

Dissertationes Forestales 113

**Comparison of field inventory methods and use of
airborne laser scanning for assessing coarse woody
debris**

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Academic dissertation

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ABSTRACT

The sustainable use of forests, which is one of the key principles of forest management in Finland, for instance, includes the goal of maintaining forest biodiversity. Dead wood (coarse woody debris, CWD) has been recognized as one of the main indicators of biodiversity in boreal forests and it plays a major role in nutrient cycling, for example. Much effort has therefore been put into the development of new cost-efficient methods for assessing CWD. However, if data are collected for large areas, field inventory may be expensive even when a sample-based method is used. In this thesis, sample-based CWD inventory methods were studied and since airborne laser scanning (ALS) is nowadays regarded as one of the most promising remote sensing methods and is gradually being adopted for predicting living tree characteristics, the possibilities for utilizing ALS data in CWD inventory were investigated.

The material comprised data from three areas. Data for a conservation area in Koli were used to study the use of ALS data for estimating downed and standing dead wood volumes in natural forests, and data for commercially managed forests in Sonkajärvi and Juuka were used to study the efficiency of sample-based field inventory methods for assessing CWD. The sampling methods were compared in terms of the accuracy of the estimated mean CWD volume with a fixed input effort specified in fieldwork hours. Furthermore, it was studied how much the use of auxiliary information derived from ALS data or other sources could improve the sampling efficiency, i.e. reduce the standard error of the mean given the same inventory costs. The auxiliary information was used either in the design phase, for 'probability proportional to size' (PPS) sampling, or in the estimation phase, for ratio or regression estimation.

ALS data proved useful for predicting CWD volumes in natural forests. The RMSEs for downed and standing dead wood, and for the total CWD volume estimates were 51.6%, 78.8% and 54.2%, respectively. It was also observed that ALS-based estimates for downed dead wood volume were substantially more accurate than those based on living tree characteristics measured in the field. The sample-based inventory methods developed for assessing CWD or other rare characteristics were observed to be most efficient field inventory methods, and especially the relascope-based sampling methods were highly efficient. The use of PPS sampling notably improved the efficiency of the CWD inventory, but efficiency was modest when auxiliary information was used in the estimation phase. The improvement in efficiency varied considerably between different inventory methods and CWD materials. Although the efficiency of other inventory methods could be improved more by introducing PPS sampling, relascope-based sampling methods remained the most efficient methods for assessing CWD. It was also observed that the sampling efficiency was not markedly better if ALS data were combined with either aerial photographs or stand-register data, and it was usually preferable to use ALS data alone as the auxiliary data source.

Keywords: Airborne laser scanning, Auxiliary information, CWD inventory

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Joensuu, March 2011

Annukka

LIST OF ORIGINAL ARTICLES

This thesis is based on the following papers, which are referred to in the text by the Roman numerals I–V. The papers I–IV are reprinted with the kind permission of the publishers while the study V is the author version of the manuscript.

- I Pesonen, A., Maltamo, M., Eerikäinen, K. & Packalén, P. 2008. Airborne laser scanning-based prediction of coarse woody debris volumes in a conservation area. *Forest Ecology and Management* 255: 3288–3296.
doi:10.1016/j.foreco.2008.02.017
- II Pesonen, A., Leino, O., Maltamo, M. & Kangas, A. 2009. The comparison of field sampling methods and the use of airborne laser scanning as auxiliary information for assessing coarse woody debris. *Forest Ecology and Management* 257: 1532–1541.
doi:10.1016/j.foreco.2009.01.009
- III Pesonen, A., Maltamo, M. & Kangas, A. 2010. The comparison of airborne laser scanning-based probability layers as auxiliary information for assessing coarse woody debris. *International Journal of Remote Sensing* 31: 1245–1259.
doi: 10.1080/01431160903380607
- IV Pesonen, A., Kangas, A., Maltamo, M. & Packalén, P. 2010. The effects of auxiliary data source and inventory unit size on the efficiency of sample-based coarse woody debris inventory. *Forest Ecology and Management* 259: 1890–1899.
doi:10.1016/j.foreco.2010.02.001
- V Pesonen, A., Maltamo, M. & Kangas, A. 2011. Auxiliary information in the design phase of different sample-based coarse woody debris inventory methods. Manuscript.

Most of the work for papers I–V was carried out by Annukka Pesonen. She constructed the models for CWD volumes and implemented the sampling simulator which was used in the simulations. The co-authors of the papers have participated in calculating the attributes for field data and planning the papers. They have also contributed to the writing stage by commenting on, and thereby improving the manuscripts.

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LIST OF ACRONYMS AND ABBREVIATIONS

ACS	Adaptive cluster sampling
a.g.l	Above ground level
a.s.l	Above sea level
ALS	Airborne laser scanning
AP	Aerial photographs
CWD	Coarse woody debris
DDW	Downed dead wood
DBH	Diameter at breast height (1.3 m)
DTM	Digital terrain model
GPS	Global Positioning System
LIS	Line intersect sampling
NFI	National Forest Inventory
NIR	Near-infrared
PPS	Probability proportional to size
PRS	Point relascope sampling
RMSE	Root mean square error
SDW	Standing dead wood
SRD	Stand-register data
SRS	Simple random sampling
TRS	Transect relascope sampling

1 INTRODUCTION

1.1 Importance of dead wood for a forest ecosystem

Forests are much more than just living trees. The forests in Finland have been used for game hunting, berry picking and tar production, for instance. By the mid-20th century, however, wood production had become the most important use, to the extent that the term ‘sustainable use’ referred mainly to the sustainability of wood production. Criticism of these intensive forest management practices arose during the second half of the 20th century, and during recent decades more emphasis has been placed on environmental aspects and forest biodiversity (Mielikäinen and Hynynen 2003). Nowadays, the sustainable use of forests is defined in a broader sense and the maintenance of forest biodiversity is one of the key principles in this, as provided for legally in the Forest Act.

Biodiversity comprises diversity at three levels: in ecosystems, species and genes. These levels are all inter-related and together they create the complexity of life on Earth. To a large extent, the maintenance of species and genetic diversity can be achieved by maintaining ecosystem diversity (Hunter 1990). Decaying wood is regarded as a biodiversity indicator, since it is a key factor for biodiversity in boreal forests and a high proportion of rare and specialized species are dependent on it (e.g. Siitonen 2001). Dead wood forms major structural features with many crucial ecological functions. It is important for carbon sequestration and nutrient cycling, it provides substrates and habitats for fungi, lichens, mosses and invertebrates, it is a long-term source of organic matter and nutrients, and it creates nesting and feeding habitats for birds, for example (Harmon et al. 1986, Esseen et al. 1997, Siitonen 1998, Siitonen 2001, Karjalainen and Kuuluvainen 2002, Enrong et al. 2006). The amount of dead wood depends on the input and decay rates (Harmon et al. 1986, Siitonen 2001). Wind, fire, insects, diseases and suppression and competition generate dead wood, while climate, site productivity tree species and tree size, for example, have an effect on how much living and dead wood is formed and how fast the decaying process is (Harmon et al. 1986).

