Modeling for Estimation and Monitoring

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IN THIS CHAPTER YOU WILL LEARN ABOUT:

- Use of models and data aggregation in NFIs and NFAs
- Estimation and modelling of biomass and carbon content in forested ecosystems
- Aspects of model predictions, model quality, model errors and model bias
- Issues in estimation and modelling of temporal change in NFI attributes

Abstract

In many forest inventory applications, numerous attributes of interest must be estimated using a lookup-table or an equation (collectively referred to as a model). Stem volume, for instance, is rarely directly measured in the field, but is estimated from dimensional measurements like diameter or height. Individual observations are usually aggregated for reporting purposes and may be grouped during field data collection, such as when trees are tallied by diameter or height class. Aggregation simplifies presentation of data, but the information content is reduced.

Variables such as volume, biomass, or carbon content are frequently estimated from equations (models). It is sometimes difficult to judge whether a given equation is applicable to a particular situation; an assessment of the quality of all equations (models) used in an inventory is important. The selection of a particular equation (model) should be guided by this assessment, as well as modeling objective and context.

Some inventories focus on assessing the state of the resource, others on the change in the resource over time. Different field procedures and sampling designs are preferred for different objectives.Sampling with permanent plots provides estimates of both state and change. Designs with a smaller (expensive) set of permanent plots and a larger set of (less expensive) temporary plots can also provide good estimates of both state and change, but the statistical analysis of such designs is quite complex and care must be taken to ensure appropriate assessment of accuracy and precision.

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1. Introduction

Many forest attributes of interest in forest inventory and monitoring applications are not measured directly as it would be impractical or too costly to do so. The best known example includes stem volume where diameters and heights are measured on individual trees and a table or an equation (collectively referred to as a model) is used to estimate the associated volume (Köhl et al. 2006, section 2.37). The volume of coarse woody debris (CWD) is another example (Köhl et al. 2006, section 6.4.6; Woldendorp et al. 2004). In practice only a small number of short segments of the CWD are measured for volume, and the total amount of (CWD) in an area of interest is estimated through a scaling of the measured pieces; the scaling depends on the sample design (Woldendorp et al. 2004). Advances in remote sensing favor the use of easy to measure and readily available variables (say X) correlated with the attributes of interest (say Y). An estimate of Y for the area or population of interest is then obtained from a small sample of Y and knowledge of the relationship between X and Y (Köhl et al. 2006, p 80)

The types of models available for indirect estimation of quantities like wood volume, biomass, and carbon content, including examples, are given in the following sections. Issues to consider in the choice of model for a specific application, along with modeling objectives and contexts, are also discussed.

2. Aggregation

Aggregation is the combination of data or observations into groups. Aggregation is done to simplify measurements and data-processing (Stage et al. 1993) or to summarize data and observations into groups and categories of interest.

The attribute data to be collected in an inventory are defined and prescribed based on the information needs of stakeholders in the forest resource to be inventoried (Dachang and Cossalter 2006, p 5). In a field inventory, it is important to measure and record all items in a sample plot that meet the definitions/specification of the desired attribute (for more information visit the chapter Sample Designs). Data definitions/criteria can be based on demographic characteristics. For trees, for example, it could be a minimum size limit, often expressed as a minimum diameter such as, say, 10 cm. Criteria may also limit measurements to certain species or tree characteristics of interest.

It is important to remember that limiting inventory data and observations to items (trees, shrubs, snags,…) that meet established definitions/criteria equally limits the inference and estimates we can derive from these data to the parts/units of the forest population that satisfy the definitions/criteria (see chapter on Observations and Measurements). For example, if stem-wood volume estimates for live trees are estimated only for trees with a diameter at breast height greater than 10 cm, then it will not be possible to estimate total volume or biomass for the forest of interest.

To paraphrase, the results apply only to population elements with a known positive probability of being included in the inventory sample (Thompson 1992, p 21) (see section on sampling design and estimation).

Sample unit summaries do not usually include values for all items measured. For example, trees are often aggregated into groups based on species, demographics such as diameter, height, or social status (section 2.2), hierarchy such as functional group (section 2.3), or the total stand. Aggregation may be one-dimensional (e.g., total volume by species) or multi-dimensional (e.g., volume by diameter class by species) as appropriate. Aggregation of inventory items can also be based on land-use pattern (e.g. shifting cultivation) or future planned use of a resource item (e.g. fuel-wood).

The consequences of any aggregation of observed/measured items on analysis and inference should always be considered carefully (Clark and Avery 1976). Once data are aggregated, it is usually difficult - if not impossible - to recover underlying details at

a later stage should it become desired (Ritchie and Hann 1997). To conserve a desired accuracy and precision of estimates, it is often better to postpone aggregation to the analytical phase that follows completion of field data collection. However, for practical and cost-saving reasons, aggregation often occurs during field observation. Instead of measuring, say, the diameter of each tree in a field plot to the nearest 0.1 cm, counts of trees by 5- or even 10-cm diameter class are often practiced due to expediency. In this case, the class mid-points are usually used in the analytical phase. Note, an aggregation always has the potential to introduce additional error and possibly a bias in the resulting estimate (Ducey 1999). Of course, aggregation greatly simplifies field procedures and may well result in greater overall precision if the savings due to efficiency is used instead to collect more field data, but the trade-off is far from simple; we reiterate our caution against uncritical aggregation.

2.1 Aggregation by Species

Estimates of totals and per unit area values for a stand, a forest, or a region, are frequently aggregated over species meeting a certain definition/criterion with respect to size or use. As stated above, it is important that all species which enter the inventory sample - and otherwise meet the definition/criterion - be duly observed and recorded. Otherwise the estimates will become biased. Note, when a species can't be identified by a field crew, it should be given a name with helpful hints towards a later identification (e.g. shape or size of foliage, fruit-bodies, branching, bark, …). Aggregation by species during field data collection may be in order during surveys of biodiversity and in count-oriented surveys of disease and insect damage, but otherwise is not recommended.

