberts (2010a) used the model-assisted difference estimator with a logistic regression model and Landsat data to infer mean proportion forest for circular AOIs with diameters ranging from 1 to 15 km. The difference estimator lends itself particularly well to inference for maps of categorical variables for which an equal probability sample of accuracy assessment data is available, because the bias and variances can be easily estimated using information from an error matrix (McRoberts, 2009b). However, if the same data are used to train the classifier and to assess accuracy, the assessment tends to be somewhat optimistic.

The primary advantage of model-assisted estimators is that they capitalize on the relationship between the observations and estimates for population units in the sample to reduce the variance of the population parameter estimate. However, as with all probability-based estimators, model-assisted estimators suffer the effects of small sample sizes, particularly when used for small area estimation.

Model-based inference

For map applications, model-based inference is intuitive in the sense that it entails simply aggregating the mapping unit predictions. The assumptions underlying model-based inference differ considerably from the assumptions underlying probability-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 constant as is the case for probability-based inference. The conceptual framework with a distribution of possible values for each unit in a finite population is characterized as a superpopulation, and model-based inference is occasionally characterized as superpopulation inference (Graubard & Korn, 2002). Secondly, the basis for model-based inference is the model, not the probabilistic nature of the sample as is the case for probability-based inference. In fact, purposive, non-probability samples may produce entirely valid model-based

inferences. For example, the sample may be selected to maximize the precision of the model parameter estimates or the precision of model predictions. However, a probability sample provides modest assurance that the ranges of values of independent variables in the sample data are similar to the ranges in the population to which the model is applied which, in turn, contributes to construction of correctly specified models. Thirdly, randomization for probability-based inference enters through the random selection of population units into the sample, whereas randomization for model-based inference enters through the random realizations from the distributions of response variables for population units.

Current approaches to model-based inference originated in the context of survey sampling and can be attributed to Mátern (1960), Brewer (1963) and Royall (1970). Given the origins of model-based inference in survey sampling, it is not surprising that forestry applications have often been in the context of forest inventory (Rennolls, 1982; Gregoire, 1998; Kangas & Maltamo, 2006; Mandallaz, 2008; McRoberts, 2006, 2010a; Ståhl et al., in press). An important aspect of the model-based approach is that when the model is correctly specified, the estimator is unbiased (Lohr, 1999); however, when the model is misspecified, the adverse effects on inference may be substantial (Royall & Herson, 1973; Hansen et al., 1983). Thus, much of the reported research on model-based inference has focused on selection of sampling designs and estimators that are robust to model misspecification, particularly for linear models (Valliant et al., 2000; Chambers, 2003).

In the context of model-based inference, the mean and standard deviation of the distribution of Y for the i th population unit may be denoted μ_i and $\sigma_{i\beta}$ respectively. Thus, an observation of Y for the i th population unit is expressed as:

$$y_i = \mu_i + \varepsilon_i, \quad (5)$$

where ε_i is the random deviation of the observation, y_i , from its mean, μ_i , which is expressed mathematically as $\mu_i = f(\mathbf{X}_i; \boldsymbol{\beta})$. The model

$$y_i = f(\mathbf{X}_i; \boldsymbol{\beta}) + \varepsilon_i, \quad (6)$$

is fitted to the sample data, where $\mathbf{X}_i$ is the vector of ancillary variables for the i th population unit, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and ε_i is the random residual.

The model-based estimator (Mod) of the population mean is based on the set of estimates $\{\hat{\mu}_i, i = 1, 2, \dots, N\}$ of the means for individual population or mapping units:

$$\hat{\mu}_{\text{Mod}} = \frac{1}{N} \sum_{i=1}^N \hat{\mu}_i = \frac{1}{N} \sum_{i=1}^N f(\mathbf{X}_i; \hat{\boldsymbol{\beta}}). \quad (7)$$

The model-based estimator of the variance of $\hat{\mu}_{\text{Mod}}$ is:

$$\text{Vâr}(\hat{\mu}_{\text{Mod}}) = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N \text{Côv}(\hat{\mu}_i, \hat{\mu}_j), \quad (8)$$

where $\text{Vâr}(\hat{\mu}_i) = \text{Côv}(\hat{\mu}_i, \hat{\mu}_i)$ is the uncertainty of each pixel estimate, $\hat{\mu}_i$, and $\text{Côv}(\hat{\mu}_i, \hat{\mu}_j), i \neq j$, reflects the fact that estimates for different pixels are correlated because they are based on the same sample data. For parametric models, first order Taylor series approximations may be used to obtain estimates of the covariances; for non-parametric approaches to prediction, such as the k NN technique, estimation of the covariances is more complex (McRoberts et al., 2007).

The primary advantages of model-based estimators are that they produce maps as by-products, estimates that are consistent with the maps in the sense that they represent the aggregation of mapping unit predictions, and possibly precise estimates for small areas for which only small numbers of sample observations are available. Their primary disadvantages are that they may be computationally intensive and they are not necessarily unbiased. Computational intensity results from the necessity of calculating variances and covariances for a large number of mapping units for even relatively small AOIs. For example, an AOI of radius 15 km includes centers for approximately 7.85×10^5 30×30 m Landsat pixels, meaning that the number of covariance estimates that must be calculated for eq. (8) is of the order of 10^{10} . However, eq. (8) is just a two-dimensional mean over all units in the AOI and can be approximated by sampling from AOIs. Thus, McRoberts (2010a) showed that the computational intensity may be greatly reduced with no discernible ill effects by using only pixels or mapping units located at the intersections of an equally spaced, two-dimensional, perpendicular grid superimposed on the AOI.