The term coarse woody debris (CWD) refers to a variety of sizes and types of woody material, including downed dead trees, logs, large branches and roots, standing dead trees, snags and stumps (Newton 2007). The definition of CWD and the minimum size limit for measuring dead trees vary widely in published works (Harmon et al. 1986, Stevens 1997). Some ecologists make a distinction between fine and coarse woody debris depending on the diameter of the dead wood pieces (e.g. Norden et al. 2004, Eaton and Lawrence 2006), but in some studies the term CWD is used for all dead wood irrespective of size (e.g. Rouvinen 2002). No distinction between fine and coarse woody debris will be made here, and all sizes of dead wood will be referred to hereafter as CWD. In some contexts, the term ‘total CWD’ is used in order to stress that all CWD materials are included.

Intensive forest management, the prevention of forest fires, the use of firewood, and the removal of damaged trees for fear of insect infestation have reduced the numbers of dying and dead trees in managed forests to a small fraction of those in natural, unmanaged forests. Thus, CWD volumes in Fennoscandian managed forests have decreased to less than 10% of those in old-growth forests (Siitonen 2001). The lack of CWD has removed woody microhabitats and has thereby reduced the amounts and diversity of bryophytes, lichens, fungi, insects and birds (Samuelsson et al. 1994). Species that are dependent during some part of their life cycle on dead wood habitat, wood-rotting fungi or other dead wood

dependent species are called saproxylics (Speight 1989). In Finland, the number of saproxylics is estimated to be 4000–5000, i.e. 20–25% of all forest-dwelling species (Siitonen 2001), while the number in Sweden is 6000–7000, of which 1126 are red-listed, i.e. classified as threatened, near-threatened or probably threatened (Dahlberg and Stokland 2004).

The main factors that determine the suitability of dead wood for saproxylics are tree species, decay stage, the fungal species decaying the wood, size, dead wood material (e.g. snag, log, stump), and environmental conditions (Siitonen 2001, Dahlberg and Stokland 2004). A larger diameter of dead wood pieces is usually preferable for many species (Samuelsson et al. 1994). Large-sized logs and snags provide more substrate and they have a higher water-holding capacity than smaller ones (Harmon et al. 1986). Even the manner in which the stumps have formed may affect their importance in this respect. Bull and Meslow (1977) observed that pileated woodpeckers (*Dryocopus pileatus* L.) preferred feeding on naturally created stumps rather than cut stumps. The bark beetle in particular has been observed to be dependent on recent dead trees, so that it prefers natural forests (Veteli et al. 2006). CWD volume is an important factor affecting species abundance, since as the amount of dead wood increases greater variation is usually found in CWD qualities (species, size, decay stage). On the other hand, even if the variation in the CWD qualities does not change, a greater amount of it will increase species richness by allowing species to build up larger local populations, which then have a lower risk of local extinction (Siitonen 2001).

In addition, the spatial and temporal continuity of CWD patches are important factors in maintaining species diversity (e.g. Hanski and Hammond 1995, Siitonen 2001, Hottola and Siitonen 2008). Some species occupy woody habitats only for a short period, e.g. if they are specialized in a certain decay stage, and it is therefore important that a temporal and spatial continuum of different CWD qualities should exist (Esseen et al. 1997). For other species, however, it is recommendable that dead trees should be located in dispersed clumps rather than uniformly over the whole area (Raphael and White 1984, cited in Samuelsson et al. 1994). The number of clumps, the preferred distance between them and the amount of dead wood in them depend on the species and forest type, for example (Samuelsson et al. 1994). The existence of small conservation areas is not sufficient to maintain forest biodiversity, and therefore it is important that the biodiversity aspects are considered and the existence of CWD is guaranteed in managed forests as well, since these cover large areas (see also Ranius and Jonsson 2007).

CWD is an important structural component of the forest floor and it has a major role in preventing erosion (Harmon et al. 1986, Stevens 1997). In addition, dead wood may retain moisture through dry periods and stabilize water conditions on the forest floor (Stevens 1997). Since decaying wood concentrates high amounts of nutrients, especially at the beginning of the decomposition process, it is important for stabilizing the nutrient and carbon cycle (Harmon et al. 1986). Dead wood pieces may have an effect on the nutrient and carbon cycle and habitat conditions for hundreds or thousands of years (Franklin et al. 1987, Stevens 1997). This means that, as a long-term source of nutrients and stabilizer of water content, downed dead wood can serve as a good seedbed for saplings (Harmon et al. 1986).

Most of the biomass in boreal forests occurs in the form of trees. When a tree dies its woody material is released into the nutrient and carbon circulation in the decomposition process (Harmon et al. 1986). CWD can account for a substantial proportion of the total biomass in a forest (Kuuluvainen et al. 1998, Sippola et al. 1998), but it is often forgotten in

biomass assessments and when calculating carbon fluxes (see Krankina and Harmon 1995, Bond-Lamberty et al. 2002, Woodall et al. 2008). Since it is predicted that the changing climate will increase the incidence of forest diseases and storm damage (Stolte 2001), it is also especially important to account for CWD in biomass and carbon assessments in order to gain a more profound understanding of global carbon dynamics (King and Neilson 1992, Krankina and Harmon 1995, Bond-Lamberty et al. 2002). International agreements nowadays (e.g. the Kyoto Protocol) also require the reporting of amounts of dead wood in connection with assessments of greenhouse gas emissions (Woodall et al. 2009).

1.2 Effects of forest management on CWD amount and quality

Forest management has been found to reduce CWD volumes and the numbers of entire dead trees and snags, and to increase the numbers of pieces of trunks, for instance (Sippola et al. 1998). Thus, forest management has considerably altered the amounts and quality of CWD. The decrease in the diversity and abundance of CWD has had a greater negative influence on the number of species in Fennoscandian forests than any other consequence of forest management (Esseen et al. 1997).

The most commonly used forest regeneration methods in Fennoscandia are seed-tree cuttings or clear-cutting followed by planting, in which case most of the cut tree volume is extracted, which differs greatly from the situation in natural forests, where fallen and dead trees remain *in situ* after natural disturbances (Siitonen 2001). In addition, the Forest Act in Finland states that recent dead or damaged coniferous trees should be removed if their volume or number of stems exceeds certain predefined limits. Most wind throws and snow breakages are therefore removed from managed forests for use as firewood, for example. The use of logging residue for energy purposes has reduced the amount of CWD even more (Esseen et al. 1997). In addition, damaged, weakened and dead trees are usually removed during thinning, in order to reduce suppression mortality and the risk for natural disturbances (Siitonen et al. 2000, Siitonen 2001). The outcome is that the CWD volume in managed forests is only few percent of that of living trees (Esseen et al. 1997).

The prevention of forest fires has reduced the incidence of charred wood, and due to short rotation times less large-diameter dead wood exists (Siitonen 2001). In addition, the continuous availability of dead wood at different decay stages is disturbed in managed forests due to the complete removal of trees, and therefore the numbers and volumes of large logs at advanced stages of decay are lower (Siitonen et al. 2000). In managed forests, the proportion of large diameter (> 30 cm) CWD of the total dead wood volume is substantially less than in natural forests, whereas the CWD volume in the smallest diameter class is the same than in natural forests or even larger (Siitonen 2001). Since forest management produces mainly small-diameter branches and tree-tops, which decompose fairly rapidly (Sippola et al. 1998), large-sized snags and logs or natural stumps are replaced by small-sized dead wood pieces and stumps with cut surfaces, respectively (Esseen et al. 1997). In addition, soil preparation after clear cutting crushes downed dead wood logs, which enhances the decay process (Esseen et al. 1997, Siitonen 2001).