It is common in temperate forests to develop estimates of stand characteristics by species. In tropical forests, this can be difficult, and probably even more difficult to interpret, due to complex stand structures or the large number of species (Higgins and Ruokolainen 2004). In some instances, species are combined by ecological functional group (e.g., canopy dominants). This often results in a manageable number of species groups that are relatively easy to interpret in terms of forest structure (Gadow 1999). Commercial utility and silvics are also considered for species grouping

In national or continental scale summaries, species groups may be developed for reporting purposes due to the large numbers of potential species (Burns and Honkala 1990). A species group labeled "Pine", for example, may include all Pinus species occurring within a geographic area of interest.

2.2 Aggregation by Size

Trees are often aggregated by demographics, meaning that trees of similar sizes or social status are combined into groups for data summaries or field data collection. Aggregation by size for reporting and analysis purposes is generally straightforward except when the inclusion probabilities (viz. expansion factors) associated with the inventory data are linked to the size of trees (Köhl et al. 2006, p 155).

In the field an aggregation of trees by diameter (e.g., 5-cm diameter class) is probably the most common method of aggregation. The number of trees in each diameter class is tallied, and diameter class midpoints are used in the subsequent analyses to estimate variables like volume or biomass. A minimum diameter of trees to be measured is usually specified in field measurement protocols. Thresholds for inclusion/measurement are defined according to the purpose of the survey. Usually the minimal commercial diameter - or one to two diameter classes below that threshold is used. A stratification of sampling efforts by size is an inevitable practical constraint when sampling odd-shaped, highly variable and scattered objects. An example is sampling for coarse woody debris (Roth et al. 2003; Williams et al. 2005).

Note, if trees are selected with a probability proportional to their size, a use of diameter classes can be problematic (Ducey 2000).

Since forest inventory data are often used repeatedly for many diverse purposes, it is preferable to keep data in the form they were captured. For example, a user who want to model the diameter distribution (Cao 2004; Gove and Patil 1998) would be better served by non-aggregated data.

Trees may also be aggregated by height class, which may have bearing on the resulting wood products that may be derived (Köhl et al. 2006, p 36). Height class may also be used to aggregate trees for analysis of grazing forage availability or wildlife habitat structure (Spetich and Parker 1998). Height aggregation is probably more common in ecological or grazing surveys than in surveys that focus on assessment of commercial fiber utilization opportunities.

Finally, trees may be grouped by their position in the forest canopy, such as canopy dominants (Gargaglione et al. 2010; Nigh and Love 2004). This type of classification is more useful in ecological surveys than in surveys attempting to inventory commercial material. Structural classification may have a great deal of importance in evaluating forage potential or other non-fiber commercial potential.

2.3 Aggregation by Hierarchy

Trees may be aggregated in various hierarchical systems for analysis and reporting (Mairota et al. 2002). Trees may be aggregated in a biological hierarchy (individual trees → species → ecological functional group→ stand). Trees could also be aggregated in a utilization hierarchy (individual trees → diameter class→ product class → species → stand). Reporting may include summaries for any or all levels of the hierarchy.

Aggregation also occurs at the spatial scale (e.g.Wolf 2005). The spatial unit can be a stand, or a smaller unit (say a pixel in a remotely sensed imaged). Aggregation is then done across all units that meet a certain requirement related to their forest attributes or data values. The purpose of a spatial aggregation could be for reporting and analysis, or to improve sampling efficiency by stratification (Köhl et al. 2006, p 105). In the analysis of spatially aggregated data, it is imperative to recover all pertinent information as to the genesis of the data (observed, sample-based, model-based, predicted, imputed, interpolated, …) and any available estimates of accuracy and bias. Spatial covariance among aggregated forest resource data types can greatly complicate the statistical analysis of spatially aggregated data (Mairota et al. 2002; Rossi et al. 2009; Schwab and Maness 2010; Waser and Schwarz 2006).

In spatial aggregations the spatial units may be aggregated by forest type (e.g., moist tropical) or geographic region for analyses at regional or national levels. Geographic region may be based on political delineations (e.g. state or provincial boundaries) or ecological zones, e.g. Holdridge life zones (e.g.Ni et al. 2005). Aggregation at the stand level may occur after estimation (prediction) of the variables of interest for each sampling unit in a stand.The appropriate methodology for the aggregation is determined by the sampling design and survey objectives. Aggregation may be built into the sampling design through use of stratified sampling (De Vries 1986, p 31).

2.4 Aggregated Class Estimation

For trees measured on fixed area plots, estimates of per hectare values are obtained by dividing the respective individual tree characteristics by the size of the area sampled:

$$Y_{ij} = A^{-1} \sum_{k}^{n_{ij}} X_{ijk}$$

Y_{ij} = estimated per hectare quantity of the measured variable for the ith sampling unit and the jth aggregation class with nij observations of X;

X_{ijk} = value of the measured variable for the kth tree in the ith sampling unit and j[th] aggregation class;

A = size in hectares of the individual sampling unit.

For trees measured on variable radius

sampling units, (see Observations and Measurements chapter for more information) estimates of per hectare values are obtained by dividing the respective individual tree characteristics by the basal area of the measured tree, and multiplying by the basal area expansion factor:

$$Y_{ij} = BAF \sum_{k=1}^{n_{ij}} \frac{X_{ijk}}{B_{ijk}}$$

Y_{ij} = estimated per hectare quantity of the measured variable for the ith sampling unit and the jth aggregation class with n_{ij} observations of X;

BAF = basal area factor, equivalent to the basal area per hectare represented by each measured tree;

X_{ijk} = value of the measured variable for the kth tree in the ith sampling unit and j^{th} aggregation class;

B_{ijk} = basal area in m² of the kth measured tree in the ith sampling unit and j^{th} aggregation class.