The issue of unbiasedness for model-based inference is closely linked to correct model specification. McRoberts (2010a) reviews non-mathematical factors pertinent for forest mapping applications that may lead to deviations between observations and predictions and contribute to model lack of fit. Several approaches to assessing the correctness of model specification have been used. At the population unit level, if the model is correctly specified, a graph of observations versus model predictions should feature points that lie along a line with intercept 0 and slope 1. At the areal level, estimates, $\hat{\mu}_{\text{Mod}}$, may be compared to estimates, $\hat{\mu}_{\text{SRS}}$, obtained

using the SRS estimators with sample observations located in the AOI. Estimates, $\hat{\mu}_{\text{Mod}}$, that are consistently within approximately two SRS standard errors of $\hat{\mu}_{\text{SRS}}$ indicate no serious lack of model fit and suggest unbiasedness of the estimator (McRoberts, 2010a) (Figure 1). Finally, when the variance estimators are complex, non-parametric or based on unverified assumptions, bootstrap resampling approaches to variance estimation merit consideration (Efron & Tibshirani, 1994). However, two cautions are advised: first, the bootstrap resampling must capture the covariance structure of the original observations, and secondly, bootstrap bias estimates do not address model misspecification.

Examples of uses of model-based approaches to inference include McRoberts et al. (2007), who used the k NN technique to infer small area means of proportion forest, basal area, volume and tree density. In addition, McRoberts (2006, 2010a, b) used logistic regression models to infer small area means of proportion forest, and Ståhl et al. (2010) used a regression model with lidar data to infer population values of biomass.

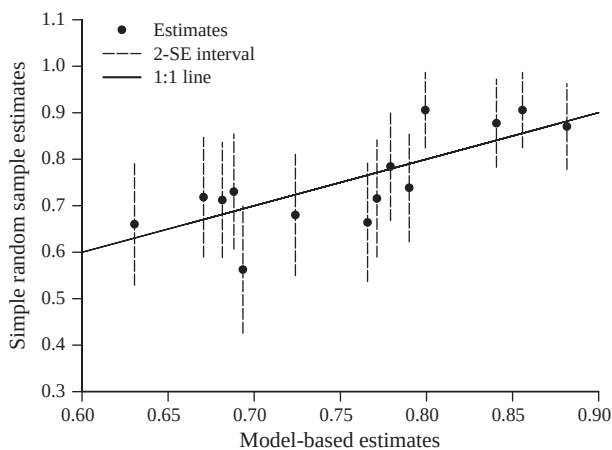


Figure 1. Assessing model misspecification for model-based inference: simple random sample estimates versus model-based estimates.

Change detection

Detecting forest change

In remote sensing, the process of analyzing image data from two or more periods for the purpose of mapping cover change is commonly referred to as change detection. Multiple publications document remote sensing-based forest change detection methods, applications, limits and comparative results (Singh, 1989; Muchoney & Haack, 1994; Coppin et al., 2004). This section provides an update on how methods have changed over the past decade, and then looks to the future with a description of

potential impacts of new approaches using both new and old data sets.

Sensor considerations

Forest composition and structure are shaped by both natural and anthropogenic forces, and understanding how forests change is crucial to predicting the character of future forests. Remote sensing methods for forest monitoring have been evolving since the Landsat program was established in the early 1970s. Since the early 1980s, detection and mapping of large-scale forest change have been possible using data from sensors such as AVHRR (Hansen & DeFries, 2004), MODIS (Langner et al., 2007) and VEGETATION (Fraser et al., 2003) (Table I). However, the coarse spatial resolution of these sensors makes detected changes associated with forest management, which are commonly at a smaller grain, difficult to map accurately (Cohen et al., 2002; Hayes et al., 2008). Detailed, local mapping of forest change is possible with data from high spatial resolution airborne and spaceborne sensors such as IKONOS and QuickBird (Table I) (Clark et al., 2004), but these data are generally costly on a per unit area basis. Moreover, because these data have not been collected on a systematic, routine basis, they have limited use for widespread forest monitoring. Data from lidar sensors have great potential for forest monitoring because of their highly relevant quality (Kim et al., 2009), but repeated lidar coverage is only now becoming available (Næsset et al., 2004). Consequently, for most of the Earth's forests, lidar will remain a sampling and target-of-opportunity instrument for the foreseeable future owing to cost and the current lack of a suitable space-based platform. The Landsat program (Table I), which has been collecting data routinely over most of the Earth's surface for nearly 40 years at a resolution commensurate with the spatial grain of forest management, has been the primary data source for monitoring forest change (Cohen & Goward, 2004; Masek et al., 2008; Huang et al., 2010). This situation is likely to continue, particularly because the data are now available at no cost if they reside in the archives of the US Geological Survey (Landsat Science Team, 2008), and because of the ongoing amalgamation of international archives and the planned continuation of the program. If long-term retrospective change detection is not important, then several other Landsat-class sensor choices merit consideration (Powell et al., 2007; Wulder et al., 2008b).

Past change detection approaches

Remote sensing-based approaches for detecting changes in vegetation can be categorized as two basic types: time series and interval. Time series approaches are based on regularly ordered images such as every 16 days for one or more years or once per year for numerous sequential years. The data for the time series are processed as a single data set to estimate trends and deviations in trends of spectral responses for the purpose of characterizing vegetation or vegetation change. Interval approaches are based on evaluations of transitions among vegetation classes for sequential pairs of multiple images acquired at either regular or irregular intervals.

Time series approaches have been largely the domain of high temporal, coarse spatial resolution sensors. For forest assessments, data from the AVHRR sensor were the first to be investigated. Largely focused on seasonality for one or more years at continental scales, these studies used principal components analysis (Johnson & Wichern, 1985) of temporal series to derive land cover classifications that distinguished forest from other vegetation cover types (Tucker et al., 1985), to examine interannual changes among forest and other land cover types (Lambin & Strahler, 1994), and to relate interannual changes in spectral responses of various vegetation types to climatic variations (Eastman & Fulk, 1993). Other studies focused on relating primary productivity in the form of vegetation growth as a function of latitude (Goward et al., 1987) or land use/cover type (Goward et al., 1985) to the sum over a growing season of spectral vegetation indices.

More recently, MODIS and VEGETATION data (Table I) have been used with interval approaches to map forest change directly. For one such study, forest harvest could not be detected for harvest patches of less than 20 ha; only when patch size was at least 50 ha could change be detected with high accuracy (Jin & Sader, 2005). Another study found that change due to fire could be accurately detected but only when burned areas were at least 10 km² (Fraser et al., 2003). To minimize errors associated with classification of forest change using coarse-resolution data, other studies examined forest change in terms of proportions of image pixels that changed and found that both disturbance and recovery could be mapped with acceptable levels of error (Hayes & Cohen, 2007).

