Design considerations for tropical forest inventories

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Abstract - Forests contribute substantially to maintaining the global greenhouse gas balance, primarily because among the five economic sectors identified by the United Nations Framework Convention on Climate Change, only the forestry sector has the potential to remove greenhouse gas emissions from the atmosphere. In this context, development of national forest carbon accounting systems, particularly in countries with tropical forests, has emerged as an international priority. Because these systems are often developed as components of or in parallel with national forest inventories, a brief review of statistical issues related to the development of forest ground sampling designs is provided. This overview addresses not only the primary issues of plot configurations and sampling designs, but also to a lesser extent the emerging roles of remote sensing and uncertainty assessment. Basic inventory principles are illustrated for two case studies, the national forest inventory of Brazil with special emphasis on the state of Santa Catarina, and an inventory for Tanzania.

Considerações sobre o delineamento de inventários de florestas tropicais

Resumo - As florestas podem contribuir substancialmente para a manutenção do equilíbrio dos gases do efeito estufa, principalmente porque, entre os cinco setores econômicos identificados pela Convenção Quadro das Nações Unidas sobre Mudança do Clima, somente o setor florestal tem potencial para eliminar as emissões de gases de efeito estufa da atmosfera. Neste contexto, o desenvolvimento de sistemas nacionais de contabilização de carbono florestal, particularmente em países com florestas tropicais, surgiu como uma prioridade internacional. Como esses sistemas são, muitas vezes, desenvolvidos como componentes ou em paralelo com os inventários florestais nacionais, é apresentada uma breve revisão de questões estatísticas relacionadas com o desenvolvimento do delineamento da amostragem de áreas florestais. Esta visão geral aborda não apenas as questões primárias de formatos de parcelas e desenhos amostrais, mas também, em menor escala, os papéis emergentes do sensoriamento remoto e da avaliação de incertezas.

Introduction

The biological richness and genetic diversity of forest ecosystems are widely acknowledged to be greater than any other terrestrial ecosystem. More than half the world's life zone classes are dominated by trees (Holdridge, 1947, 1967), and seven of the earth's major habitat types are forest types (Dinerstein et al., 1995). Depending on definitions, 20-30% of the earth's surface is covered by forest and wooded land (FAO 2010). These lands provide habitat for 70% of known animal and plant species (Matthews et al., 2000) and contribute almost half of the terrestrial net primary biomass production (Groombridge & Jenkins, 2002). Thus, forests provide vital economic, social, and environmental benefits by supplying wood and non-wood forest products and services, supporting human livelihoods, supplying clean water, and providing habitat for half the species on the planet.

The forestry sector also contributes substantially to the global greenhouse gas (GHG) balance. Among the five economic sectors identified by the United Nations Framework Convention on Climate Change (UNFCCC) as sources of anthropogenic GHG emissions, the Land Use, Land Use Change and Forestry (LULUCF) sector is the only terrestrial sector with the potential for removal of GHG emissions from the atmosphere. Conversely, the annual conversion of approximately 13 million ha of forest land to other land uses contributes to the net annual forest land decrease of 5.2 million hectares (ha) (FAO, 2010). These forest and related land use changes have been estimated to account for 17% of human-induced carbon emissions (Intergovernmental Panel on Climate Change, 2007). Parties to the UNFCCC treaty recognized the contribution of GHG emissions from deforestation in developing countries to climate change and the need to take action to reduce such emissions. After a two-year process, the Conference of Parties adopted a decision on "Reducing Emissions from Deforestation and Degradation in developing countries: approaches to stimulate action" (REDD), Decision 2/CP.13 (United Nations Framework Convention on Climate Change, 2008). The decision provides a mandate for actions by parties relating to reducing emissions from deforestation and forest degradation in developing countries. In particular, REDD is an effort to offer financial incentives for developing countries to reduce emissions from forest lands and to invest in low-carbon paths to sustainable development. REDD+ goes beyond deforestation and forest degradation, and includes the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks. As part of REDD programs, the importance of national carbon accounting systems has been highlighted (FAO, 2008).

As a form of carbon accounting, GHG emissions accounting assesses emissions from the forestry sector. Approaches to emissions accounting are of two types: the stock difference and the gain-loss approach. The stock-difference approach relies heavily on ground sampling and estimates annual emissions as the mean annual difference in carbon stocks between two points in time. The stock-difference approach is fairly easy to implement for countries with well-established national forest inventories (NFI), but may be financially and logistically difficult for developing tropical countries, particularly those with remote and inaccessible forests. For the latter countries, the gain-loss approach may be a more feasible alternative; in fact, the gain-loss approach is often used approach for estimating GHG emissions for national measurement, reporting, and verification (MRV) systems under the auspices of the IPCC. With the gain-loss method, additions to and removals from a carbon pool are estimated as the product of two factors, the area of land use change, called activity data, and the carbon stock changes for particular land use conversions, called emission factors. MRV systems may include a remote sensing-based component for estimating activity data and a ground-based inventory to obtain data for estimating emission factors, calibrating volume or biomass models, and training and/or assessing the accuracy of remote sensing classifiers and predictors.