An estimate of a total $\left(\hat{Y}\right)$ or a mean $\left(\bar{\hat{Y}}\right)$ for a population parameter - obtained by a probability sampling design - follows the basic principles behind the Horwitz-Thomson estimator (Overton and Stehman 1995):

$$\hat{Y} = \sum_{i \in s} Y_i \times \pi_i^{-1}, \bar{\hat{Y}} = \hat{Y} \times N^{-1}$$

where summation is over the units (i) in the sample (s) and π_i is the sample-inclusion probability of the ith sampled unit (see section on Sampling Design). For a population with N units, the estimation is sometimes done with a mixture of n sample-based unit-level observations, and N-n estimates derived from models or otherwise imputed (McRoberts 2006; McRoberts et al. 2002). In this case the estimator for the total is simply the sum of all N unit-level values (observations and estimates). The associated estimator of accuracy may follow directly from statistical theory (Overton and Stehman 1995). In more complicated cases an application of the delta-technique is required (Davison 2003, p 33-35).

Estimation of population parameters from units of observation is done on a routine basis in forest inventories (see chapter on sampling design). There are two basic sampling units commonly used in forest inventory applications: 1) fixed area plots, and 2) variable radius plots (e.g. Corona et al. 2010). Transect sampling are special cases of fixed area plots and can be treated similarly in many applications (Hedley and Buckland 2004). In most cases, estimates of the variables of interest are obtained for each sample unit, and then combined to obtain estimates for the larger area (aggregate) of interest. The method of combining estimates from individual sampling units, and the methods of estimating associated precision of the estimates, depends on the sampling design.

2.5 Implications of Aggregation in Estimation and Modeling

Aggregation at the field data collection phase simplifies field data collection and may improve the relative accuracy. We have already outlined some of the statistical issues in connection with data aggregation. A summary is provided next.

The potential downside of data aggregation during the data collection phase is a possible introduction of bias and an almost certain reduction in both accuracy and precision of resulting estimates due to the introduction of error (Clark and Avery 1976). Combining all trees within a species class, for example, results in a loss of information on individual tree sizes. Since forest inventory data are typically used for multiple purposes and in multiple combinations, it is in general advisable to limit any aggregation to the reporting/analysis phase of an inventory.

Decisions about aggregation during field data collection also affect future utility of the collected data. New and emerging issues important to forestry may require details that were lost due to economic pressures of expediency. It is not possible, for example, to explore many aspects of biodiversity if

species have been aggregated during field data collection. The increased use of remote-sensing techniques in forest inventories (Tomppo et al. 2008) can be viewed as an aggregation process (in extremis).

A disaggregation of aggregated data is only possible if one is willing to make assumptions about the frequency distribution of possible data values that have been aggregated into a single value (Papalia 2010). Only rarely can such assumptions be justified.

3. Volume estimation

Volume is the most widely used measure of wood quantity. It is usually estimated for the assessment of economic value or commercial utilization potential. The wood volume may refer to a specific portion or part of a tree or the whole tree. The total wood volume of a tree includes the volumes of stem(s), branches, stump, and roots. For standing trees, aboveground volume production is generally based on stem wood volume for conifers, but may include branch volume for broad-leaved tree species.

Depending on measurement objective and local traditions, measurements or predictions of wood cubic volume may refer to, for example, total stem volume, total tree volume (stem and branches), or the volume of portions of a tree intended for a specific utilization (Köhl et al. 2006, p 47). Volume estimates may include or exclude bark and, for aboveground estimates, include or exclude the stump. Volume is always a cubic measure, and usually expressed in cubic meters. Merchantable volume, however, is sometimes expressed in other units related to commercial use (Skovsgaard 2004).

In the field, the volume of standing trees is typically estimated from such measurements as diameter, or diameter plus some height of interest (e.g. merchantable height, total height, or height to a usage specified diameter limit). A subsequent application of a suitable volume equations, taper equations, or a log-rule will then produce the desired volume estimate (Lynch 1988; 1995; Tesfaye 2005; Tomé et al.

2007; Yamamoto 1994a; 1994b).

Volume may be measured directly on felled trees or logs, but is often estimated from dimensions such as minimum diameter or piece length (Husch et al. 1972). Direct measurement of volume is usually done by sectioning a tree into smaller pieces assumed to be cylinders (Köhl et al. 2006, p 50). Volume may be estimated for stacks of logs or processed products by measuring their dimensions. Local knowledge is needed to make the appropriate transformation to an estimate of the solid wood volume.

With the advance of remote sensing technology, especially LiDAR (see chapter on Remote Sensing), it is now possible to combine field-based estimates of volume for a spatial unit (plot) with a suite of remotely sensed ancillary variables in order to obtain either model-based predictions of per-unit area volume or per-tree estimates of volume for trees large and distinct enough to be identified with a high degree of confidence (Maltamo et al. 2004a; Maltamo et al. 2004b; Parker and Evans 2004; Popescu et al. 2003).

3.1 Volume Equation Forms

Stem volume (V) is usually expressed quantitatively as a function of diameter (D), or diameter and height (H) or merchantable length. Occasionally, other variables such as clear bole length are used to estimate volume (Husch et al. 1972). An important consideration is that any variable needed to predict volume should be observed during field data collection. The following two 'classic' models are often used (Köhl et al. 2006, p 50) : $V = \alpha + \beta \times D \times H$, alternatively $V = \omega \times D^{\varepsilon} \times H^{\psi}$ where, in both cases, α, β and γ are coefficients to be determined from specific (small) samples where tree volumes are carefully determined, or known from previous studies viz. subject knowledge. When tree height can be expressed as a function of diameter (Begin and Raulier 1995; Huang and Titus 1992; Jayaraman and Lappi 2001; Moore et al. 1996; Nanos et al. 2004;

Zhou and McTague 1996) the relationship can be built into a volume prediction based on diameter alone. Tabulated look-up tables of stem volume for a given species, location, and stem diameter are called volume-tariffs (Fonweban and Houllier 1997; Magnussen 1998; Paine and McCadden 1988).