Interval approaches have largely been the domain of finer spatial resolution sensors such as Landsat, primarily because this class of sensors provides data that have both a lower temporal repeat cycle and, until recently, historically greater data cost. Early methods were based on postclassification comparisons (Singh,

1989; Coppin et al., 2004), whereby cover classifications from two separate images for a given location were compared (Hall et al., 1991). Other studies have been based on defining thresholds in two-date spectral space to classify change using a variety of statistical methods based on image subtraction, image division and principal components analysis, or by defining spectral change vectors having direction and magnitude (Muchoney & Haack, 1994; Cohen & Fiorella, 1998; Coppin et al., 2004). These methods have been extended to multiple two-date sets of imagery to classify forest changes associated with harvest (Cohen et al., 1998), fire (Eidenshink et al., 2007), insects (Goodwin et al., 2008) and forest recovery (Hayes & Sader, 2001). Recently, interval approaches have been extended to very broad areas, a strong indication of their continued utility.

Emerging developments in Landsat change detection

Time series approaches to forest change detection are not solely the domain of coarse-resolution sensors such as AVHRR and MODIS. However, whereas analyses based on the latter sensors rely primarily on the phenological signal contained in intra-annual time series, analyses based on Landsat time series (LTS) take advantage of annual or near-annual series for numerous years.

Lawrence and Ripple (1999), who were among the first to use LTS for forest change detection, examined primary forest succession for 15 years after a volcanic eruption by characterizing differences in rates of cover accumulation. Schroeder et al. (2007) used a 20-year annual LTS to characterize variation in secondary succession after harvest. Healey et al. (2006) used LTS to map forest thinning for the purpose of understanding the deleterious effects of harvest on bird habitat. Kennedy et al. (2007) were the first to develop a conceptual model for automated analyses of LTS for purposes of detecting forest change. Using high temporal density LTS increases the signal to noise ratio for forest change detection, thereby increasing the sensitivity of the data to subtle disturbance trends associated with chronic insect infestation, minor spectral departures associated with thinning and variations in recovery after disturbance.

The previously cited LTS studies were limited to a small number of Landsat scenes for two basic reasons: first, the analytical methods were nascent and in need of further development towards automation, and second, the high cost of data. Methods have now been developed to automate the analyses of time series over a large number of Landsat scenes (Huang et al., 2010). In addition, Landsat data for much of the Earth's surface are now free and

available in a standard, high-quality, preprocessed format (Landsat Science Team, 2008).

One particularly promising LTS approach was based on use of a limited set of expected spectral changes or deviations associated with a limited set of disturbance and regrowth combinations over the temporal series (Kennedy et al., 2007). This approach was based on comparing observations and expected sets of spectral trends to identify and label changes. Although this was a convenient way to initially frame the analysis, it had the effect of limiting resultant change maps to the predefined set of expectations. Because the observation period for the analysis was approximately 25 years, a large proportion of image pixels did not fit the expected set of conditions. Consequently, this approach is being altered by dropping the set of expectations in favor of identifying and defining temporal breaks in observed spectral trends and labeling the segments between two sequential break points as disturbance, recovery or stable, based on the direction or sign of spectral change.

Integrated change detection methods

In response to needs for detailed analyses for which Landsat-class resolution data may not be available at the temporal resolution desired because of image cloudiness or data gaps (Powell et al., 2007; Wulder et al., 2008b), new methods are being developed that blend data from multiple passive sensors. In addition, blending passive reflectance data from sensors having different temporal and spatial resolutions with data from active sensors such as lidar and radar that detect the strength and/or timing of reflectance of that energy will define the future of monitoring across a range of scales. A few examples highlight the potential for forest monitoring using fusion or blending methods.

One promising method for blending MODIS and Landsat data uses a variety of weighting functions derived from the co-occurrence of these data sets in time and space to predict Landsat images for dates where MODIS is available but Landsat is not (Gao et al., 2006). This algorithm, STARFM, is theoretically capable of predicting near-daily Landsat data from a single pair of MODIS and Landsat images and a daily time series of MODIS, although the results are improved if multiple Landsat anchor dates are used. Predicted Landsat images are degraded in quality for cases featuring fine-grained spatial heterogeneity and complex mixtures of cover types. Hilker et al. (2009) demonstrated the value of STARFM for monitoring forest disturbance in Canada, where clouds often obscure Landsat images for several sequential 16-day acquisitions, by adapting the algorithm using 8-day

MODIS composites to detect the 8-day period within which individual, Landsat-resolution disturbances occurred.

The Deformation, Ecosystem Structure, and Dynamics of Ice (DESDynI) space mission is to be launched later this decade (<http://desdyni.jpl.nasa.gov/>) with a primary goal of measuring and establishing monitoring protocols for vegetation structure and for understanding the carbon cycle. The DESDynI system will include both a mapping radar sensor and a sampling lidar sensor. The conceptual framework for blending disparate data sets from these two sensors for vegetation analysis is not new (Treuhart et al., 2004), but at least some initial attempts at integrating lidar and radar data have demonstrated minimal advantage over lidar alone (Hyde et al., 2006; Nelson et al., 2007). However, the greatest value will be the extension of high-quality characterizations of forest structure from samples of lidar data to non-lidar-sampled areas through the spatially comprehensive radar data. Beneficial methods for integrating these data sets are likely to be developed, particularly for cloudy areas where radar has distinct advantages.

With the increasing number of sensors and data sets available, new paradigms are being developed for forest monitoring that take advantage of existing and advanced methods for specific sensor classes. The concept of multistage sampling in forestry is not new (Czaplewski, 1999), but successful integration of a variety of data sets for ongoing monitoring purposes has yet to be realized. Although DESDynI is one major step in that direction, many other sensor classes including MODIS, Landsat, QuickBird (Table I) and airphotos will ultimately be effectively integrated for monitoring forest change (GOFCC-GOLD, 2009) in ways yet to be imagined.