Due to intensive forest management, the spatial and temporal continuity of dead wood has become endangered, and the spatial distribution of CWD is very uneven, especially at the landscape level (Siitonen 2001). The distribution of habitats has become more fragmented, which has reduced patch sizes and increased isolation (Esseen et al. 1997).

1.3 CWD inventories

Accurate information on forest characteristics is needed for forest management planning and decision-making, for example (see e.g. Duvemo and Lämås 2006). The inventory results can also be used for planning future guidelines for forest management operations, for the optimal focusing of conservation efforts and for monitoring the quality of forests from an ecological point of view. The quantity of CWD is a commonly used measure of the ecological goodness of an area (Ståhl et al. 2001). Usually CWD quantity is assessed in terms of volume (e.g. Sippola et al. 1998, Siitonen et al. 2000, Grove 2001, Ståhl et al. 2001), although biomass or the number and length of CWD pieces, for example, have also been used (Arthur et al. 1993, Kirby et al. 1998, Carmona et al. 2002).

When conducting a CWD inventory a distinction is generally made between standing dead trees (whole or snags) and downed dead trees (whole downed trees, logs and branches). Stumps may also be classified as a separate group. In this thesis, only downed and standing dead trees were studied, and stumps were ignored completely. The characteristics reported for dead trees include, in addition to size measures (diameter and length or height, volume, biomass), species, decay stage, amount of bark remaining etc. (Samuelsson et al. 1994). Ståhl et al. (2001) note that the volumes quoted for single CWD pieces may be biased since it is assumed that tree trunks are circular, which is not true, especially in the case of highly decayed trees. The volumes of single dead trees and CWD pieces are calculated using taper curves or volume functions developed for living trees, or using a sectioning method, i.e. partitioning a tree into several pieces.

Harmon et al. (1986) describe few simple methods for determining the input of CWD from living trees. The rate of tree mortality can be estimated in permanent sample plots by tagging the trees and observing later which of the tagged trees have died, but this method underestimates the total dead wood volume, since it does not take into account dead branches or tree tops which fall to ground. Other options for determining the input rate would be to use cleared plots or to mark all dead wood pieces at the beginning of the observation period. Nevertheless, since the amount of CWD is affected by the speed of the decaying process and the occurrence of natural disturbances as well as the input rate (Harmon et al. 1986, Siitonen 2001), other methods for assessing current CWD amounts need to be used.

Woodall et al. (2009) note that many countries have recently begun to perform inventories of dead wood, and CWD is assessed nowadays in approximately 13% of countries around the world, accounting for a total of 41% of the area of the world's forests. In those countries where there is a long forest inventory history, it is also common for dead wood to be included nowadays. In Finland, for example, CWD inventory began at the national level in 1996, in the ninth National Forest Inventory (NFI). Dead trees are assessed on the basis of fixed-sized circular sample plots using a systematic location of clusters. In the latest Finnish NFI (NFI10 in 2004–2008), dead trees were inventoried only on permanent sample plots (a total of 10 959 plots), and the average CWD volume was estimated to be $5.4 \text{ m}^3\text{ha}^{-1}$ over the whole country, with figures of $3.2 \text{ m}^3\text{ha}^{-1}$ and $7.6 \text{ m}^3\text{ha}^{-1}$ in Southern and Northern Finland, respectively (Ihalainen and Mäkelä 2009). CWD volumes varied notably between areas managed on different principles: the average CWD volume being only $4.7 \text{ m}^3\text{ha}^{-1}$ in commercially managed forests but $12.7 \text{ m}^3\text{ha}^{-1}$ in conservation areas.

As with other forest characteristics, it is important when assessing CWD that the inventory method should be objective and based on probability sampling (see Särndal et al.

1992). Sample-based inventories are commonly used as a survey of the total population is often impossible or too expensive and it would not be possible to reliably compare CWD volumes between regions or points in time on the basis of subjective inventories. Therefore, when good-quality, unbiased data are needed, objective inventory methods should be used and visual assessment avoided (Ståhl et al. 2001).

It has been observed that the assessment of rare and clustered forest characteristics such as CWD is not cost-efficient if inventory methods originally designed for living trees are used (Kangas 2006). The increasing awareness that CWD is an important ecological component of a forest has raised interest in developing more efficient methods for assessing the quantity and quality of dead wood (Ringvall et al. 2001). Strip sampling was a common inventory method for use with living trees in the past, but nowadays it is mainly used for rare forest characteristics (Tomppo and Heikkinen 1999, Stehman and Salzer 2000), while fixed-sized sample plots, which are widely used in forest inventories, are also common in CWD inventories (Ståhl et al. 2001). Other methods for assessing CWD include, for example, line intersect sampling (LIS) (Warren and Olsen 1964), transect relascope sampling (TRS) (Ståhl 1997, 1998), point relascope sampling (PRS) (Gove et al. 1999, 2002), adaptive cluster sampling (ACS) (Thompson 1990), perpendicular distance sampling (Williams and Gove 2003) and guided transect sampling (GTS) (Ståhl et al. 2000).

Choosing the right inventory method in each case can be difficult, since the nature and occurrence of the phenomenon to be studied and the area concerned can greatly affect the efficiency of the methods. This complicates comparisons and choice situations (see Päivinen 1987). Ståhl et al. (2001) list cost-efficiency, robustness with regard to measurement errors, simplicity and the provision of contextual information as the most important issues that should be accounted for when selecting the proper method, although it is also important to bear in mind what is the purpose of the inventory, and the skills of the inventory staff should not be forgotten, either.

Since it has been observed that CWD volume is correlated with living tree characteristics (Sippola et al. 1998, Siitonen 2001), models for predicting CWD volume from these characteristics have been developed in order to reduce the amount of field inventory effort. Ranius et al. (2004) and Ranius and Kindvall (2004) estimated the amount of dead wood from the growth of living trees, tree mortality rate and CWD decomposition rate, while Chojnacky et al. (2004) also used climatic variables. Chojnacky and Heath (2002) observed that the basal area of standing dead trees was a good predictor of the downed dead wood volume. Nevertheless, the accuracy of the models for predicting CWD volume has been rather poor (see Chojnacky and Heath 2002, Chojnacky et al. 2004). National dead wood carbon stocks in the USA were previously estimated on the basis of living tree characteristics calibrated by reference to preliminary field estimates, but nowadays field inventory-based estimates are used (Woodall et al. 2008).