Choice of model may depend on modeling objective and data (Skovsgaard 2004). The listed equations implicitly assume a single-stemmed tree form and may require modification or replacement for species with a more complex form. At times a volume equation is easier to fit to data after a logarithmic transformation because the transformation brings the model into a linear form. However, a negative bias is introduced when the predicted logarithm of V is converted back to arithmetic units (Baskerville 1972; Bi et al. 2001; Lee 1982; Wiant and Harner 1979). This bias is approximately the order of magnitude of one-half of the residual variance of the equation, at least when it can be justified to assume a normal distribution of model residuals.

In the absence of a trusted local volume equation(s), it is possible to utilize geometric relationships to approximate volume. The volume of a cylinder is simply the area of the base times the height, and the volume of a cone is one-third of the volume of a cylinder with the same area of the base and height. Trees are neither cones nor cylinders, but empirical analyses often indicate that the volume of a single-stemmed tree is between that of a cone and a cylinder, with tree volume often lying between 0.40 and 0.45 times that of an equivalent cylinder. Using a value of 0.42, for example, we get $V \approx 0.42 \times B \times H$ where B is tree basal area at breast height and H is tree merchantable height. This equation will often overestimate volume of open-grown trees with more conic form, underestimate the volume of trees with more cylindrical form, and may need to be modified for species with more complex forms. Nevertheless, it does provide a first approximation, that subsequently can be modified following local experience.

Volume equations derived from remotely sensed predictors are typically linear (possibly after a logarithmic transformation) with a model form that depends on the sensor type, data resolution and scale (Biggs 1991; Magnusson et al. 2007; McRoberts et al. 2007; Straub et al. 2010; Yu et al. 2008).

Application of any model means that the ensuing estimates are not exact. Estimates derived from models may be biased due to limitations of the model, and in all cases they are predictions of the value that is expected given the value of the predictors (Kangas 1996). For example, if you predict a stem volume from D and H using a local volume equation then the estimated value of V should be interpreted as the average value of all trees in the population with the exact same D and H values. The actual tree in question may have a volume that is either greater or less than the expected value (Gregoire and Williams 1992). If a model turns out to produce estimates with an unacceptable high level of bias it may become necessary to either develop an improved model or to calibrate an existing model (Erdle and MacLean 1999; Kangas and Maltamo 2000; Lappi 1991).

4. Biomass estimation

Biomass is defined as the total mass of living plant organic matter expressed as oven-dry tons or oven-dry tons per unit area. Estimates of biomass may be restricted to the aboveground portion of the vegetation, to trees, or to tree components (such as foliage, wood, etc.) (Gschwantner et al. 2009).

Biomass of a forest stand (compartment) is often proportional to the volume and basal area of the stand. Conversely, the biomass of a single tree is typically proportional to its diameter and height (Teobaldelli et al. 2009). Allocation of biomass to various functional components is related to species, growing conditions, and the water-, nutrient-, and energy-requirements of individual plants and stands (Gargaglione et al. 2010; Zhang and Borders 2004). The carbon content of vegetation is directly related to biomass as discussed in the following section.

Direct estimation of forest biomass is a labor-intensive and costly proposition. A stratified sampling for a field-based estimation of biomass per unit area is the only realistic approach (Loaiza Usuga et al. 2010). Strata are typically defined based on clearly identifiable components of the living vegetation (e.g. fungi, mosses, herbs, grasses, shrubs, seedlings, saplings, trees, epiphytes). The biomass in each sampling unit is determined by weighing after drying following standard protocols (Gabriëls and Berg 1993). Sample items (e.g. trees) too large for a practical and cost-effective handling, are sectioned to smaller piece-sizes, and a sample of the smaller pieces is then taken for biomass estimation. It is critically important that the dissection and sample plan ensures an unbiased estimator of the biomass of large items (Ahmed et al. 1983; Cancino and Saborowski 2005; Good et al. 2001; Gregoire et al. 1995).

4.1 Biomass Components

Biomass may be estimated in total for stands or portions of stands as noted, but information on biomass distribution by plant component is often needed. Biomass components may be divided as necessary for a given application, but often include categories such as stem wood, branch wood, foliage, bark, roots, etc., with more or fewer subdivisions as needed. A common constraint is that the sum of the component biomass estimates must equal the total biomass for the stands or portions of stands of interest.

In many applications, only above ground biomass estimates are used. There are obviously belowground components to biomass (such as coarse roots, fine roots, etc.), but studies quantifying these values are difficult to conduct, are available for only a small number of species and ecosystems, and typically have low precision in the data (Lukac and Godbold 2010; Macinnis-Ng et al. 2010; Niiyama et al. 2010; Pramod and Mohapatra 2010; Zhang et al. 2010a).

At the stand level, biomass may be estimated for the overstory, shrubs, herbs, lichens, moss, etc. In forested situations, the overstory biomass usually dominates. There are cases where tree cover is low and overstory or tree biomass is smaller compared to that of other ecosystem components. The decision on which biomass components are necessary to consider is dependent on the ecosystems to be surveyed and the intended use of the resulting information.

Cannell (1982) presents a compendium of worldwide biomass data from a cross-sections of ecosystems. The compendium includes ratios for various biomass components for many forest types. As per 2010 this compendium remains the single most authoritative compilation of benchmark biomass figures. A smaller set of biomass estimates can be found in a recent re-evaluation of forest biomass and carbon storage (Keith et al. 2009).