The IPCC Good Practice Guidance (Penman et al., 2003) is a starting point for the development and implementation of MRVs under the auspices of REDD. Additional guidance is provided by the GOFC-GOLD Sourcebook (Global Observation of Forest Cover and Land Dynamics, , 2012). The IPCC guidance focuses on methods for obtaining estimates of activity data and emissions factors. The term *approaches* is used to categorize methods for estimating activity data: *Approach 1* estimates total area for individual land-use categories but does not provide detailed information on area changes between categories and is not spatially explicit other than at regional or national levels; *Approach 2* tracks land use changes between categories and produces a non-spatially explicit land use change

matrix; and *Approach 3* tracks land use changes on a spatial basis and generally requires sampling with broad geographic coverage or remote sensing-based mapping. The IPCC guidance also uses the term *tiers* to describe methods for estimating GHG emissions and removals by source: *Tier 1* uses default emissions factors and spatially coarse estimates of land use change such as national or global deforestation rates; *Tier 2* uses emissions factors and fine resolution land use change estimates for specific regions and specialized land-use categories; stock change methods can also be used; and *Tier 3* uses fine resolution land use change estimates and estimates of emissions factors obtained using models and inventory measurement systems tailored to address national circumstances. An underlying assumption is that the highest tier possible would be used. Thus, because the stock change method can be readily used with Tier 2, it would not usually be used with Tier 1. Similarly, although the gain-loss method can be crudely implemented with Tier 1, transition to Tier 2 or 3 is usually the goal.

Although MRVs and NFIs share some objectives and features, they are not equivalent. For example, MRVs are typically less comprehensive than NFIs in the sense that they may be restricted to biomass- or carbon-related variables and lands that are subject to human-induced GHG emissions. In addition, by definition, a monitoring program emphasizes change and trends so that an MRV may emphasize estimation of change to a greater degree than do traditional NFIs. Nevertheless, despite their differences, the similarities between MRVs and NFIs are such that tropical developing countries often design their NFIs so that they can also serve as MRVs, or they design their MRVs so that they can easily be extended to complete NFIs. As a means of supporting efforts to initiate both MRVs and NFIs in tropical countries, a brief review of issues related to the development of ground sampling designs for both purposes simultaneously follows. In terms of context, multiple tiers and approaches are relevant. First, the stock change method, as included in Tier 2, may be readily implemented using an NFI. Second, estimates of emissions factors as required for both Tiers 2 and 3 may be obtained using either an NFI or an MRV. Finally, the ground sample data obtained for both NFIs and MRVs may be used for both training remote sensing-based classifiers and assessing the accuracy of land cover and land cover change classifications

Plot configuration

Plot configuration choices include determination of whether single contiguous plots, subdivision of plots into subplots, or clusters of plots should be used. All three configurations require size and shape considerations. In addition, for all three configurations, a single sampling point serves as the basis for the locations of subplots within plots or plots within clusters. When plot configurations are characterized as subplots within plots, the subplots are usually relatively small and in close relative geographic proximity to the selected sampling point. In addition, the data for the subplots are usually aggregated and analyzed at the plot level rather than individually by subplot. The Forest Inventory and Analysis program of the U. S. Forest Service, which conducts the NFI of the United States of America (USA), uses a plot configured as a central subplot and three peripheral subplots at azimuths of 0º, 120º, and 240º (McRoberts et al., 2005)

When plot configurations are characterized as clusters of plots, the individual plots are often at greater distances from the selected sampling point. In addition, data for clusters of plots are typically analyzed on a plot-by-plot basis. A large proportion of the cost of measuring a plot in boreal and temperate forests is the cost of travel to and from the plot location. Configuring plots in clusters contributes to minimizing these travel costs by establishing multiple plots in relatively close spatial proximity. This rationale may be even more important for tropical forests which are often remote and difficult to access (Tomppo et al., 2010a, 2011). NFIs use a variety of configurations for plots within clusters, although most select locations for plots within clusters systematically rather than randomly. The Finnish NFI configures plots as square clusters or clusters along L-shaped tracts (Tomppo et al., 2010b). Several factors must be considered when planning a cluster-based sampling design. If distances between pairs of plots are less than the range of spatial correlation, then observations will tend to be similar and the sampling will tend to be less efficient. The number of plots per cluster represents a compromise between the size of individual plots, the total area of all plots necessary to acquire adequate tree data, the number of clusters necessary to assure spatial balance, and the costs associated with travel to and from cluster locations.

Plot configuration choices also include selection of a method for determining which individual trees should

be included in the sample. Variable area plots may use angle count (Bitterlich) sampling, which selects trees in proportion to their basal area and is particularly efficient for precisely estimating forest attributes related to tree size. Fixed area plots, which select all trees satisfying criteria such as minimum diameter and maximum distance, are not necessarily optimal for any particular forest attribute. However, they tend to be more compatible with auxiliary data and often represent a reasonable compromise among competing precision factors when sampling is intended to produce estimates of parameters for a wide variety of forest attributes.

Selection of a configuration for a fixed area ground plot is based on multiple general principles, many of which are the same for boreal, temporal, and tropical inventories, although some are also different. Precise estimation of change is known to be more difficult than precise estimation of current conditions, particularly when the change is small or only for a small area. The precision of change estimates can be increased by remeasuring the same plots on successive occasions. Thus, the emphasis on estimation of change in MRVs argues in favor of a relatively large proportion of permanent plots. Although establishment and measurement of a temporary plot is less expensive than establishment and measurement of a permanent plot, establishment and measurement of two different temporary plots on two occasions is not necessarily less expensive than establishment and measurement of the same permanent plot on two occasions.