1.4 Remote sensing and its application to the assessment of ecological values

As the time spent on fieldwork increases, the estimates for the variable of interest in the whole population become more accurate. Fieldwork cannot be extended arbitrarily in order to achieve the desired accuracy, however, since the inventory costs are usually constrained. In large, remote areas or in difficult terrain, fieldwork is usually very expensive, time-consuming, or even impossible. This means that inventory costs for large areas are conventionally reduced by using remote sensing methods. Field samples can be used in

combination with remote sensing to derive regional or nation-level estimates. The multisource NFI in Finland, for example, uses satellite images to produce maps for large areas containing spatial information on forest characteristics (Tomppo 2006). One further reason for using remote sensing is that field measurements based only on sparse field samples do not provide accurate information for decision-making in small areas (Tomppo 2006). The problem of acquiring sufficiently accurate estimates is further emphasized in inventories of rare forest characteristics (see Kangas 2006).

As passive remote sensing methods, satellite imagery and aerial photography have a long tradition in forest inventories (Standish 1945, de Steiguer 1978). The spatial and spectral resolution of satellite images was not initially accurate enough for distinguishing forests from an ecological point of view, but the improved availability of higher resolution satellite images has now made it possible to use satellite data in ecological applications as well (Kerr and Ostrovsky 2003, Nagendra and Rocchini 2008). Moderate and high resolution satellite images has been used to identify species richness (Levin et al. 2007, Rocchini 2007, St-Louis et al. 2009) and to map land cover fractions (Olthof and Fraser 2007), for example. The advantage of aerial photographs is that they have a higher spatial resolution, and it is possible to exploit the textural properties of the image in order to estimate forest characteristics (see Tuominen and Haakana 2005). Nevertheless, rapid development in the spatial and spectral resolution of space-borne data has narrowed the difference in resolution between satellite images and aerial photographs (Kerr and Ostrovsky 2003). Aerial photographs have been successfully used for assessing standing dead trees (e.g. Uuttera and Hyppänen 1998, Haara and Nevalainen 2002, Pasher and King 2009), and even though canopy closure was observed to significantly affect the detection, Bütler and Schlaepfer (2004) achieved promising results in their mapping and quantification of large snags using aerial photographs. Poorer results have nevertheless been reported for the prediction of downed dead wood volumes using aerial photographs (Pasher and King 2009). Other ecological uses of aerial photographs include the detection of drought, insect and wind damage (see Bütler and Schlaepfer 2004, Holopainen et al. 2006, Meentemeyer et al. 2008).

One of the main problems affecting the use of optical remote sensing data is the fact that weather conditions may have notable effects on image quality, and the characteristics visible in images from the same area differ over time. Currently one of the most promising remote sensing techniques for increasing the accuracy and efficiency of large-scale forest inventories is the active remote sensing method airborne laser scanning (ALS) (Næsset 2002, Maltamo et al. 2006b). This measures directly the physical dimensions of the Earth's surface and its vegetation, so that its usability is not limited by the illumination conditions, for example (Næsset 2004). ALS can measure both intensity (strength of the return signal) and height information, and multiple returns can be recorded for each emitted pulse (Wehr and Lohr 1999). This situation can arise if the pulse encounters an object through which it at least partly penetrates. Only the first and last return pulses are usually taken into account, however. The usefulness of ALS for forest inventories is based on the fact that the height distribution of ALS data is related to the vertical structure of the vegetation (Magnussen and Boudewyn 1998). The vegetation structure is represented by various ALS metrics, including canopy height, density and intensity characteristics, and these metrics can be used to predict stand characteristics (Næsset 2002, Korpela 2008). ALS systems also enable information to be collected from beneath closed tree canopies and allow measurement of the roughness of the forest floor.

The estimation of tree and stand variables using ALS metrics as independent variables has been studied widely in recent years (e.g. Hyyppä et al. 2001, Næsset 2002, Lim et al. 2003, Heurich et al. 2004, Maltamo et al. 2004, Hopkinson et al. 2006, Packalén and Maltamo 2006, 2007). ALS data for increasingly large areas are being acquired for forest inventory purposes in the Nordic countries (e.g. Holmgren and Jonsson 2004, Næsset 2007, Maltamo et al. 2009), and since the accuracy of ALS data is sufficient for predicting the living tree characteristics, it has gradually acquired operational uses (e.g. Næsset 2007). ALS data are also acquired and used in nationwide topographic mapping in many European countries, including Finland and Sweden (Ahokas et al. 2008).

Besides inventories of living trees and topographic mapping, the usefulness of ALS data for defining stand structure has also been studied in relation to fire behaviour models and biodiversity aspects (Riano et al. 2003, Zimble et al. 2003, Maltamo et al. 2005, Goodwin et al. 2007, Hill 2007). Hinsley et al. (2002), for example, used ALS data to assess the quality of bird habitats, and Müller et al. (2009) observed that ALS was superior to aerial photographs for estimating the abundance of birds in Southeastern Germany. In addition, ALS data have been used, for identifying large aspens (Säynäjoki et al. 2008) and stands with high herbaceous plant diversity (Vehmas et al. 2009).

Thus, the number of studies concerning the use of ALS data for assessing ecological aspects and biodiversity has gradually increased. Even at the beginning of 21st century, however, the applicability of this technique to CWD inventories was a less extensively studied subject (Seielstad and Queen 2003), even though it had been observed that ALS data can be used for assessing the roughness of the forest floor and are widely used for creating digital terrain models (DTM), for instance (Van der Veen et al. 1998, Axelsson 2000, Hyyppä et al. 2005). Bater et al. (2007) found that the percentage of dead trees in unmanaged forests could be estimated with high accuracy using ALS data, and both Kim et al. (2009) and Bater et al. (2009) subsequently adopted this approach for assessing standing dead trees in the USA. Kim et al. (2009) used ALS-derived intensities to estimate the standing dead wood biomass in a national park area, and Bater et al. (2009) estimated the wildlife tree class distribution of standing dead trees in a multi-use area where both harvested and mature forests were to be found. In addition, Martinuzzi et al. (2009) used ALS data and topographic metrics to assess the presence of snags in different diameter classes. The best classification accuracies were observed to be 86–88% (kappa 0.70–0.71), varying from one diameter class to another.

1.5 Sampling

1.5.1 Principles of probability sampling

In sample-based inventories a *sample*, or part of the whole population, is selected and observed in order to make inferences about the whole population (de Vries 1986, Shiver and Borders 1996). The uncertainty in estimates obtained by sampling is due to only part of the population being observed, so that the estimate depends on which sample units are included in the sample. This is referred to as *sampling error* (Särndal et al. 1992, Thompson 2002). Sampling error is a commonly used measure of the accuracy of sampling methods, and it is typically expressed as the standard error of the mean (e.g. Newton 2007).

Sampling can be divided into two categories: probability sampling and non-probability sampling (e.g. Stehman and Overton 2002). In probability sampling, each population unit

has a known probability of being selected for the sample, but in non-probability sampling some units have an unknown selection probability (Särndal et al. 1992, Schreuder et al. 1993). A sampling approach is called probability sampling if it satisfies the following conditions: the set of samples can be defined, each sample has a known probability of selection, every sample unit in the population has a strictly positive selection probability, and the sample is selected exactly in accordance with these selection probabilities (Särndal et al. 1992). The sample must be representative of the whole population, since otherwise the inference drawn from it will be biased (Särndal et al. 1992, Schreuder et al. 1993). The use of probability sampling makes it possible to calculate unbiased estimates for the population mean or total and also an unbiased estimate for the variance (Thompson 2002). Probability sampling is typically used in sample-based inventories, because then it is possible to estimate the sampling error and make inferences from the sample to the population. Only probability sampling methods were used in the present work.