4.2 Biomass Equations

Biomass equations are used to predict biomass from readily available ancillary variables ($\mathbf{X}$). The equations may predict the biomass of a single tree or the tree biomass on a unit of forest land. Tree-level equations express biomass as a function of tree dimensions (diameter and height). Equations for unit-area predictions of biomass vary according to the ancillary variable(s) ($\mathbf{X}$). Equations driven by field-related $\mathbf{X}$-variables generally apply stand-level attributes such as basal area, mean tree size (height/diameter) or similar aggregates of tree-level attributes. Equations driven by $\mathbf{X}$-variables obtained via remotely sensed data (Gallaun et al. 2010; Wijaya et al. 2010; Zhao et al. 2009) vary according to the sensor-type and resolution behind X. In many cases, the biomass used as the dependent variable (Y) in these equations is rarely a direct estimate of biomass but rather an estimate obtained by another set of models that 'expands' available inventory estimates of tree and stand attributes to the desired biomass component(s) (Albaugh et al. 2009; Gallaun et al. 2010; Jalkanen et al. 2005; Lehtonen et al. 2004; Levy et al. 2004; Schroeder et al. 1997; Somogyi et al. 2008; Teobaldelli et al. 2009;

Wijaya et al. 2010; Zhao et al. 2009).

Equations applied to forest inventory data are usually developed for particular species or species groups, and may be developed with data collected from narrow geographic ranges. There are some examples described below where more widely-applicable equations have been developed through a synthesis of published studies. Cannell (1984) presented equations to estimate stand level woody biomass from total stand basal area and average tree height for a wide range of temperate and tropical stand types; most of the equations are for temperate coniferous forest types. These equations are simple to apply since they use variables commonly obtained during field data collection. Application is, as a rule, for stand level (plot) estimation rather than for tree level estimation.

At the individual tree level, Jenkins et al. (2003) give composite equations applicable for temperate species across North America. Teobaldelli et al. (Teobaldelli et al. 2009) provide a similar set of generalized equations for five species groups in Europe. These equations could be applied, with appropriate qualification, to other temperate forest types.

We shall give an example of a generalized equation used by Jenkins et al. (2003). Specifically, the Schumacher equation where total aboveground biomass is estimated for individual trees based on an allometric relationship with diameter at breast height: $B = e^{(b_0 + b_1 \ln(D))}$ where B is total aboveground biomass (kg) for trees 2.5 cm and larger in diameter at breast height (D). Coefficients are given for both deciduous and coniferous species groups throughout all regions of the United States. Broad species groupings are utilized (Pine, for instance, and Spruce, with a total of five coniferous and four deciduous species groups). Teobaldelli et al. provide equations for the expansion factor (BEF) needed to convert an estimate of growing stock (X) to an estimate of biomass (B). A widely used expansion equation has the form $BEF = b_0 + b_1 \times X^{-b_2}$ whereby X is a measure of the growing stock.

Brown (1997) presents equations for individual trees in tropical forests. For broadleaved species, two equations are presented for Tropical Dry forests, two for Tropical Moist forests, and one for Tropical Wet forests. In addition, one equation is presented for palms and another for Tropical Conifer forests. All of these equations express individual tree biomass as a function of diameter and height, though different specific equation forms are used in different applications.

The biomass of various biomass components is commonly estimated from models of the distribution (allocation) of the above-ground forest tree biomass to specific components (stem, bark, stump, branches, foliage, fruit/seed). Continuing the example from Jenkins et al. (2003), the proportion of the total biomass in the ith biomass component of a tree can be estimated from, say, the tree's diameter at breast height as in $r_i = e^{b_0 + b_1 \times D^{-1}}$.

Note, the 'conversion' from one or more readily available inventory attributes of growing stock to biomass, and then to biomass components via a set of generalized equations is only simple in principle. There are many factors and circumstances that can cast doubt on an estimate of biomass obtained with generalized equations (Albaugh et al. 2009; Jalkanen et al. 2005; Lehtonen et al. 2004; Retzlaff et al. 2001). It is therefore incumbent upon the analyst to exercise great diligence with respect to choice of model and intended application of a chosen model. The limitation and error-structure of many generalized models and allometric biomass-allocation formulae are often not well documented.

5. Carbon content estimation

Regional and national estimates of ecosystem carbon content, and change in ecosystem carbon content over time, are important components for an assessment of global

carbon cycling and its impact on atmospheric greenhouse gases and climate (Birdsey 2006; Cairns and Lasserre 2006; Waterworth and Richards 2008; Watson 2009). International agreements are requiring improvements in the ability to assess forest carbon stocks and their change (Dutschke and Pistorius 2008; Kägi and Schmidtke 2005; Zhang et al. 2009).

In this context, it has become increasingly important to quantify the carbon content that resides in forests and forested ecosystems and its contribution to the carbon cycle. Forest inventories make significant contributions to estimates of carbon in forested ecosystems because the carbon content is relatively easy to assess for the components of the vegetation captured by an inventory (Dupouey et al. 2010; Nabuurs 2010; Rodeghiero et al. 2010; Tupek et al. 2010). In many cases, vegetative carbon is used as a surrogate for total ecosystem carbon since it is relatively easy to derive from existing information or ongoing inventory efforts. Total ecosystem carbon, which includes inorganic ecosystem components such as soil, is more difficult to assess, especially if the precision of the estimates must be quantified (Baritz et al. 2010; Loaiza Usuga et al. 2010). Expensive estimates of carbon are typically derived from a few intensively studied plots, each considered as representive of a very large area with similar soils, vegetation, and climate.

Today many unit-area estimates of carbon content in forest vegetation are generated from a suite of explanatory variables (regressors) delivered from various satellite or air-borne sensors (Maselli et al. 2010; Sánchez-Azofeifa et al. 2009; Tagesson et al. 2009). Invariably these estimates build on a modeled relationship between field-based estimates of biomass (carbon) and one or more sensor-based ancillary variable.

5.1 Carbon Content of Vegetation

The carbon content of vegetation is surprisingly constant across a wide variety of tissue types and species (Baritz et al. 2010;

Mäkelä et al. 2008; Munishi and Shear 2004; Nogueira et al. 2008; Rana et al. 2010; Wauters et al. 2008). Schlesinger (1991) noted that the C-content of biomass is almost always found to be between 45 and 50% (by oven-dry mass).