Lidar

The use of data from lidar sensors, also known as laser altimetry, is growing rapidly, and lidar is about to become a major remote sensing technology for forestry applications. Lidar instruments are of many types and are operated from multiple platforms. This section provides a brief overview of technical aspects of lidar, illustrates the broad range of potential forest applications and emphasizes forest management inventories, with particular focus on the use of different types of instrumentation.

Lidar technology

Most lidar sensors emit a short duration pulse of light and measure the elapsed time between emission and detection of the reflected energy back at the

sensor. The time is converted to distance or range by multiplying half the signal's travel time by the speed of light. Lidar instruments operated on the ground are known as terrestrial lidar, those carried on platforms such as fixed-wing aircraft and helicopters are known as airborne lidar, and those aboard satellites are known as spaceborne lidar. Although all types of platforms have been used in forest applications, this section focuses on airborne and spaceborne applications. When a lidar system is operated from aircraft, the sensor is usually integrated with systems that record the platform's three-dimensional (3D) position and orientation. Thus, highly precise ground positions on the order of 0.1 m or less can be provided for every laser measurement (Ahokas et al., 2003).

Laser pulses emitted from near nadir positions typically have circular or near circular outlines when they hit the ground. The diameter of the circle is known as the footprint diameter and typically varies from 0.1 to 20 m for airborne instruments and from 20 to 100 m for spaceborne instruments. Small-footprint systems with footprint diameters of 0.1–2.0 m are used primarily for commercial purposes such as operational mapping of topography and forest management inventories, whereas large-footprint systems with footprint diameters of 5–10 m are usually used for research purposes.

Lidar systems are further distinguished with respect to discrete return and full waveform. With discrete return lidar, a few distinct peaks of the continuous distribution of backscatter energy from the pulse reflection at the target on or near the ground are recorded as discrete echoes. Discrete

return systems can usually store two to five distinct echoes per emitted pulse, the information necessary to produce 3D coordinates, and the echo intensity. In a forest, one or more echoes will often be reflected from vertical positions within and on the outer surface of the forest canopy, with the last echo reflected from the ground (Figure 2). In forest gaps, only the single ground echo will be recorded. When aggregated over a target area such as a sample plot or forest stand, the collection of heights estimated from canopy echoes depicts the 3D structure of the forest and thus mimics the distribution of biological material in various vertical height layers. The first tasks with discrete return lidar data are usually to determine the terrain surface and then to estimate the height of each echo relative to the terrain. Discrete return systems are the most common with proprietary airborne lidars used for operational surveys.

With full waveform lidar, the entire distribution of backscatter energy is recorded at discrete intervals for every emitted laser pulse. Thus, the waveform can consist of a vertical distribution of heights recorded at intervals such as 15 cm. Each individual waveform mimics the vertical distribution of biological material (Figure 2). Large-footprint lidars are usually waveform systems and have been developed and used mainly for research purposes. However, the waveform principle is now also becoming available for small-footprint proprietary lidar systems. Full waveform systems generate much larger volumes of data than discrete return systems. Mallet and Bretar (2009) provide a comprehensive review of full waveform lidar systems.

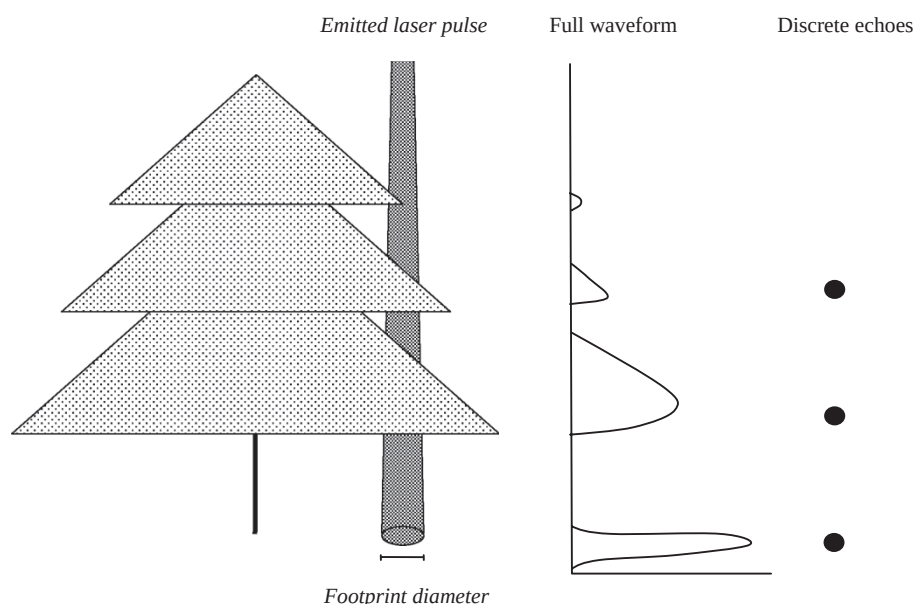


Figure 2. Data recorded from an individual laser pulse emitted by small-footprint full-waveform lidar (the entire backscatter is recorded) and a discrete return lidar (discrete echoes are recorded; in this particular illustration a first echo, an intermediate echo and a last echo).

Emitted laser pulses are distributed using both profiling and scanning mechanisms. With profiling lidar, data are collected for consecutive footprints in a narrow strip beneath the platform. This mechanism was used by the first small-footprint lidars when they were introduced in forest research about 1980 and is still in use by small-footprint discrete return lidar research instruments and by large-footprint waveform lidars operated from aircraft or from space. The scanning mechanism is a feature of all proprietary lidars used for operational surveys. Multiple scanning mechanisms are used, but they all distribute the pulses continuously in wider swaths along the aircraft flight paths than the narrow strips characteristic of profiling systems. With small-footprint airborne lidars, also known as airborne laser scanning (ALS), swath widths range from 500 to 2000 m. Thus, scanning is an efficient means to collect data with full areal coverage. Small-footprint scanning lidar systems are used for topographic mapping and have to a large degree replaced photogrammetry in recent years. ALS is also used operationally in forest management inventories, as discussed below. An ALS data set with high density of measurements is shown in Figure 3. Wehr and Lohr (1999) provide further details regarding physical and technical aspects of airborne lidar and also describe various scanning mechanisms. Hyypä et al. (2008) provide an overview of small-footprint airborne lidar systems and their applications in forest research. Lim et al. (2003) and Næsset et al. (2004) report experiences with a broader suite of airborne lidar systems for forest applications.