If permanent plots are used, their locations must be accurately documented so they can be remeasured at later dates. One approach is to mark plot control points, mask the marks from normal view, and then carefully document the marks relative to conspicuous locations, perhaps several kilometers distant. The control points are masked from normal view so that plot locations are not discovered and treated differently than the surrounding forest area. A sample plot will not be representative if it receives special treatment such as protection from harvesting or other disturbances.

Circular plots are generally preferred for boreal and temperate inventories because they require only single control points, the plot centers, whereas strip plots require two control points at the ends of a central transect, and large rectangular plots require four control points, one at each corner. In addition, for a given plot area, a circular plot has a smaller perimeter, meaning

that fewer decisions will be necessary as to whether particular trees are or are not on a plot. Also, coordinates for individual trees, which are necessary to relocate them at later dates, require only azimuth and distance from centers of circular plots. However, if visibility on a plot is difficult, as may be the case in dense tropical forests, strip or narrow rectangular plots may be preferable because all trees are only relatively short distances from the long axis of the plot. When strip or long rectangular plots are used, caution must be exercised to check the inclusion of trees. Further, rectangular plots have often been traditional in tropical countries (Kleinn, 2004 Kleinn & Bhandari, 2004) and have been recommended by the Food and Agriculture Organization of the United Nations (Saket et al., 2002).

Plot size is subject to multiple important considerations, all of which are generally related to logistical, cost, and precision considerations (Tomppo et al., 2010a, 2011). First, a plot cluster or a plot with its subplots should be small enough that a field crew can complete all measurements in a single day. As previously noted, a large proportion of the cost of measuring a plot in boreal and temporal forests is the cost of travel to and from the plot location, and this proportion is likely to be even greater for tropical forests. Thus, greater efficiency is achieved if field crews are not required to travel great distances to the same plot location on multiple occasions. Second, plot features such as radius for circular plots and lengths for strip and rectangular plots must be measured on a horizontal plane, not along irregular terrain. Apart from use of electronic distance measuring instruments, determination of horizontal plot boundaries is more difficult for larger plots, particularly in hilly and mountainous terrain. Thus, smaller plots may be preferable. Third, establishment of permanent rather than temporary plots to facilitate estimation of change usually requires either marking or determining coordinates for individual trees. The latter approach is more difficult for large plots in dense tropical forests because more trees will be located between the tree of interest and control points. An argument in favor of larger plots for tropical inventories is that tropical forests are typically more diverse than boreal and temperate forests, meaning that the total area of an inventoried plot or plot cluster should be greater to capture the greater diversity. However, this greater size could be achieved by increasing the number of small plots in the same plot cluster. This approach is cost

efficient when spatial correlations among observations of the variables of interest are large but decrease with increasing distance.

Greater sampling efficiency is also achieved by using smaller nested subplots for measurement of smaller diameter trees. The particular sizes of the subplots and the diameter thresholds corresponding to the subplots should be based on the expected number of trees to be found on the subplots, the expected similarities of trees, and the travel time between plots in the same cluster or subplots of the same plot. Kleinn & Bhandari (2004) recommend plot sizes that, on average, include 15-20 trees, although this average depends on small scale forest variability with respect to attributes such as species composition and size.

Sampling design

Purposive sampling

Sampling design issues pertain primarily to the distribution of sampling points across the landscape. Two general sampling approaches are common: subjective or purposive sampling and probability sampling. Purposive sampling may have varied bases including professional judgment to select sampling points believed to be representative of the entire population, quantitative analyses to optimize criteria such as model parameter estimates, or convenience factors that minimize travel costs. With purposive sampling, the probability of selection for any one potential sampling location is unknown with the result that statistical theory cannot be rigorously applied. Although purposive sampling yields data that accurately describe conditions on the sampled sites, broader populations may not be accurately characterized.

Probability sampling

Probability sampling replaces subjective judgments with objective rules based on known probabilities of selection for each sampling point. The important principle is that probability sampling is an objective method with precise rules and a statistical foundation for estimating population attributes based on a sample. Thus, probability rather than purposive sampling is highly recommended for MRVs and NFIs, at least partially because discrediting the accuracy of population estimates from a purposive sample is much easier than defending the estimates.

Many of the challenges associated with selecting a sampling design arise from two factors: first, sampling units are distributed in a space and, as such, observations of them may be spatially correlated; second, different sampling designs have different costs. Spatial dependence among observations of variables of interest strongly influences selection of sampling designs. Ecological, climatic, and soil factors and forestry management practices cause observations from plots that are near to each other to be more similar than observations from plots that are separated by greater distances. Although spatial dependence does not necessarily invalidate variance estimators, it does contribute to larger variance estimates and, therefore, less efficient sampling.

In a strict sense, construction of a completely optimal sampling design is an impossible task because the numerous NFI and MRV variables vary quite differently in space. Therefore, because optimal sampling designs would be different for different variables, optimization may require focusing on a single feature such as the standard error of the estimate of a single important variable such as wood volume or on a weighted function of multiple features such as the standard errors for a small number of variables. One partial solution is to minimize the detrimental effects of spatial correlation on efficiency by selecting sampling points as far apart as possible, subject to travel and cost constraints. Finally, the important challenge is to develop a sampling design that is as simultaneously optimal as possible for both an MRV and an NFI.