In many applications, the carbon content (C) of vegetation may be estimated by simply taking a fraction of the estimate of oven-dry biomass (B), as in $\hat{C} = 0.475 \times \hat{B}$. The accuracy of an estimate of this nature is typically not great due to errors in $\hat{B}$, and one should also expect it to be biased.

For dead material, carbon content is a function of the state of decomposition (Boulanger and Sirois 2006; Garrett et al. 2010; Mukhortova and Trefilova 2009; Vávrová et al. 2009; Yang et al. 2010). For material that can still be identified, such as fresh litter or standing dead trees, the above equation may be used to estimate the C-content if the mass of the material can be estimated, see section 5.2 below. For severely decomposed material, it may be necessary to determine the C-content in subsamples taken from the material collected at a site, and then combine this with an estimate of the total (bio) mass of that class of material before the C-content for that vegetative component can be estimated. Even small errors due to sampling, measurement and handling of the material can have a serious impact on the accuracy of an estimate for a vegetation component that is orders of magnitude larger than the taken sample (Woodall et al. 2008).

Total carbon content of vegetation goes beyond trees. It includes all parts and components of the plant community, such as herbs, shrubs, mosses, etc. Field-based estimation of carbon typically begins with an estimation of biomass (see above) and then a conversion along the lines detailed above. To accomplish this task it becomes necessary to stratify the community and sample from each stratum. The necessary strata must be defined based on the composition, structure and extent of the community in question (Clark et al. 2008; Friedel 1977; Kenow et

al. 2007). In some cases, it may make sense to obtain C-content estimates for life forms such as epiphytes, while in other cases this is irrelevant. The approach follows the above for all classes of vegetation: first estimate the biomass in each stratum (component) using appropriate sampling methods and then apply the ratio to estimate the C-content.

5.2 Ecosystem Carbon Content

In addition to the carbon content of vegetation, it may be necessary to estimate total ecosystem carbon content (Jia and Akiyama 2005; Wang and Sun 2008; Wise et al. 2009). This includes biotic as well as abiotic carbon pools. Avian (Pautasso and Gaston 2005) and mammalian (Desbiez et al. 2010; Plumptre and Harris 1995) biomass and carbon content is often ignored since it is usually a small fraction of total ecosystem carbon. At times it may be required to estimate arthropod biomass and carbon content in order to obtain a good estimate of total ecosystem C (Fisk et al. 2010; Tovar-Sanchez 2009). Colonizing insects may comprise a significant portion of the total biomass of some systems (Vasconcellos 2010; Yamada et al. 2003), and abiotic materials incorporated into nests and colonies may also be a significant portion of total C.

A major abiotic carbon pool is the soil organic matter (Chang et al. 2010; Rovira et al. 2010; Tipping et al. 2010), which is particularly important at high latitudes or high altitudes. This may in some cases be greater than the vegetative carbon. Dead plant material at the soil surface and in the upper soil horizons may also have a significant C-content that should be considered in any estimate of ecosystem C-content (Fisk et al. 2010; Gasparini et al. 2010). McKenzie et al. (2000) provide a compendium of methods for field data collection for carbon estimation in soil, litter, and coarse woody debris. Quantitative data on forest litter may be sparse. However, several countries, with an elevated risk of forest fires may have extensive information because they conduct surveys of the elements on the forest floor that significantly increases the fire hazards during periods of drought (Fernandes 2009; Kessell et al. 1978).

Carbon content of litter should usually be determined from field samples designed for this specific purpose. The carbon content of litter depends on the stage of decomposition. Application of a ratio approach such as that described for vegetation can be used -see section 5.1 above- but will often underestimate the C-content of the litter layer due to the escape of carbonic gases during the process of decomposition (Fioretto et al. 2007; Hosseini and Azizi 2007; MacDicken 1997).

Estimates of soil C may be obtained from field sampling, and this is the most precise and appropriate method to estimate site-specific carbon content. Field data collection should be used whenever precise estimates of soil C are needed, but it is important to consider temporal variation throughout a growing season in large studies that may require an extended sampling period. If a soil classification map for the area of concern exists, there may be information on carbon content for different soil types in the area (Geissen et al. 2009; Zhang et al. 2010b). A given soil type may yet have different mean carbon content depending on the dominant vegetative cover and land use; soil under an agricultural field may have a very different C-content than a similar soil under a mature forest. Estimates of soil C-content may or may not be available for all conditions in an area of concern. Batjes (2009) provides access to an extensive database of global soil physical and chemical properties, including information that may be used to approximate soil C-content in the absence of site specific information. These estimates will be less precise than those obtained from field samples, but may be cost-efficient when high precision, site-specific estimates are not required. In many applications, it may be more cost effective, and ultimately result in higher precision in the final estimates, to use a greater number of less precise estimates of C-content for individual sampling units, than to measure C-content of a subset of sampling units with high precision (MacDicken 1997).

The trade-offs are a function of sampling design and cost, and must be evaluated in that context (see chapter on Sample Designs). Note, however, that if expedient less expensive C-estimates are biased, the opportunities for an attractive trade-off between a small sample with expensive observations and a larger sample with less expensive observations can be severely curtailed (Köhl et al. 2006, p 79).

6. Judging model quality

A model summarizes a conceptual relationship between one or more dependent variables ($\mathbf{Y}$) and one or more predictors ($\mathbf{X}$). The model can be stated as a single equation (for example, Fehrmann et al. 2008), a system of related models (for example, Gertner et al. 2002) or a hierarchical (multi-level) model (for example, Pedersen 1998). Models are mostly used for predicting new value(s) of an unobserved entity from available predictors. The volume, biomass and carbon equations given above provide examples of the most basic types of models. A model may be formulated through subject knowledge (Curtin 1970), adopted from other studies, or suggested by apparent trends in observed data. The following references provide access to a broad selection of forest models (Amaro et al. 2003; Dykstra and Monserud 2009; Schwab and Maness 2010; van Laar and Akça 2007).