Lidar metrics as predictors of forest attributes

Airborne profiling lidar metrics. Raw lidar data collected by small-footprint, discrete return, profiling lidar represent a two-dimensional height profile (Maclean & Krabill, 1986; Nelson et al., 1988) from which metrics such as cross-sectional areas and canopy heights have been shown to be related to forest attributes such as stand height, merchantable volume and biomass (Nelson et al., 1984, 1988). Over time, metrics derived from the profiles have been extended to include maximum height and mean of all or a selected number of the largest heights (Nelson et al., 1988), proportion of ground echoes to total number of emitted pulses, which is a measure of openness, and proportion of canopy hits to total number of emitted pulses, which is a measure of canopy cover. Quadratic mean height, calculated as the square root of the arithmetic mean of the individual squared lidar heights, gives greater weight to the higher measurements and has been commonly used. Based on their successful use in ALS studies, height percentiles such as the median have been proposed recently (Nelson et al., 2007). Height metrics have been used to represent different vertical canopy components by using varying lower threshold values such as 3 m.

Airborne scanning lidar metrics. The first ALS studies commonly used metrics such as maximum and mean height values of canopy echoes and canopy cover density calculated as the proportion of canopy echoes to total number of emitted pulses for all

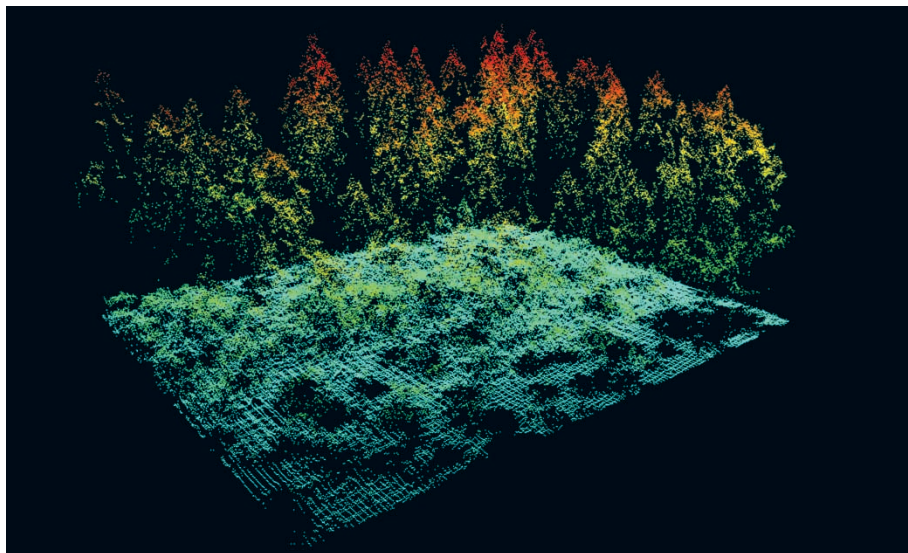


Figure 3. Height measurements from an airborne laser scanning (ALS) data set of a spruce forest with high pulse density.

pulses within a defined target area such as a sample plot or stand (Næsset, 1997a, 1997b). Since about 2000, ALS metrics have included means, medians, standard deviations, various percentiles of both tree and canopy heights, order statistics from the distribution of all echoes and proportions of the total numbers of echoes in vertical layers (Næsset, 2002).

A broad list of tree- and stand-level attributes may be estimated from ALS-derived metrics. Commonly estimated tree-level attributes include heights, cross-sectional crown areas and species (Hyypä & Inkinen, 1999; Persson et al., 2002). Stand- or plot-level areal attributes include mean height, timber volume, canopy cover, tree size distributions (Næsset, 1997a, 1997b, 2002; Gobakken & Næsset, 2004, 2005) and species-specific proportions of stand attributes (Packalén & Maltamo, 2007; Hudak et al., 2008). In addition, recent studies have focused on attributes related to wood quality such as crown height, dead branch height and timber assortments (Næsset & Økland, 2002; Peuhkurinen et al., 2007; Maltamo et al., 2009).

Airborne and spaceborne full-waveform lidar metrics. Because the entire distribution of backscatter energy is recorded for every emitted pulse with a full waveform lidar, the analysis of data acquired with such systems is usually conducted at a pulse level rather than as aggregates of echoes from multiple pulses along a segment as with a profiling discrete return lidar, or for areas as with ALS. For large-footprint systems, in particular, common metrics derived at the pulse level coincide to a large degree with those used for aggregates of echoes for discrete return systems. For example, maximum, median, mean and quadratic mean height have been used (Lefsky et al., 1999b), as well as the full range of percentiles (Drake et al., 2002). In addition, for data obtained from the spaceborne Geoscience Laser Altimeter System (GLAS), metrics related to the length of the waveform, which is the distance from the start to the end of the signal or from the start of the signal to the last peak of the signal, have been used as measures of vegetation height. Multiple other metrics, some rather complex, have been proposed, including those noted by Nelson et al. (2009) for estimating timber volume.

Relating forest attributes and lidar metrics. Regression modeling techniques are most frequently used to describe relationships between forest attributes and lidar metrics for data obtained from profiling and ALS systems. However, non-parametric methods

such as the k NN technique have also been used with good results (Maltamo et al., 2006b, 2009; Packalén & Maltamo, 2007; Hudak et al., 2008). For full waveform data, regression approaches have also been commonly used. When the footprint diameters for the latter data are on the order of 10 m, regression analyses have even been conducted at footprint level using field measurements for every footprint (Lefsky et al., 1999b). Table III provides a summary of forest attributes predicted using lidar metrics; the emphasis is on providing examples from different continents and with different instrumentation.

Lidar applications for forest structure, composition and ecology

Lidar data's unique capability to depict the 3D structure of the ground surface, trees, canopies and other vegetation attributes with fine spatial resolution over large geographical areas has attracted the attention of researchers in many forest resource and ecological disciplines. A few examples suffice to illustrate the diversity of applications.