When every sample unit in the population has the same probability of being selected for the sample, this is called sampling with equal probabilities. On the other hand, if the probabilities differ it is called sampling with unequal probabilities, or probabilities proportional to size (PPS) sampling. If PPS sampling is performed with replacement, i.e. the sample units drawn can be reselected, the estimate for the total population is calculated by weighting the values for the sampled units according to their selection probabilities (Särndal et al. 1992, Thompson 2002). In without replacement case, the inclusion probabilities for the sample units are used instead of the selection probabilities (Särndal et al. 1992).

It is desirable to select a sampling method in which the estimates obtained from different samples are as close to the true population characteristics as possible, so that the uncertainty will be small. On the other hand, the sampling method should provide unbiased or nearly unbiased estimates and be easy to perform and cost-efficient (Thompson 2002). The aim of achieving as many of these goals as possible under different conditions has led to the development of hundreds of sampling methods and designs (see Hájek 1981, Brewer and Hanif 1983, Särndal et al. 1992, Schreuder et al. 1993, Thompson 2002).

1.5.2 Auxiliary information

The obtaining of accurate estimates for certain forest variables of interest can be highly expensive even when a sample-based inventory is used. It is possible in some cases, however, that some auxiliary information may be available on the area, i.e. data that are not accurate enough to be used as the only source for estimating values for the variable of interest but are correlated with that variable. If easily assessable, low-cost auxiliary information is available on all the population units in the area concerned, it may be beneficial to use that information to improve the cost-efficiency of the inventory (de Vries 1986). A large number of possibilities exist how auxiliary information can be utilized, and combinations of these possibilities have been used as well.

Auxiliary information can be used as a basis for pre-stratification in the design phase before drawing the field sample, or in PPS sampling (Särndal et al. 1992, Shiver and Borders 1996, Stehman and Overton 2002, Thompson 2002, Tuominen et al. 2006). In the latter case, the field inventory can be guided and sampling efforts concentrated in areas where there is a higher probability of finding the variables of interest. Auxiliary information can also be used for a given sample, to improve the accuracy of estimates. In this sense, it is possible to utilize auxiliary information which is not available at the time of

the field inventory but is obtained at a later date (Thompson 2002). The estimates can also be improved in the estimation phase after the field inventory by using ratio or regression estimation or post-stratification (Särndal et al. 1992, Stehman and Overton 2002, Thompson 2002, Lehtonen and Pahkinen 2004). The difference estimator is similar to the ratio and regression estimators, but it is less often used (Stehman and Overton 2002). In ratio and regression estimation, it is assumed that the relationship between the variable of interest, y , and the auxiliary variable, x , is at least approximately linear (or can be linearized). It is also assumed in ratio estimation that when x is zero y will also be zero, but in regression estimation x can be zero without y being zero and the relationship between x and y can be negative (Thompson 2002). An example of how auxiliary information can be used in the design (PPS sampling with replacement) or estimation phase (ratio or regression estimation), or in both, is shown in Figure 1. In this thesis, however, auxiliary information was used either in the design phase or in the estimation phase but not in both.

The use of auxiliary information in combination with a field inventory has been studied widely (see Smith et al. 1995, Stehman 1996, Ringvall et al. 2007, Lianfa et al. 2009). Ringvall et al. (2007), for example, observed that the use of auxiliary information on host tree species derived from satellite images or field inventory data improved the estimates for sparse species. It was noted, however, that the correlation between the variable of interest and the auxiliary data values should be relatively high to benefit from the use of auxiliary information. Roesch (1993) used PPS sampling in ACS when surveying rare and clustered tree characteristics and selected the initial sample of trees on the grounds of probability proportional to basal area. Meanwhile, Smith et al. (1995) estimated the density of

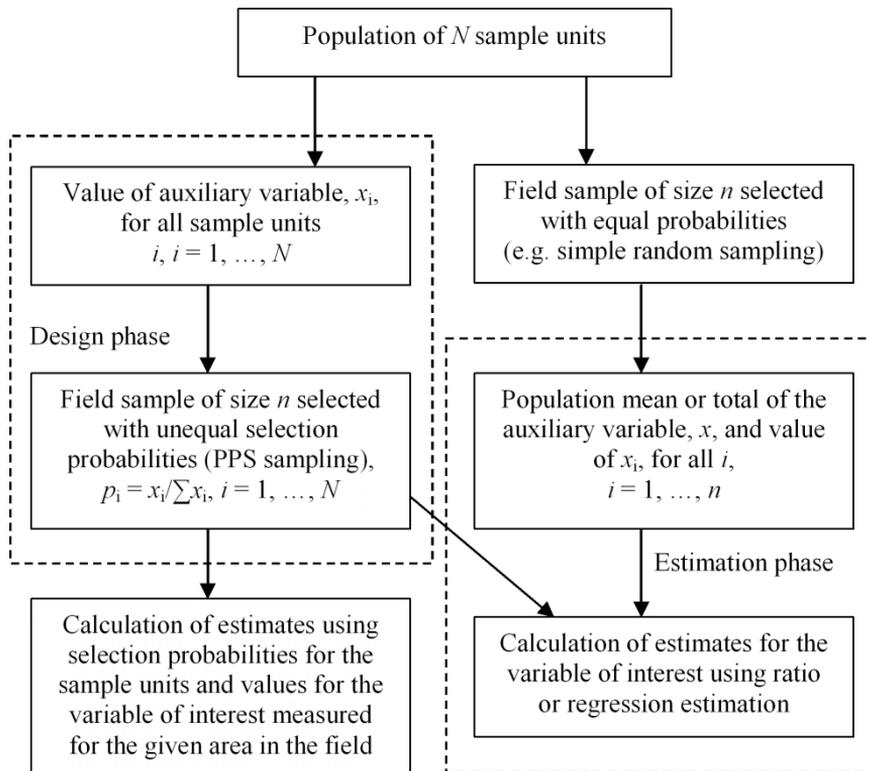


Figure 1. Use of auxiliary information in the design and estimation phases.

wintering waterfowl by selecting the primary sample units on the basis of probability proportional to available habitat. Auxiliary information occupies a key role in GTS for CWD inventories, for example, since the auxiliary data values are used to increase the probability of the transects measured in the field passing through areas where the variable of interest exists (Ståhl et al. 2000).

Remote sensing is the most obvious source of auxiliary information, since it enables mapping over large areas at low costs. In addition, the development of remote sensing methods has meant that more accurate data are available for use as auxiliary information. The use of ALS data as auxiliary information in forest inventories has also been studied recently. Corona and Fattorini (2008) noted that the accuracy of living tree volume estimates improved notably when ALS data were used in ratio estimation. Hawbaker et al. (2009) used ALS data for stratifying the area to be examined and compared the use of a random field sample and a stratified sample for modelling living tree characteristics and biomass. The models constructed using the stratified sample provided considerably more accurate predictions for the full data range than those based on the random sample.