In forest inventory and biological sciences, data exhibit a large amount of natural variation and models are limited to predicting the expected value of the dependent variable given the input data. The quality of any model is judged by its ability to provide unbiased (accurate) estimates of these expectations and the precision of model predictions. Models with deterministic (fixed, invariable) model parameters generate a single prediction (the expected value) given a set of predictor values. Stochastic models contain one or several parameters that are random (Biging and Gill 1997; Rennolls 1995). Hence, they can generate both conditional predictions for a random unit (say a tree, a plot, or a forest stand) and population averaged predictions (Schabenberger and Gregoire 1996).

When fitting a model to data, a comparison of values predicted by a model and the actual values of the dependent variable provide an initial assessment of model quality. It is generally desirable for models to be unbiased, meaning departures from model predictions (residuals) to average to zero for any input, and precise, meaning residuals are distributed tightly around the predicted values.

The quality of a model for prediction purposes is assessed by comparing a prediction of a new observation not used in model development to the actual value of the new observation. Common criteria for assessing model quality include, for examples, a t-test of the hypothesis of a zero mean model prediction error, the variance of model errors, the magnitude of the median absolute deviation (Venables and Ripley 1994), the sign test for testing equal medians of, say, the observed and predicted values (Conover 1980, p 122). The Wald-Wolfowitz runs test can be used to test the hypothesis that the elements of a sequence of model errors along a gradient of predictor values are independent (Conover 1980, p 136). Additional assessments are often geared towards: testing the assumption of a normal distribution of model residuals (Brown and Hettmansperger 1996), an analysis of errors in 'curve' models (Ducharme and Fontez 2004; Huang 1997), and homogeneity of error variances across a range of input (McKeown and Johnson 1996; O'Brien 1992; Shoemaker 2003). Reynolds (1984) provides a basic approach to model quality assessment. Vanclay and Skovsgaard (1997) provide a brief overview and an operational frame for judging model quality. It is common to see an assessment of model-quality done by excluding a portion of the data from the model-fitting phase or by a leave-one-out cross-validation scheme by which the model is estimated repeatedly by leaving out one observation and then comparing the actual and predicted value for the withheld datum (Efron 2004). We prefer the latter approach, since one can

rarely afford to withhold a large portion of the data without affecting the properties of the model to be assessed. To wit, with fewer observations for modelling the chosen model may be sup-optimal. When sample sizes are small, we recommend model-building based on robust techniques (Choi et al. 2010; Lange et al. 1989; Wang and Leng 2007).

When applying a general model, such as the volume and biomass equations given earlier, or a model developed for a given species in a different geographic area, it is important to attempt to assess model quality prior to application. This may require the collection of new field data, or it may be possible to utilize existing data for this purpose. Failure to assess model quality forces the user to make an untested, implicit assumption that the model used is appropriate for the species and geographic area to which it is applied, which may or may not be true. Users of models should always keep in mind that a model may generate unusual predictions. Extrapolations, i.e. application of the models with one or more of the predictor values falling outside the range of the data used during model-fitting should be avoided whenever possible because bias and precision may quickly become unattractive for otherwise well-founded models (Schreuder and Reich 1998)

With the advance of models that rely on input from remotely sensed data, it is increasingly important to consider (check) whether the predictors are actually the same (i.e. with identical information content, collected at identical spatial scales, and with identical measurement error-structures) as the data used during model-fitting. If not, then the impact of errors-in-variables must be considered as well (Carroll et al. 1995; Fuller 1987).

Users of existing models are rarely in a position to conduct a full-fledged model-check, or for that matter a validation. Key information about the statistical properties and data behind a model is often missing or difficult to retrieve.

Instead of relying entirely on model predictions it may be a better strategy to take a small probability sample of the variable(s) of interest and then combine them with predictions from a model. This model-assisted type of estimation (Särndal et al. 1992) has become popular. In the statistical literature the approach goes under the name of "Small Area Estimation" (Pfeffermann 2002; Tomppo 2006). Also, users concerned with the quality of a model may adopt a Bayesian paradigm whereby user-defined prior distributions on model-parameters capture model uncertainty and possibly bias and integrates this uncertainty in their predictions (Gertner et al. 2002; Green et al. 1999; Green and Strawderman 1996; Green and Valentine 1998).

Validation of complex models for large scale applications (e.g. ecosystem predictions of carbon content) is rarely possible. Validation of individual components of the model may not guarantee that all the interactions of model-components are adequately captured. It is always the user's responsibility to check model assumptions and model predictions.

7. Model error contribution to total error

Methods of estimating the precision of inventory estimates are dependent on the sampling design used to collect the data. These methods, however, generally assume that the individual observations are measured without error. For model-based estimates like volume, biomass, and carbon, however, there are model errors to consider. Consequently, there are three main sources of error: measurement error, model error, and sampling error. The sample-based precision estimates, therefore, should be considered to be underestimating the variance, or conversely, as implying confidence intervals that are too narrow, for derived variables such as volume, biomass, or carbon content. Similarly, methods of estimating the sample requirements to achieve a desired level of precision will indicate fewer samples than really needed

unless consideration of model error is taken into account in addition to sampling error. For more information see Sampling Designs chapter.

Inventory models are never perfect. The discrepancy between the actual (unknown) value (Y_A) and the predicted value from a model (Y_P) is called the model error (ε_p). In equation form, this becomes: $Y_A = Y_P + \varepsilon_P$. This simple (linear) equation also implies that the variance of a series of predicted values is less than or equal to the variance of the actual values. Equality holds only for perfect models with no error variance. For example, if we predict the volume of trees in a plot from a suitable volume equation then the calculated variance of the volume predictions will be less than the actual variance of the volume of the trees in the plot. Consequently, the standard error of a predicted mean volume for a plot will be biased downwards. The variance of prediction errors must be included to obtain an unbiased estimate of the total error.