A common starting point in selecting a sampling design is knowledge of the acceptable upper bounds for the standard errors of the estimates and an upper bound for cost. Optimizing the sampling design requires prior information on sampling variability within the population of interest and involves selecting a procedure for spatially distributing the sampling points in such a way that standard errors are minimized while not exceeding the total allowable costs. A simple random sampling design randomly selects sampling points within the population. Although by chance, the distribution of sampling points may include spatial groups or spatial voids, the sample remains a valid probability sample. The geographic coordinates for each sampling point in a simple random sample may be selected with a random number generator with the allowable coordinates restricted to the sampled population. Otherwise, no consideration is given to safety, difficulty of measuring

plots, or travel to and from plot locations. From an inferential perspective, this is the least risky probability sampling design, but it is also usually the least efficient with respect to cost, precision of estimates because of spatial correlation, and spatial balance as characterized by avoidance of large gaps in spatial coverage.

Because NFIs are national in scope, sampling designs must provide spatial coverage of the entire country, albeit not with the same intensity everywhere. Sampling designs for MRVs, however, are not necessarily required to provide coverage for lands that are not subject to human-induced carbon emissions. In addition, because of logistical and budgetary constraints, ground sampling for new NFIs and MRVs may be implemented sequentially with initial priority given to regions with greater emissions. Although substantial regional differences in plot configurations and sampling designs may be accommodated, estimation is facilitated if differences are minimized.

Systematic sampling

A common approach to assuring spatial balance and decreasing the adverse effects of spatial correlation on sampling variability is to use systematic sampling designs based on fixed arrays or rectangular grids. The advantage of systematic sampling is that it maximizes the average distance between sampling points and therefore minimizes spatial correlation among observations and increases statistical efficiency, while yet assuring spatial balance. For example, sampling points could be selected at the intersections of a 10-km x 10-km grid. The starting point and orientation for this grid should be randomly selected, but no other randomization is necessary. Variations on this sampling design are common in forestry. The greatest risk is that the orientation of the grid may, by chance, coincide with or be parallel to natural or man-made features such as roads, rivers, or other topographical features. Systematic aligned sampling designs feature sampling points at regular intervals such as at intersections of grid lines or at centers of array or grid cells, whereas systematic unaligned sampling designs combine features of both simple random and systematic sampling designs by randomly selecting a location within each grid or array cell (Cochran, 1977). Statistical variance estimators used to estimate uncertainty typically assume simple random sampling. When they are used with systematic sampling, variance estimates are usually conservative in the sense that they are slightly too large (Särndal et al., 1992).

For very large geographic areas, consideration should be given to the effects of the orientation of gridlines along lines of longitude. In higher latitudes the converging nature of north-south gridlines causes sampling points to be closer together than in lower latitudes. In such cases, plots located at greater distances from the equator will represent less population area than plots located closer to the equator. Multiple solutions are possible including using different coordinate systems, weighting plot observations, and basing sampling designs on hexagonal arrays rather than rectangular grids (White et al., 1992; McRoberts et al., 2005).

Stratification

Stratified approaches to sampling are used for multiple reasons but primarily to increase precision or to vary sampling intensities to accommodate criteria related to political and ecological priorities, spatial coverage, logistical effort, and cost. For example, for an MRV that emphasizes geographic regions subject to human-induced carbon emissions, smaller sampling intensities and less precision may be acceptable for remote, inaccessible regions that are less likely to be developed or harvested. In addition, the cost associated with greater sampling intensities in remote regions may be prohibitive. Nevertheless, sampling, albeit perhaps with varying intensities, must be conducted in all regions of the population to achieve spatial balance.

Multiple principles guide stratified approaches to sampling. First, strata with stable boundaries are generally preferable. Otherwise, changes to boundaries of strata with different sampling intensities lead to different probabilities of selection and complicate estimation. In particular, stratified sampling designs for which the strata are based on land cover attributes that change present difficulties for two reasons. Second, because land cover attributes, and hence the strata, change, plots may need to be re-allocated to strata for each remeasurement. This means that some plots selected for a previous measurement will be abandoned, and some new plots must be established for the succeeding measurement. Such procedures make precise estimation of change more difficult. If plots are not abandoned or added, then the sampling intensities within the new strata are not uniform which leads to difficulty in re-calculating new probabilities of selection. Third, stratified estimation requires that a plot be assigned to one and only one stratum. If the stratum to which a plot is assigned changes between measurements, then difficulties arise as to the stratum to which a plot change observation

should be assigned. Thus, strata defined by topography, climatic zones, biomes, or political boundaries that are relatively stable may be preferable to strata defined by changing forest attributes such as density or forest type. However, assignment of plots to strata has no effect on the unbiasedness of the stratified estimator; the only effect of different assignments of plot to strata is the degree to which stratified estimation contributes to reducing estimates of population variances.