Forest structure and composition. For forest ecology applications, estimates of structural parameters obtained from lidar data have been used to model the probability of vegetation types in boreal forests (Vehmas et al., 2009), to map woodland understories (Hill & Broughton, 2009) and to quantify forest floristics (Tickle et al., 2006). Hill and Thomson (2005) reported strong relationships between tree and shrub species composition and structure as forest attributes and structural metrics obtained from lidar data. Strong correlations have been found between indicators of the success of natural regeneration and structural lidar metrics in unmanaged forests (Bollandsås et al., 2008). Because lidar data with high pulse density can detect trees shorter than even 1 m, they have been suggested to be useful for monitoring tree migration in the alpine and arctic tree lines in response to climate change and changing land use (Næsset & Nelson, 2007). Korpela (2008) found that lidar intensity values discriminated well between lichens and other ground vegetation. Precise lidar-based estimation of leaf area index (LAI) from small-footprint data (Morsdorf et al., 2006) contributed to the detection of defoliation of Scots pine in Norway due to a severe insect attack (Solberg et al., 2006).

Lidar data can be used to predict the species of individual trees, at least in boreal forests with relatively few tree species. Such predictions can be improved using a fusion of lidar data and aerial imagery (Holmgren et al., 2008). However, dense

Table III. Relationships between forest structural attributes and lidar metrics.

Reference	Structural attribute	Geographical area	Forest type	Lidar system
Coops et al. (2007)	Stand height, basal area, vertical foliage distribution	British Columbia, Canada	Coniferous forest	DR, S, SF
Drake et al. (2003)	Biomass	Panama Costa Rica	Neotropical forest	FW, S, LF
Hopkinson & Chasmer (2009)	Fractional cover	Canada	Seven sites across Canada	DR, S, SF
Lefsky et al. (1999a)	Basal area, biomass	Maryland, USA	Deciduous forest	FW, S, LF
Lefsky et al. (2002)	Biomass	Oregon, USA Maryland, USA Manitoba, Canada	Coniferous forest Deciduous forest Boreal forest	FW, S, LF
Magnussen & Boudewyn (1998)	Stand height	British Colombia, Canada	Coniferous forest	DR, S, SF
Maltamo et al. (2005)	Tree numbers and height of different tree layers	Finland	Boreal forest	DR, S, SF
Means et al. (1999)	Height, basal area, leaf biomass, total biomass	Oregon, USA	Coniferous forest	FW, S, LF
Miura & Jones (2010)	Opening above ground, opening above low vegetation, presence of understory, canopy cover, presence of midstory, presence of high trees	Tasmania, Australia	Native forests	FW, S, SF
Morsdorf et al. (2006)	Leaf area index, fractional cover	Switzerland	Inner alpine valley	DR, S, SF
Næsset (1997a)	Mean tree height	Norway	Boreal forest	DR, S, SF
Næsset (1997b)	Stand volume	Norway	Boreal forest	DR, S, SF
Næsset & Gobakken (2008)	Above-ground biomass, below-ground biomass	Norway	10 boreal sites	DR, S, SF
Nelson et al. (1984)	Canopy closure, tree height	Pennsylvania, USA	Coniferous forest	DR, P, SF
Sherrill et al. (2008)	Mean height, biomass, leaf area index	Rocky Mountains, USA	Subalpine temperate	DR, S, SF
Takahashi et al. (2005)	Tree height	Japan	Coniferous forest	DR, S, SF
Weller et al. (2003)	Tree height, foliage projected cover	Queensland, Australia	Native forests	DR, P, SF
Zimble et al. (2003)	Tree height variance	Idaho, USA	Coniferous forest	DR, S, SF

Notes: Lidar systems: DR = discrete return; S = scanning; SF = small footprint; FW = full waveform; LF = large footprint; P = profiling.

lidar data have been shown to produce accurate tree-level species classification, even without supporting aerial imagery (Vauhkonen et al., 2009). Hyypä et al. (2008) provide a review of studies dealing with tree species classification.

Habitat. Lidar data have been shown to be particularly important for forest habitat studies. Nelson et al. (2005) used structural lidar metrics to model habitat suitability for small mammals such as squirrels. Müller and Brandl (2009) demonstrated that the richness and composition of assemblages of forest-dwelling beetles are strongly correlated with structural lidar metrics. In their pioneering study on habitat quality for great tits and blue tits in the United Kingdom, Hinsley et al. (2002) reported a significant relationship between mean chick mass

and vegetation height derived from lidar data. In an analysis of the suitability of a forest reserve in the Alps as habitat for capercaillie, Graf et al. (2009) reported good relationships between presence-absence patterns and lidar-derived metrics of horizontal and vertical canopy structure. Bradbury et al. (2005) provide a brief review of other studies linking bird characteristics to estimates of forest structure obtained from lidar data.

Wildfire. For purposes of modeling wildfire behavior, relevant canopy structural features such as tree height, tree cover, surface canopy height, surface canopy cover, crown bulk density, crown volume and foliage biomass have all been shown to be strongly correlated with metrics derived from lidar data (Riaño et al., 2003; Morsdorf et al., 2004).

Sensitivity analyses of fire behavior models have shown that lidar data can improve the accuracy of fuel mapping and can provide more detailed information about fire characteristics (Mutlu et al., 2008). Erdody and Moskal (2010) provide a short review of studies investigating relationships between lidar data and the canopy properties typically used in wildfire modeling.

Lidar applications for forest management inventories

Forest inventory is one of the most investigated and potentially most useful applications for lidar data. For this discussion, the focus is on management inventories; McRoberts et al. (2010) address applications for national forest inventories.

Airborne scanning lidar. The first operational and commercial ALS-supported management inventory was conducted in Norway in 2002 (Næsset, 2004b), and such inventories have since become standard practice in the Nordic countries. Laser pulse densities of 0.5–1.0 pulses m^{-2} are typically used for area-based inventories and provide stable and accurate results, at least in conifer forests (Maltamo et al., 2006a; Gobakken & Næsset, 2009; Magnussen et al., 2010). Wulder et al. (2008a) assert that lidar now has moved from research and development to operational implementation over a broad range of forest inventory attributes. Tests are also being conducted to incorporate ALS as an operational tool to facilitate forest management and inventories in other parts of the world: Australia (Rombouts et al., 2010), Austria (Hollaus et al., 2007), Canada (Thomas et al., 2006), Germany (Breidenbach et al., 2008) and the United States of America (Jensen et al., 2006).