In many applications it should also be considered that the parameters in models used in an estimation procedure are themselves estimates with associated errors. One may choose to include also this extra source of uncertainty in the estimation of the total errors. For sample surveys with large sample sizes this type of model error would usually constitute a large portion of the total error (variance)

The variance of prediction errors may be substantially larger than the residual variance obtained during model fitting, especially when the mean and covariance of the input variables vary from those of the data used for model fitting. Application of the model outside the recommended application domain raises the specter of serious additional underreporting of error.

8. Monitoring over time

Monitoring over time allows estimation of change and trends in forest attributes (Köhl et al. 2006, p 143). The changes and trends can be estimated from a set of permanent sample plots -see section 8.1-or temporary plots -see section 8.2- or a combination of both (see chapters on sampling design and observations and measurements) . Temporary plots can be used to obtain estimates of the current state of the forest, while permanent plots or a mixture of permanent and temporary plots are pre requisites for obtaining estimation of change over time (Picard et al. 2010). Estimation of change is a complex challenge. There are three major types of temporal changes in forestry: 1) change conforming to the expected progression of living and dead material in a forest during the period of interest (e.g. volume increment of living trees), 2) unexpected biotic or abiotic disturbances (e.g. mortality due to insect, snow, wind, fire, ..), 3) forest management activities (thinning, harvesting, planting, seeding,..). Each category operates at different temporal and spatial scales. Given the multivariate nature of forest resources, and the wide range of rates and modes of change, it follows that the efficiency of most sampling designs for estimation of change can be highly efficient for one attribute of change (e.g. net volume increment), yet inefficient for capturing other types of change (e.g. rates of deforestation, volume destroyed by fire, insect mortality). Few practical designs are efficient for capturing change in sensitive but small subpopulations (e.g. number of specimen of a rare or possibly endangered species) (Christman 2000; Magnussen et al. 2005). To adequately capture changes related to abiotic and biotic disturbances and to forest management practices, it is common to conduct a census of correlated ancillary variables via remote sensing (see chapter on remote sensing) at the start and the end of the period covered by the change estimate(s) (Coppin et al. 2004; Stehman 2009; Tomppo et al. 2008).

Change estimates are frequently evaluated against expectations or a set of targets, and estimates of the precision of the change estimate are important in this situation. When the change is estimated from a combination

of field-observations and remotely sensed ancillary variables, estimators of change and their precision can become very complex and the actual estimation may require the assistance of a statistician (Stehman 2009). Unless it can be argued on statistical grounds, that an estimate of change is unbiased one should accept that bias could be a potential issue.

The simplest change equation is for a trait Y observed at time t and then again at some future time t + Δt. We have $Y_{t+\Delta t} = Y_t + \Delta Y_{\Delta t}$ where Y_t is the initial measurement at time t, $Y_t + \Delta t$ is the future measurement at time t + Δt, and $\Delta Y \Delta_t$ is the change in Y from time t to time t + Δt. The variance of the estimate of $\Delta Y \Delta_t$, depends on the type of plots (or mixture of plots) used for the data collection. Any correlation between measurements at two points in time must be accounted for when estimating the variance of a change.

Continuing our simple example, the estimate of change is $\Delta Y_{\Delta t} = Y_{t+\Delta t} - Y_t$. In this case, the variance of the change estimate is equal to:

$$\text{var}(\Delta Y_{\Delta t}) = \text{var}(Y_t) + \text{var}(Y_{t+\Delta t}) - 2\rho(Y_t, Y_{t+\Delta t})$$
$$\sqrt{\text{var}(Y_t)\,\text{var}(Y_{t+\Delta t})}$$

where var denotes a variance, and cov a covariance, and ρ is a correlation coefficient (between the original and future measurements). A strong positive correlation reduces the variance of a change measurement.

When a sample selection has been with an unequal probability sampling design, the analyst must take into account that these probabilities may have changed over time (Roesch et al. 1993).

As discussed in section 7, if the above change estimation involves the use of quantities that are predictions of expected values from one or more models, then it will again be necessary to account for the 'hidden' errors in Y_t and $Y_{\Delta t}$. This will commonly be the case in forestry.

Compounding the issue is the fact that the errors in Y_t and $Y_{\Delta t}$ often tend to be correlated. Additional complications arise when the method (protocol/process) for obtaining Y_t differs from that of $Y_{t+\Delta t}$. The assistance of a professional statistician may be called for.

8.1 Estimating Change Using Remeasured Permanent Plots

Permanent plots refer to forest sampling locations that are monumented or otherwise uniquely identified and remeasured at different points in time (Köhl et al. 2006, p 144).

From a statistical and data-analysis perspective the major advantage to permanent plots is an improved precision of estimates of change due to a typically strong correlation of sampling errors (see above expression for the variance of a change). A higher data quality may also materialize from additional attention and quality control. Finally, permanent plots permit inference about cause and effect (Augustin et al. 2009). For undisturbed and carefully measured permanent plots the correlation between subsequent measurements tends to be both positive and relatively strong, which, as outlined above, lowers the variance of an estimate of change. Yet the correlation between successive measurements can deteriorates quickly with the length of a measurement interval and disturbances (e.g. fire, wind, snow, drought, forest management interventions). A high data quality facilitates error checking in current data and scanning for anomalies in past data.

8.2 Estimating Change Using Temporary Plots

Temporary plots offer a maximum of flexibility: Independent surveys can be established at different times, with plots only measured at one time. Since the surveys at different times are taken on different plots, the above advantage of the above discussed positive correlation of

plot-specific observations at time t and $t + \Delta t$ no longer exists (there is no natural pairing of the two sets of observations).

Individual trees on temporary plots are usually measured more quickly and with less precision than those on permanent plots, reducing the precision in the estimates and the resulting estimate of change. Less precise observations will also make it more difficult to spot outliers and anomalies in the data (Cerioli 2010). A lower data precision can, to a degree, be offset by the use of a greater number of temporary plots but the final tradeoff depends, in a complicated way, on where and how errors enters the observations and on the assumed model behind the observations (Carroll et al. 1995).

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