Stratified sampling is most often implemented using one of three plot allocation schemes. With equal allocation, the same number of plots is allocated to all strata, regardless of strata sizes. This scheme is preferred if the objective is estimates for individual strata. With optimal allocation, sampling intensities selected for strata are based on optimization criteria such as measurement costs and/or within-stratum variation of observations of variables of interest such as volume or biomass, or their likely changes. Greater sampling intensities are selected for strata with greater variation and/or lesser measurement costs. With proportional allocation, strata sample sizes are proportional to strata sizes. Cochran (1977) provides a comprehensive discussion regarding alternative strategies.

For tropical countries with remote and nearly inaccessible regions, some form of optimal allocation will usually be necessary to mitigate the excessive costs associated with sampling these regions. Proportional and optimal allocation can be easily implemented using sampling designs based on networks of perpendicular grid lines. With proportional allocation, sampling points are established at grid intersections without regard to the stratum associated with the points. One approach is to overlay a dense systematic grid over the entire country and vary the portion of the grid that is actually used with respect to desired sampling intensity. For example, in regions, topographies, or strata requiring greater sampling intensities, sampling points may be established at all grid intersections or at randomly selected locations in the cells bounded by all grid lines. Where lesser sampling intensities are required, sampling points may be established only at the intersections of every second grid line or at randomly selected locations in cells bounded by every second grid line.

Even if stratified sampling is not used, stratified estimation may still contribute to substantial increases in precision. For example, McRoberts et al. (2002) showed how an existing, relatively stable land cover classification can be used as the basis for stratification. Stratified variance estimates were smaller by factors ranging from 1.5 to 4.0, depending on the area, than simple random sampling estimates. In addition, post-stratification based on classifications obtained from both optical and lidar data have been demonstrated to be effective (McRoberts et al., 2006, 2012). Beneficial effects may be realized in two ways, either by increasing precision or by permitting reduced sample sizes with no loss in precision.

A popular approach to stratified estimation, as was used for the Tanzania case study discussed in detail below, is a two-phase approach characterized as double sampling for stratification. With this approach, a large number of first-phase plots is randomly distributed throughout the population, often using a systematic sampling design. Evaluation of these plots focuses on strata assessment, is often conducted using aerial photography or high resolution imagery, and produces estimates of stratum weights. In the second phase, a proportion of the first-phase plots is randomly selected for field measurement using any valid probability sampling design. Information from the first phase may be used to optimize the second phase, within-strata sample sizes. An important aspect of double sampling for stratification is that the stratum weights are estimated, whereas when a climatic, topographical, or biophysical map is used as the basis for defining the strata, the stratum weights are often considered to be known.

Variance estimation

Inferences in the form of confidence intervals or tests of hypotheses require estimates of uncertainty which are typically expressed in terms of variances which are defined as $E(\hat{\mu} - \mu)^2$, where E(.) denotes statistical expectation, μ is a parameter of interest, and $\hat{\mu}$ is an estimator of μ. Variance is also characterized as mean square error, and often standard error, which is the square root of variance, is reported. Although a complete discussion of issues related to variance is not possible, two items warrant consideration. First, and most importantly, for design-based inference which relies on probability sampling designs for validity, variance estimators are completely dependent on sampling designs. In particular, variance estimators for simple random, clustered, and stratified sampling designs are considerably different. Failure to select the variance estimator appropriate for the sampling design produces erroneous variance estimates and invalidates inferences. Multiple texts address derivation

and selection of variance estimators including Cochran (1977), Särndal et al. (1992), Gregoire & Valentine (2007), Mandallaz (2008), and Tomppo et al. (2011). Second, variances of estimates of change are invariably greater than variances of estimates of current conditions.

Sample size

Determination of sample size is one of the most important steps in constructing a sampling design. If the sample is too small, then uncertainty will be great; if the sample is too large, then the cost will be unnecessarily large. As the number of sampling points increases, the variance of the estimate of a mean decreases, the precision of the estimate increases, and more confidence can be placed in the estimate. With probability samples, the probability that an estimate is within a specified range of the true value may be approximated. These are the roles of confidence intervals which are estimated ranges of estimates of the parameter of interest that are likely to include the true, but unknown, parameter value.

Numerous references for calculation of sample size are available (e.g., Cochran, 1977), and all require preliminary estimates of means and standard deviations of plot observations which may be obtained using existing data, a pilot study, or a small sample of plots. For purposes of an example, assume simple random sampling, that volume (m^3 ha^{-1}) was measured on 50 plots, that the mean was $\overline{x} = 100$ m^3 ha^{-1}, and that the standard deviation was $s = 30$ m^3 ha^{-1}. If the precision requirement is to estimate the mean within a specified percentage tolerance ($\pm tol$) with confidence 1-α, then the approximate required sample size, n, is,

$$n = \left(\frac{Z_{1-\frac{\alpha}{2}} \cdot s}{tol \cdot \overline{x}} \right)^2$$

where Z denotes the percentage points of the Normal or Gaussian distribution. For this example, $Z_{1-\frac{\alpha}{2}}$ is used rather than $Z_{1-\alpha}$ because two-sided confidence intervals are of interest. Thus, for tolerance, tol=$\pm$5 percent, and confidence of 1-α=0.95, $n = \left(\frac{1.96 \cdot 30}{0.05 \cdot 100} \right)^2 \approx 139$, whereas for tol=$\pm$1 percent and confidence of 1-α=0.99, $n = \left(\frac{2.58 \cdot 30}{0.01 \cdot 100} \right)^2 \approx 5991$. For stratified sampling, these estimates pertain to within strata sample sizes. These simple calculations assume independence of the observations; spatial correlation among observations increases sample sizes.