With the introduction of small-footprint, proprietary ALS systems for forest research in about 1995 (Næsset, 1997a, 1997b), lidar-based height information became available as 3D, wall-to-wall data. The first studies pointed toward great opportunities for accurate estimation of stand-level inventory attributes such as mean tree height and timber volume (Næsset, 1997a, 1997b; Magnussen & Boudewyn, 1998; Means et al., 2000). Although ALS data were shown to underestimate tree heights (Næsset, 1997a; Magnussen & Boudewyn, 1998), adjustments using field data could be used to correct the estimates. Næsset (1997a, p. 55, 1997b, p. 252) proposed an approach featuring construction of models of stand properties using data from georeferenced field sample plots and corresponding ALS metrics distributed over AOIs as large as 100–500 km^2 . The models would then be used to predict

properties for individual stands within the larger areas. For this type of application, the models are considered synthetic in the sense that they are based on data external to the AOI to which they are applied (Särndal et al., 1992). Means et al. (2000) asserted that ALS offers great potential for savings compared to conventional management inventories, and Eid et al. (2004) confirmed that ALS can be more cost-efficient for management inventories than the extensive use of aerial photography combined with field checking.

For stand-level estimation, approaches using models and model predictions typically have four components: (1) construction of models of the relationships between ground plot observations of forest attributes and ALS-derived metrics; (2) division of stands into grid cells equal in size to the ground plots; (3) prediction of forest attributes of interest for every cell; and (4) aggregation of the individual cell predictions to obtain stand-level estimates. Although the primary purpose is to estimate stand-level attributes, the cell predictions actually constitute a forest attribute map. Næsset and Bjerknes (2001) and Næsset (2002) provided proofs of concept for this approach; the concept was later validated for forest stands of 0.02–5.00 ha using both small control studies and full-scale operational tests in multiple countries. Næsset (2002, 2004a, 2004b, 2007), Holmgren (2004) and Maltamo et al. (2006a) all reported that ALS-based management inventories can produce estimates of stand attributes such as mean tree height, dominant height, mean stem diameter, stem number, stand basal area and stand volume under boreal forest conditions that are more accurate than estimates obtained from conventional management inventories based on fieldwork and aerial photography. Næsset's (2007) review of Nordic studies indicates that varying levels of precision, expressed as percentages of means, may be expected: mean height, 3.0–6.4%; dominant height, 3.4–8.0%; mean diameter, 5.9–15.5%; stem number, 11.6–29.3%; stand basal area, 8.6–14.4%; and stand volume, 7.9–14.3%. Of particular recent interest, Asner (2009) proposed monitoring above-ground biomass and carbon in tropical countries under the UN-REDD (Reducing Emissions from Deforestation and Forest Degradation) program (<http://www.un-redd.org/>) using areal estimation methods with wall-to-wall ALS coverage. Whenever the lidar data are available as canopy surface models only and not as raw data consisting of echoes from the individual laser pulses, only the lidar height information may be used for inventory purposes, i.e. information on canopy density must be ignored. For such a special case Corona and Fattorini (2008)

reported an interesting probability-based sampling approach.

Estimators using synthetic regression models for small domains such as individual forest stands for which no field data are available have been shown to be very precise, albeit with possibly large biases (Särndal et al., 1992, pp. 410–411). Estimation does not provide any means for controlling potential bias and depends entirely on correctly specified models. Næsset (2007) reported that for Nordic conditions application of synthetic models to local AOIs with no use of local data to adjust estimates, stand-level bias is moderate, generally less than 10% and in most cases less than 5%. In a simulation study, Andersen and Breidenbach (2007) compared estimators using synthetic models with no local adjustment to modified estimators with local adjustments and reported that local stand-specific plot data can be used to adjust estimates to reduce the effects of local model misspecification. However, collection of stand-level field data is not feasible for local bias control in large area operational forest management inventories.

Airborne profiling lidar. The very first investigations of small-footprint discrete return lidar in forest research used profiling systems (Solodukhin et al., 1977; Nelson et al., 1984). Because profiling systems only collect data along a narrow strip beneath the platform, profiling lidar data must be considered along separate flight lines. Thus, in forest inventory, the use of profiling lidar has been limited to sample survey and has not found any applications in management inventories.

The first forest sample survey with airborne profiling lidar was conducted in Delaware, USA (Nelson et al., 2003b, 2004), where data were collected with the Portable Airborne Laser System (PALS) (Nelson et al., 2003a) profiling lidar system for 56 flight lines spaced 1 km apart. Models of the relationships between merchantable volume and biomass estimated from ground samples and crown closure and height metrics derived from the lidar profiles obtained separately were used to predict biomass and volume along all the flight lines. State-wide volume and biomass estimates based on data for only every fourth flight line were within 1–16% of the estimates reported by the Forest Inventory and Analysis program of the US Forest Service (Nelson et al., 2004). A forest inventory using the PALS lidar and a similar design was later conducted in Ehime Prefecture, Japan (Tsuzuki et al., 2008).

In 2006, Hedmark County, Norway ($\sim 27,000 \text{ km}^2$), was sampled with the PALS profiling lidar using 105 parallel flight lines spaced 3 km apart that coincided

with the $3 \times 3 \text{ km}$ grid of 250 m^2 permanent sample plots of the Norwegian National Forest Inventory. Regression models of the plot-based estimates of biomass versus lidar-derived height and canopy density metrics were constructed for use with two sample-based estimators, one assuming a probability-based framework (Gregoire et al., in press) and the other a model-based framework (Ståhl et al., in press). The county was also sampled with an ALS instrument flown along 53 flight lines spaced 6 km apart. Similar sample-based estimators were developed as for the profiling application.