1.6 Objectives of the thesis

The aim of this thesis was to study the possibilities for rendering CWD inventories more efficient by making use of remote sensing data, for example. The main focus was on the ALS-based estimation of CWD volumes and the use of ALS data as auxiliary information in sample-based field inventories of CWD. Each of the individual papers concentrated on one topic, and provided new information and study subjects for the following papers. The specific objectives of the individual papers were:

- I. To analyse the potential of ALS metrics for modelling downed and standing dead wood volumes in natural forests.
- II. To compare the sampling efficiencies of various inventory methods for assessing the volumes of different CWD materials in managed forests, and to study whether the sampling efficiency can be improved by using ALS-based auxiliary information on the area in question in PPS sampling.
- III. To study how much the sampling efficiency of an inventory of CWD volumes can be improved by using ALS-based auxiliary information gathered from an independent area either in the design phase when implementing PPS sampling or in the estimation phase when using ratio or regression estimation.
- IV. To compare the sampling efficiencies of various inventory methods for assessing the volumes of different CWD materials using varying sample unit sizes and data sources as auxiliary information in PPS sampling.
- V. To study how auxiliary information could be used and how efficient it is to use ALS data as auxiliary information in PPS sampling when assessing the volumes of different CWD materials using strip sampling, LIS, PRS or TRS.

2 MATERIALS

The material for this thesis consisted of data on three forest areas. The data used to model downed and standing dead wood volumes based on ALS metrics in paper I applied to the Koli National Park in Eastern Finland (63°07'N, 29°46'E), while the data used in the other papers (II–V) to study the sampling efficiencies of inventories of CWD performed by different methods with and without auxiliary information were from Sonkajärvi in Central Finland (63°40'N, 27°31'E). In addition, data from Juuka in Eastern Finland (63°14'N, 29°15'E) were used in paper III to study the relationships between ALS metrics and CWD volumes in an independent area (Figure 2).

2.1 Study areas and field data

2.1.1 Koli

The field data from the Koli National Park in Eastern Finland comprised measurements obtained from 33 sample plots with two separate experimental designs. These comprised a total of 18 plots belonging to the nationwide permanent sample plot network representing natural forests, established between 1998 and 2000, together with 15 plots located subjectively in mature stands of aspen (*Populus tremula* L.) which had been subject to silvicultural operations in the past. The data for the aspen stands had been obtained initially



Figure 2. Location of the study areas.

in 2005 for another purpose, to develop ALS-based methods for the recognition of large aspens (Säynäjoki et al. 2008). Site fertility on the various plots varied from fertile to relatively fertile.

The 18 permanent sample plots were circular in shape and of size 900–1600 m², and all the living and standing dead trees with a diameter at breast height (DBH) greater than 5 cm were measured. The plot size varied depending on the stand density. The Global Positioning System (GPS) with differential correction signal from the base station was used to determine the mid-point of each plot. DBH, total height, tree species, disturbances and the tree layer were recorded for living trees, and height (length) and DBH were measured for standing dead trees and snags. The 15 plots measured in the aspen stands were square in shape and of size 900 m² (30 m×30 m), except for one plot of 600 m² (20 m×30 m). The plots were situated in accordance with the cardinal directions and located by GPS using differential correction. The characteristics measured for every living and standing dead tree with a DBH greater than 5 cm (3 cm on the 20 m×30 m plot) were: DBH, diameter at six metres, height (length) and species.

Downed dead trees were measured on each of the 33 plots if they were not totally decayed, i.e. provided there was some above-ground mound visible. The diameter limits were the same as in the case of living and standing dead trees. Whole downed dead trees and logs on the 18 permanent plots, were measured if their large end was inside the plot. In the aspen stands, however, only the portions of the downed dead trees and logs which were lying inside the plot boundaries were measured. The characteristics measured for the downed dead trees were total length and the diameter at the assumed breast height. If the breast height could not be assessed, the diameter at the mid-point was measured (mid-diameter).

The height model of Näslund (1937) was fitted to the data for undamaged living trees by tree species, and the fitted models were then used to predict the total heights for the broken trees for which DBH had been measured. This enabled the volumes of the living and dead trees for which DBH had been measured to be calculated using either Laasasenaho's volume functions or taper curves (Laasasenaho 1982). Huber's formula was used to calculate the volumes of those trees which had their diameter measured at the mid-point (Schreuder et al. 1993). The mean CWD volume in the Koli area was 46.0 m³ha⁻¹, consisting of 18.7 m³ha⁻¹ and 27.3 m³ha⁻¹ for standing and downed dead trees, respectively.

2.1.2 *Sonkajärvi*

The forests of the area studied in Sonkajärvi in Central Finland are subject to commercial management and the age structure is slightly biased towards younger age classes. The field data were collected in 2007 by measuring 33 randomly located 100 m wide strips running in a north-south direction. The strips were restricted to areas for which stand-register data were available, and therefore their lengths varied from 188 m to 2824 m. The total area examined in the field was approximately 300 ha.

All the dead trees and at least 0.5 m long CWD pieces with a minimum large end (or stump-height) diameter of 10 cm were measured if the large end of the downed dead tree or log or the mid-point of the standing dead tree or snag was inside the strip. The height (length) and DBH or diameter at the mid-point were measured for downed and standing dead trees, snags and logs, and the direction of falling was recorded for the downed dead trees and logs. The diameter at the mid-point was measured instead of the DBH if the snags or logs were shorter than 1.3 m or the breast height could not be ascertained. Huber's

formula (e.g. Schreuder et al. 1993, Husch et al. 2003), or Laasasenaho's volume functions or taper curves (Laasasenaho 1982) were used to calculate the volumes of single trees and CWD pieces. In cases where piles of trees left from commercial thinnings or other human activities were found, the pile or single tree dimensions were used to estimate the timber volume. GPS with differential correction was used to determine the positions of all the observations. The mean CWD volume in the Sonkajärvi area was $2.7 \text{ m}^3\text{ha}^{-1}$, consisting of $1.1 \text{ m}^3\text{ha}^{-1}$ and $1.6 \text{ m}^3\text{ha}^{-1}$ for standing and downed dead trees, respectively.

In addition, stand-register data that had been obtained in 2006 or updated for the situation in 2006 by means of growth models were available for the Sonkajärvi area. These data were used only in paper IV. The data had been collected by means of a compartment-wise field inventory (see details in Kangas et al. 2004). The stand-register data included data on the living trees: basal area, mean volume, mean height and mean diameter by tree species.

2.1.3 Juuka

The field data from Juuka in Eastern Finland were collected within an area of $22 \text{ km} \times 5 \text{ km}$ in commercially managed forests in 2006 and comprised measurements of downed and standing dead trees on 301 plots altogether.

Circular sample plots, each with a radius of 9 m (254 m^2), were located mainly in a systematic network, although the locations of some plots were selected subjectively in order to introduce more variation into the data. GPS with a 4 m external antenna and differential correction was used to determine the mid-point of each plot. All the dead trees and CWD pieces at least 1 m in length and with a large end diameter of over 5 cm were measured if the large end of the downed dead tree or log or the mid-point of the standing dead tree or snag was inside the plot. The DBH and in most of the cases also the height (length) were measured for all the standing and downed whole dead trees. For snags and downed logs, the height (length) and the diameters of the large and small ends and at the mid-point were measured. If it was not possible to measure the diameters at both the large and small ends, only the diameter at the mid-point was measured.