Remote sensing considerations

The use of remotely sensed data to support and enhance forest inventories has become common practice in Europe and North America (McRoberts et al., 2002, 2010; McRoberts & Tomppo, 2007; Tomppo et al., 2008a, 2008b). For tropical forest inventories, the remote and inaccessible nature of forest land means that inventories may have to rely more heavily and in different ways on remotely sensed data. The intent here is not to provide a comprehensive discussion on the topic but rather simply to highlight a few remote sensing issues that merit consideration when selecting a plot configuration and a sampling design. For example, if satellite imagery is used, plots should be large enough to constitute adequate samples of the image pixels that contain plot centers. Further, if plots are configured in clusters, distances between plots in the same cluster should be at least as great as pixel widths. However, the detrimental effects of persistent cloud cover may inhibit acquisition of sufficient cloud-free optical satellite data.

Lidar (<u>li</u>ght <u>d</u>etection <u>an</u>d <u>r</u>anging) data, which are mostly acquired from airborne platforms and use laser techniques, are emerging as an attractive and relevant alternative (Næsset, 2002; Næsset & Gobakken, 2008; McRoberts et al., 2010, 2013; Vibrans et al., 2013). If plots are located at the intersections of perpendicular grids, acquisition of lidar data from airborne platforms is facilitated because straight flight lines can be used. To facilitate lidar acquisition even more, grid lines separated by greater distances in one direction than the other may be used whereby plots are placed at grid intersections along the grid lines with the greater intersection intensity. A plot boundary effect that merits consideration for lidar analyses is that biomass within the vertical extension of a plot boundary may be part of a tree whose stem is outside the plot. Circular plots, which minimize the ratio of circumference to area, may help to alleviate this problem.

Because field measurements are expensive to acquire, particularly in tropical forests, the requirements for ground data for training remote sensing-based classification and prediction techniques and for

assessing the accuracy of remote sensing-based products and estimates should be considered in advance. For example, ground data to be used with satellite imagery to construct a land cover map should include samples of all land cover classes of interest. This requirement may necessitate a form of stratified sampling. Similarly, if a map of deforestation is to be constructed, then sufficient numbers of plots whose land cover has changed should be included in the sample. Again, a form of stratified sampling may be required.

In practice, the same sample data are often used for estimation using only the ground data and estimation based on a combination of ground and remotely sensed data. If the remote sensing sampling requirements can be accurately anticipated before sampling, then a single ground sampling design that is efficient for multiple purposes may be possible. If not, the challenge is to develop an accuracy assessment sampling design that satisfies the remote sensing requirements and that can be readily integrated into the original sampling design. Finally, if ground data from sample plots are to be co-registered geographically with satellite image or lidar data, accurate plot locations must be determined which, in turn, requires accurate geographical positioning system (GPS) receivers. Failure to correctly register ground and remotely sensed data means that remotely sensed data may be associated with incorrect ground data. For homogeneous ground cover the consequences may not be severe, but for fragmented or rapidly changing forest conditions the consequences may be quite detrimental. McRoberts (2010b) showed that when GPS receivers with accuracies in the range 15-20 m are used, approximately half of ground plots may be associated with incorrect 30-m x 30-m Landsat pixels. The result is inaccurate classification of the imagery and erroneous estimates based on the classification.

Assessment of total uncertainty

All sources of uncertainty have detrimental effects on the accuracy of estimates, the precision of estimates, or both. For this discussion, accuracy pertains to the deviation of an estimate from the true value, whereas precision is associated with the statistical concept of variance and pertains to the confidence in the estimate.

Multiple sources of uncertainty contribute to lack of accuracy. First, a sample mean may deviate considerably from the true value, even if the sample is properly selected, observations and measurements are correctly obtained, and an unbiased estimator is used. This is simply a case of random effects and natural variability in the population and should not be characterized as "error" which connotes a mistake. The solution is greater sample sizes or more optimal plot configurations. Second, an estimate that is based on model predictions may be inaccurate because the model was incorrectly specified, the data used to calibrate the model were not representative of the population to which the model was applied, or observations and measurements of variables were incorrectly acquired. Uncertainty accruing from this source is correctly designated as error. An example of such error is use of individual tree volume or biomass models that were developed for different climatic, topological, or ecological zones or for different species. The solution is acquisition of sufficient sample data to validate existing models or to construct new models.

Multiple sources of uncertainty contribute to lack of precision. First, sample sizes may be inadequate to estimate means or to fit models with sufficient precision. Three additional sources of uncertainty contribute to imprecision in model predictions. The first source, residual variability around model predictions, cannot usually be reduced apart from a better mathematical form of the model or use of additional predictor variables. Second, the input variables for a model may themselves be predicted from other models. In such cases, the uncertainty in the estimates of the input variables should be propagated through to the output variables. An example is the use of model-based estimates of tree height as input to a model that uses tree diameter and tree height to estimate tree volume or biomass. The third source is the uncertainty of the model parameter estimates. Assuming the model is correctly specified, the effects of this source of uncertainty can be reduced by using a larger sample to fit the model. Overall, the total uncertainty of model predictions must accommodate all three sources: residual variability, propagation of uncertainty in predictor variables, and parameter uncertainty. In general, the effects of the first source cannot be reduced; the effects of the second source are often inappropriately ignored; but the effects of the third source can be reduced via construction of a better model and increasing sample sizes.