Spaceborne lidar. The GLAS onboard the ICESat satellite has been the only spaceborne lidar sensor with the capacity to assess vegetation structure. The GLAS instrument is a full waveform, profiling lidar with nominal ground footprint diameter of approximately 65 m (Schutz et al., 2005). For an inventory in Quebec, Canada, Boudreau et al. (2008) used a two-phase, model-based design to estimate above-ground forest biomass. GLAS footprints systematically distributed over the entire AOI were used as the first phase sample, and PALS airborne profiling lidar data for a subset of the GLAS footprints constituted the second phase sample. A model based on the relationship between plot biomass for a purposive sample of ground plots and corresponding PALS lidar metrics was used to predict biomass for the GLAS footprints, and a second model of the relationship between the predicted biomass and the GLAS lidar metrics was used to predict biomass for all the GLAS footprints. Among the important results, 36% of the above-ground biomass was found to be north of what is considered to be Quebec's commercial forest. For a study in central Siberia, Nelson et al. (2009) used a model of the relationship between timber volume obtained from field plots corresponding to a purposive sample of GLAS footprints and GLAS lidar metrics to predict volume for all footprints. The estimate of total timber volume corresponded well with an estimate from a previous independent inventory.

However, both GLAS studies identified difficulties. For the Quebec study, the large GLAS footprint caused the laser pulses to strike lower elevation canopy tops at the same time as higher elevation ground in areas with moderate to high relief and produced a waveform that was complex and difficult to interpret (Harding & Carajabal, 2005). For the Siberian study, volume tended to be overestimated for terrain with slopes greater than 10 degrees because of confounding of higher altitude topography with the forest canopy. Future large area inventories using data from spaceborne

lidar systems may profit from smaller footprints such as the ~25 m footprint of NASA's planned DESDynI mission (<http://desdyni.jpl.nasa.gov/>).

Additional considerations

Accurate co-registration of field plots and ALS footprints is crucial to exploit the full potential of lidar data (Gobakken & Næsset, 2009). Current, state-of-the-art global positioning systems may be expected to produce location accuracies in the 0.1–1.0 m range for field plots in boreal forests.

When planning ALS acquisition for forest inventories, the properties of ALS data obtained with different sensors must be considered. For example, factors such as flying altitude, pulse repetition frequency and footprint size on the data may affect estimates of forest attributes (Næsset & Gobakken, 2008; Næsset, 2009). When the instrument and acquisition parameters are kept constant between inventories, models developed for one AOI can be applied to adjacent AOIs and hence reduce the necessary fieldwork and reduce costs (Næsset *et al.*, 2005; Næsset, 2007). However, when sensors or acquisition parameters differ between AOIs, models should be constructed using locally acquired data to reduce the risk of bias in the estimators as a result of model misspecification (Næsset, 2009). Wulder *et al.* (2008a) identifies factors that should be considered when planning acquisition of ALS data for forest inventories with specific focus on Canadian conditions.

Summary and conclusions

The relatively recent, but nevertheless widespread, availability of remotely sensed data has been a boon to forest researchers, particularly those interested in spatial analyses. Techniques for predicting forest attributes from remotely sensed data as a means of constructing maps have often simply been borrowed from other disciplines. Therefore, it is not surprising that the general topic area of parametric approaches to classification for categorical response variables and prediction for continuous response variables is one of the more mature aspects of remote sensing-based applications. Non-parametric approaches to classification and prediction, however, continue to attract attention, at least partially because forest attribute and remotely sensed data often cannot be characterized using familiar statistical distributions. Similarly, accuracy assessment may also be considered a relatively mature topic area, although selection of accuracy assessment sampling designs that are cost-efficient and produce acceptably precise

estimates of accuracy measures still merits considerable attention.

The status of approaches to inference using remotely sensed data reflects both perplexity and mixed levels of maturity. The perplexity arises from the relative lack of reported attempts to construct inferences for maps or using map data, even though probability-based approaches to inference are both relatively familiar and easy. Thus, despite their relative lack of use, probability-based approaches to inference may be regarded as relatively mature. Such is not the case for model-based approaches to inference, which are less familiar, much less commonly reported, more complex, subject to a greater degree of computational intensity and require bias assessments. Nevertheless, the utility of model-based inference, particularly for small area estimation and map applications, justifies continued exposition and research.

As classification and prediction techniques matured and as acquisition of remotely sensed data was replicated for annual and near-annual time steps, the extension to change detection was natural. Whereas the first approaches to change detection were based on comparisons of separately classified images, later more powerful approaches were developed that combined data for multiple time steps into a single data set. Change detection may properly be characterized as an emerging topic area on the basis of a lack of accepted standardizations, although the expected demands for change detection products will surely promote rapid increases in maturity.

Nearly anything related to lidar is currently a topic of interest for the forest research community. To an even greater degree than change detection, lidar applications must be considered immature because of the variety of kinds of lidar data, the lack of consensus on prediction methods, the lack of very large area applications, the lack of accepted methods for accommodating the quantity of data and the costs. Nevertheless, progress made on incorporating lidar data into operational forest management inventories suggests that increased maturity will be forthcoming shortly.

Five conclusions may be drawn from this review. First, and most importantly, remotely sensed data have greatly contributed far beyond field data alone to two important functions: adding a spatial component to forest attribute information via the construction of maps and reducing the costs of forest inventories. Secondly, continued attention to non-parametric, multivariate approaches to forest attribute classification and prediction using remotely sensed data is warranted. Thirdly, greater attention should be paid to map-based inference, particularly when it can be approached as a relatively easy

extension of accuracy assessments. As a necessary component, methods for estimating the variances of mapping unit estimates must become familiar and must be incorporated into standard software packages. For model-based inference, three areas merit consideration: (1) educating researchers and practitioners on the utility of model-based inference; (2) developing consensus on methods for easily assessing model misspecification as it pertains to bias; and (3) investigation of methods for reducing the computational intensity. Fourthly, despite the current relative immaturity of change detection methods, their relevance and utility for assessing the effects of climate change on forests and for assessing deforestation and forest degradation under the auspices of the UN-REDD program cannot be underestimated. Broad, generalized comparisons of approaches to change detection and development of supporting inferential methods merit attention. Fifthly, the intense interest in lidar-based research will without doubt lead to exciting developments and greater consensus. The development of inferential methods for use with lidar data indicates progress toward maturity.

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