The volumes of the whole trees were calculated using Laasasenaho's volume functions with one or two predictors (Laasasenaho 1982). Huber's formula (Schreuder et al. 1993, Husch et al. 2003) was used if the CWD piece had a diameter measurement only for its mid-point. If the diameters were measured at both the large and small ends, the formula for truncated cones was used. In cases where a broken trunk had three diameter measurements, the volume was calculated using Newton's formula (Husch et al. 2003). The mean CWD volume in the Juuka area was $6.3 \text{ m}^3\text{ha}^{-1}$, consisting of $2.9 \text{ m}^3\text{ha}^{-1}$ and $3.4 \text{ m}^3\text{ha}^{-1}$ for standing and downed dead trees, respectively.

2.2 Remote sensing data

The Georeferenced ALS point cloud data from Koli were collected in July 2005 using an Optech ALTM 3100 laser scanning system operated at a mean altitude of 900 m a.g.l (above ground level) using a half-angle of 11 degrees. This resulted in a swath width of 350 m and a nominal sampling density of about 4 measurements per m^2 . The sampling density varied across the scanning area, however, because the elevation within the area

varied from 95 m to 350 m a.s.l (above sea level). The area covered by the ALS data was approximately 25 km². The divergence of the laser beam (1064 nm) was 0.26 mrad.

The ALS data for Juuka were collected in August 2005 using the same laser scanning system as at Koli, at a mean altitude of 2000 m a.g.l. using a half-angle of 15 degrees and a pulse frequency of 50 kHz. This resulted in a swath width of 1070 m and a nominal sampling density of about 0.6 measurements per m². The ALS data for Sonkajärvi were collected in July 2006 using the same equipment, pulse frequency and scanning angle as in Juuka. The mean operating altitude at Sonkajärvi was 2500 m a.g.l., which resulted in a nominal sampling density of 0.5 measurements per m² and a swath width of 1350 m.

The aerial photographs available for the study area in Sonkajärvi had been taken with a Vexcel UltraCamD digital aerial camera in July 2006, at an altitude of 5800 m a.g.l. with a sidelap of 30% and an endlap of 60%. The sensor consisted of panchromatic, colour (red, green, blue) and near-infrared (NIR) bands. The final multispectral images were produced with the spatial resolution of the panchromatic band by means of a pan-sharpening process. Only the pan-sharpened NIR, red and green bands were used in the present work.

3 METHODS

3.1 Creation of a DTM and calculation of variables from the remote sensing data

The Optech ALTM 3100 laser scanner records up to four echoes (range measurements) for each pulse, of which only the categories ‘last of many’ and ‘only’ were used to create the DTM. The laser points were first classified as ground and non-ground hits using the TerraScan software and the method explained in Axelsson (2000), and then a raster DTM with a cell size of 1 m was created by calculating the value for each pixel as the mean height of the ground points located inside each cell. Values for raster cells which did not include ground points were derived using Delaunay triangulation and bilinear interpolation.

Heights above ground level, i.e. canopy heights, were obtained for the laser points by subtracting the DTM at the corresponding location. The ground points were excluded by assuming that the points for which the canopy height was less than the set lower height limit were ground points, and the remaining points were regarded as canopy points. A lower height limit of 0.1 m was used to separate the canopy points from the ground points in the Koli data (paper I), whereas at Juuka and Sonkajärvi (papers II–V) the limit was 0.5 m. The canopy points were then reclassified to ‘first echo’ or ‘last echo’ such that the first pulse data included both echo categories ‘first of many’ and ‘only’, and the last pulse data included the categories ‘last of many’ and ‘only’. Intermediate echoes were ignored completely.

ALS metrics were calculated for areas measured in the field in all papers (I–V). The heights of the canopy points were used to create the height distribution of the first and last pulse data for each sample unit. When data for Koli (paper I) or Juuka (paper III) were used, the sample units were the sample plots used in the field inventory, while in the case of the Sonkajärvi data (papers II–V), a systematic network of sample units was formed to cover the area. Canopy height percentiles for 0, 1, 5, 10, 20, ..., 90, 95, 99 and 100% (h_0 , h_1 , ..., h_{100}) were computed, and the corresponding proportional canopy densities (p_0 , p_1 , ..., p_{100}) were calculated (see Næsset 2002, 2004). In addition, the following variables were

calculated: intensities accumulating in the percentiles ($i_{10}, i_{30}, \dots, i_{90}$), means and standard deviations of the height and intensity values of the canopy points, and the proportion of ground points versus canopy points. The intensity values were used as indicated by the sensor, without any calibration. All metrics were calculated separately for both the first pulse data and the last pulse data. The actual ALS metrics used varied between the papers.

Spectral and textural features calculated for the aerial photographs were used in paper IV. The aerial photographs were orthorectified to a pixel size of 0.5 m using the DTM generated from the ALS data, and intensities (spectral values) were calculated for each sample unit, and the mean and accumulation by percentiles (0–100%) was calculated for each band. Grey-tones were used to calculate the textural features for the sample units using the method presented by Haralick et al. (1973).

3.2 Regression models

3.2.1 Models for CWD volume

In paper I, linear regression models were fitted for predicting plot-level downed and standing dead wood volumes in natural forests. ALS metrics were used as independent variables in the models, which were constructed separately for downed and standing dead trees. The sum of these estimates for downed and standing dead wood volumes provided an estimate of the total CWD volume. Downed dead wood volume was also estimated in paper I using measured living tree characteristics as independent variables. In order to compare the accuracy of models for CWD and living tree volumes, a model was fitted in which the living tree volume was predicted using ALS metrics as independent variables. Different combinations of predictors and several transformations of independent and dependent variables (e.g. logarithmic, square root and inverse) were tested when fitting the models.

It was observed here that it was not possible using the available data to construct logically functioning models in a biological sense that were of sufficient accuracy to predict CWD volumes in managed forests (see also Kotamaa 2007). Since the CWD volumes predicted with ALS-based models were not accurate, the focus in the case of managed forests was on improving the efficiency of sample-based field inventories of CWD using ALS data as auxiliary information. Hence, linear regression models were constructed in paper IV for use as auxiliary information. These employed ALS metrics and variables based on aerial photographs or stand-register data as independent variables for predicting the volumes of different CWD materials in the sample units. The square root of the dependent variable was used in each fitted model, since it was then guaranteed that the predictions would be positive.

The models were fitted with the R software (R Development Core Team 2006) using an ordinary least-squares method that minimizes the sum of squared residuals. The volume models were of the following general form:

$$Y = X\beta + \varepsilon, \quad [1]$$

where Y is the dependent variable, X is a matrix of independent variables, β is the parameter vector and ε is a random error term. When there was some transformation of the dependent variable but the interest lay in the values on the original scale, a bias correction

was used when calculating the back-transformed predictions (Baskerville 1972, Flewelling and Pienaar 1981, Snowdon 1991, Lappi 1993).