Finally, variance estimation for purposes of quantifying precision is often complex and computationally

intensive, particularly when estimates are obtained from remote sensing-based maps. In fact, parametric estimators in the form of simple equations may not be available or may be very difficult to incorporate into estimation software. For some applications, the variance estimators are just now beginning to appear in the literature (McRoberts, 2010a, 2012; McRoberts & Walters, 2012; McRoberts et al., 2013; Gregoire et al., 2011; Næsset et al., 2013). An increasingly popular alternative is to use resampling estimators such as the jackknife (Quenouille, 1949) or the bootstrap (Efron & Tibshirani, 1994; McRoberts, 2010a). However, caution is advised, because these resampling estimators quantify only the portion of uncertainty resulting from sampling, not the uncertainty resulting from model misspecification or lack of fit. In addition, the resampling procedures must mimic the original sampling features such as clustering.

Case studies

Brazil

The NFI of Brazil (NFI-BR) is conducted by the Brazilian Forest Service (BFS) of the Ministry of Environment. The BFS was created in 2006 as a means of promoting sustainable forest production through forest management in public forests, as well as promoting forest development at the national level. One of its legal mandates is to implement a national forest information system (NFIS) of which the NFI is one of the most important components.

The main purpose of the NFI-BR is to generate information on forest resources, both natural and plantations, to support the formulation of public policies and projects aiming at forest development, use, and conservation. The NFI is nationwide and multisource and reports information on forest resources based on a 5-year measurement cycle.

The sampling design for field data collection features plot clusters located at the intersections of a systematic grid of 648 x 648 seconds of geographical distance which, at the Equator corresponds to an approximate 20-km x 20-km grid of potential sampling points. Plots to be measured in the field are visited regardless of their forest or non-forest status. Multiple sub-grids of 10-km x 10-km or 5-km x 5-km can be adopted whenever states and municipalities wish to invest in greater sampling intensity to increase the precision of estimates for forest types of high economic or ecological value or when a

state's forested area is small. Fixed-area sampling units are grouped into clusters of four rectangular sample plots located 50 m from a central sampling point in the cardinal directions (Freitas et al., 2010). Plot sizes and shapes are defined according to biome characteristics. Each sample plot is 20-m x 50-m for measurement of trees with diameter at-breast-height (dbh, 1.3 m) of at least 10 cm, although for Amazonian biome the plot is 20-m x 100-m to increase inclusion of large trees with dbh≥ 40 cm. Each sample plot includes 10-m x 10-m and 5-m x 5-m nested subplots for measurement of saplings and seedlings. At the central point of each cluster, a soil sample is collected and two perpendicular 10-m transects are used to collect data on down dead woody material. Data collection on sample clusters includes observation and measurement of both continuous and categorical forest variables such as classical dendrometric variables, species identification, and qualitative variables that are useful for forest ecosystem characterization. NFI-BR is currently being implemented with Santa Catarina and the Federal District as the first states to complete field data collection.

Santa Catarina

As part of NFI-BR, the southern Brazilian State of Santa Catarina, with a surface area of 95,346 km² and representing 1.1 percent of Brazilian territory, completed the data collection portion of its inventory in accordance with the NFI guidelines (Brasil, 2007), between 2007 and 2011. The Floristic and Forest Inventory of Santa Catarina (IFFSC), however, is more detailed in some aspects than the NFI to accommodate special data requirements associated with local socio-economic and conservation purposes. IFFSC was designed to evaluate the conservation status of forest remnants and to support a new forest conservation and land use policy (Vibrans et al., 2010, 2012).

Therefore, IFFSC included a floristic survey focused on endangered tree species that included five components: (1) digitalization and integration of Santa Catarina's herbaria data sets, (2) a field inventory, (3) evaluation of the genetic structure of endangered tree populations, (4) analysis of the socio-economic importance of forest resources and (5) an online geo-referenced database accessible by decision makers and the public.

Based on recent remotely sensed data (Santa Catarina, 2005) and the potential vegetation map (Klein, 1978), forest land was evaluated using a systematic sampling

design based on 4,000-m², fixed area clusters, each containing four 20-m x 50-m (1,000-m²) plots located 50 m from the center in the cardinal directions. Grid densities for the design varied: a 10-km x10-km grid was used for coastal rain forests and mixed ombrofhylous forest with *Araucaria*; a 5-km x5-km grid was used for more threatened and fragmented deciduous forests in order to obtain a minimum number of plots to support statistical analyses; and a 20-km x 20-km grid was used for non-forest land to achieve cost efficiency. Initially the FAO definition of forest (FAO, 2009) was to be used, but mapping and analyses conducted subsequent to field data collection were based on IFFSC criteria that specified woody formations with a minimum age of approximately 15 years, canopy cover greater than 50%, and minimum canopy height of 10 m, as also noted by Ribeiro et al. (2009). Forest regrowth below these threshold values was sampled on non-forest land. On the whole, 421 forest clusters and 157 non-forest clusters were established and are to be remeasured at 5-year intervals; additionally 19 clusters were established independently of the grid-based design in conservation units as examples of forests with attributes more characteristic of primary forests such as greater species and size diversity, greater tree heights, and greater biomass.

Within the sample units two vegetation classes were measured: the main stratum consisted of all woody individuals with DBH ≥10 cm, and the secondary stratum consisted of regeneration and understory shrubs with height >0.50 m and DBH <10 cm. In each forest class, sample plot dendrometric data for 2-4 sampled trees were collected to support construction of individual tree height and volume models and to validate existing regional biomass models. Epiphyte diversity was specifically assessed by field crews for eight forophytes at 30 selected sample plots using arborism techniques. The floristic survey included collection data for all fertile trees, shrubs, herbs and epiphytes within the sample unit and its surroundings. For all sampled remnants, a detailed physiognomic description was prepared, including disturbance factors and any type of human impact within the sampled forest and its surroundings.

For data processing, sample plots were stratified based on two factors: first, spatial distribution patterns of species composition and density, and, second, successional stages. The latter stratification was particularly important for assessing regrowth stages and plant communities in landscapes with highly fragmented and mostly secondary forests under permanent pressure due to land use changes, intensive agriculture, and forest plantation activities. Using multiple remote sensors and a time series approach, basic landscape ecology analyses are conducted for randomly selected 10-km x10-km windows located on the 20-km x 20-km grid and focus on land-use-changes and landscape metrics such as patch area, density, perimeter and edge classes and connectivity of forest patches.

Tanzania

For a sampling design for Tanzania, Tomppo et al. (2010a) used double sampling for stratification and optimal allocation of plots to strata. The first phase sample consisted of an office assessment of a dense grid of field plots for assignment to volume and cost classes. Based on these assessments, strata were constructed using predicted cluster-level average volume of growing stock and estimated cost to measure a plot cluster. Volume classes were based on volume predictions using satellite imagery, observations for ground plots outside Tanzania, and robust models whose predictions were calibrated using areal volume estimates for Tanzania. Neyman allocation (Cochran, 1977) was used to select boundaries for the volume classes so as to maximize the precision of the overall volume estimate assuming a fixed sample size. Cost classes were based on geographic information system (GIS) analyses and local expert opinion of the number of days (one, two, more than two) necessary to measure a plot cluster. Selection of the class intervals, which affects the gain that can be achieved with stratification, requires greater investigation. The second phase sample consists of field measurement of plots where within-strata sampling intensities were selected using optimal allocation (Cochran, 1977). With optimal allocation, sampling intensities are proportional to the quantity $\sigma_h / \sqrt{c_h}$ where σ_h is the within-stratum standard deviation for observations of the variable of interest (mean growing stock volume) and c_h is the average cost in terms of measurement time for a plot cluster in stratum h. The second phase consisted of field measurement of 32,660 plots configured into approximately 3,400 clusters. Concentric circular plots with radii of 15-, 10-, 5- and 1-m, with corresponding dbh thresholds of 20-, 10-, 5- and 1-cm, were used. Measurements for the smallest of these circular plots were acquired only for permanent plots. More details concerning the sampling design and plot configuration can be found in Tomppo et al. (2010a).

Lessons learned from case studies

In the tropics, use of available vegetation maps to delineate land into forest and non-forest is sometimes appealing. However, if plot clusters are not established on delineated non-forest land in the same manner as on delineated forest land, map errors could contribute to bias because forest land erroneously delineated as non-forest land will not be sampled. The additional costs associated with sampling delineated non-forest land can be decreased by allocating lesser sampling intensities to these lands. In addition, field measurement of plot clusters entirely outside forest and without growing stock can be often avoided by assessing such clusters with land use information obtained from other reliable sources such as was proposed for Brazil (Establishing…, 2009).

The lack of transportation routes, other than rivers, presents a special challenge for tropical forest inventories such as in the Amazonian biome. For example, roads may be available only a part of the year, approximately six months in the Amazonian biome. In addition, some forests may be designated for nature conservation purposes or for the sole use of indigenous peoples. Stratification based on relevant variables such as the likelihood of changes and measurement costs promote both cost efficiency and adherence to sound statistical inventory principles.

Conclusions

The forestry sector makes substantial contributions to the GHG balance as both a source resulting from deforestation in developing countries and as a sink through sequestration of atmospheric GHG emissions. Development of carbon accounting programs in tropical countries, either through new NFIs or MRVs, requires scientifically valid and credible ground sampling programs.

Although the general statistical principles for configuring plots and constructing sampling designs are the same for tropical forests as for boreal and temperate forests, the particular features may differ considerably. Compelling factors contributing to the unique features of tropical inventories include the remote and inaccessible nature of many tropical forests, greater species diversity, and the necessity of relying on remotely sensed data as a primary data source rather than simply as a means of enhancing estimates obtained from ground sampling. The case studies for the Brazilian NFI, the inventory for the Brazilian state of Santa Catarina, and the NFI for

Tanzania illustrate application of the general principles previously discussed. In addition, they illustrate how specific applications can be tailored to unique ecological, climatic, economic, and demographic conditions. Completion of these inventories, including data analyses and reporting, will permit further modification to accommodate emerging NFI requirements such as biodiversity assessment, carbon accounting, and standards and expectations associated with MRVs conducted under the auspices of the IPCC.

Acknowledgements

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