3.2.2 Models for the existence of CWD

Logistic regression models describe the relationship between binary outcomes and continuous independent variables (Dobson 1990, Alenius et al. 2003). In order to use ALS-based auxiliary information in inventories of CWD in managed forests, logistic regression models were fitted in papers II and III to predict the probabilities of different CWD materials existing in the sample units. When constructing the logistic regression models, the presence of different CWD materials (volume limit $0 \text{ m}^3\text{ha}^{-1}$) was given a binary outcome and the probability of CWD occurring in the sample units was predicted with the continuous independent variables derived from the ALS data. The logistic regression model can be expressed as follows (Hosmer and Lemeshow 1989, Dobson 1990):

$$\text{logit}(\pi_i) = \beta_0 + \beta_1 x_{1i} + \dots + \beta_j x_{ji} \quad [2]$$

$$\Leftrightarrow \pi_i = \frac{\exp(\beta_0 + \beta_1 x_{1i} + \dots + \beta_j x_{ji} + \varepsilon)}{1 + \exp(\beta_0 + \beta_1 x_{1i} + \dots + \beta_j x_{ji} + \varepsilon)} \quad [3]$$

where π_i is the probability for observation y_i , β_0 is the constant of the model and β_j is the parameter to be estimated for an independent variable x_j . x_{ji} is the j th independent variable connected with the observation y_i and ε the error term of the model, $i = 1, 2, \dots, N$. Equation 3 is intrinsically bounded within the interval $[0, 1]$. The GLM function with the R software was used to find the parameter estimates for the logistic regression models (R Development Core Team 2006).

3.2.3 Assessing the models

The parameters of all the fitted models (papers I–IV) were examined for logical consistency and biological realism (see Mabvurira and Miina 2002). Scatter plots were produced and the correlations were examined to check that the signs of the respective regression coefficients in the models corresponded to the response between the independent and dependent variables. The significance of the parameters in the models was assessed, and all the parameters were required to be statistically significant at the level $p = 0.05$. In addition, scatter plots in which the residuals were drawn as a function of the predictions or independent variables were inspected when fitting the linear regression models in paper I.

The means of the residuals (bias) and root mean square errors (RMSE) were used as reliability figures for the linear regression models to determine the accuracy of the predictions. These metrics were regarded as important criteria when selecting the forms of the model and their independent variables. The absolute bias and RMSE were calculated as follows:

$$bias = \sum_{i=1}^n \frac{(y_i - \hat{y}_i)}{n}, \quad [4]$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}, \quad [5]$$

where n is the number of observations, y_i is the observed value for observation i and \hat{y}_i is the predicted value for observation i . The relative figures were calculated by dividing the absolute values by the means of the observed values. Reliability figures were calculated for the back-transformed and bias-corrected models, and when using the complete modelling data sets.

When selecting the logistic regression models the predictions were compared with the observations by forming error matrixes and calculating the overall rates of corrections for the classifications in the modelling data sets. The classification accuracy was then regarded as an important criterion when selecting the models.

3.3 Compared sample-based field inventory methods for CWD

The sampling efficiencies of the inventories of the volumes of different CWD materials by the various inventory methods was studied without using auxiliary information in paper II, and with the use of auxiliary information in the design phase, by implementing PPS sampling when selecting the sample units in papers II–V. Auxiliary information was used when selecting the primary sample units for ACS in papers II–III, when selecting the sample units for the inventory of fixed-sized plots in papers II–IV and for strip sampling in paper V, and when using PRS, TRS or LIS in paper V. It was also used in the estimation phase in paper III, where the fixed-sized plots were first selected without using auxiliary information and then auxiliary information was used when calculating the estimates using ratio and regression estimators.

The efficiency comparisons were made by simulating the various inventory methods and designs in the Sonkajärvi study area. For this purpose, the strips measured in the field, which were dispersed throughout the area, were artificially gathered together to form a contiguous study area. The strips measured in the field were placed in their authentic spatial order and still oriented in a north–south direction but with a new coordinate system so that the resulting compilation was a rectangle with an area of approximately 300 ha. The same compilation was used in papers II, III and V, while the area examined in paper IV was smaller (250 ha), since not all the auxiliary data sources used in that paper were available for the whole inventory area. When the plots with fixed area were assessed in papers II–V (fixed-sized plots, ACS, strip sampling), a CWD piece was included in the sample if the stump or large end of a downed dead tree or log or the mid-point of a standing dead tree or snag lay inside the plot.

When the sampling efficiency of the inventory of fixed-sized plots was compared with other CWD inventory methods without the utilization of auxiliary information, in paper II, the fixed-sized plots were placed in the area to be examined using different sampling

strategies, including simple random sampling (SRS) (PLOT_{SRS}), systematic sampling ($\text{PLOT}_{\text{systematic}}$) and cluster sampling ($\text{PLOT}_{\text{cluster}}$) (see Gregoire and Valentine 2008). A cluster consisted of five plots: one in the middle and the others 30 m away in the cardinal directions. The simulated fixed-sized plots were circular, with a radius of 11.28 m, resulting in an area of 400 m². The sample plots (or points or lines) in the other inventory methods considered in paper II were located using SRS. Strip sampling was performed by defining 1100 m strips of varying widths (1–25 m) running in an east–west direction within the area. The estimators used in strip sampling are those presented in Cochran (1977) and Kangas (2006), for example.

When the use of PRS_{ddw} and TRS_{ddw} for assessing downed dead wood volumes was studied in paper II, a wide-angle relascope was used and all the downed dead tree logs which were long enough to fill an angle-gauge when viewed from a relascope point (PRS) or at any point along the transect (TRS) were included in the sample (Ståhl 1998, Gove et al. 1999, 2002). Correspondingly, when PRS_{sdw} and TRS_{sdw} were used in assessing standing dead wood volume, the trees with a diameter large enough to fill the angle-gauge when viewed from a relascope point or line were included in the sample (see Bitterlich 1947). In the relascope-based inventory methods, relascope angles of 25–75 degrees and relascope factors of 1–2 m²ha⁻¹ were tested when assessing downed and standing dead trees, respectively. The sample lines simulated in TRS and LIS were 1100 m long and ran in an east–west direction. All the downed dead trees which intersected the sample lines were measured in LIS (de Vries 1973), and the estimator presented by de Vries (1973) and Shiver and Borders (1996) was used to calculate estimates for the downed dead wood volume. In ACS, an initial sample of 20 m×20 m primary sample units was selected, and whenever the amount of dead wood in these exceeded the initially set critical value (10–30 m³ha⁻¹), four neighbours of that sample unit were added to the sample until no more secondary sample units could be added to the resulting network. A network in which only the primary sample unit was assessed formed a network of size one (see Thompson 1990, Thompson and Seber 1996, Salehi 2003). The estimators used in ACS are described by Thompson (1990) and Salehi (2003), for example.

The sample designs which were observed to be the most efficient for the different sampling methods when sampling with equal probabilities (paper II) were used to study the efficiency of PPS sampling in papers II–V. The shapes and areas of the sample plots assessed in the field were equal to the sample units, or else the sample points or lines were randomly located inside the sample units selected. In the case of fixed-sized plots and ACS (papers II–IV), both the sample units and the plots assessed in the field were square and of the same area. In paper V, the sample units varied in size and shape depending on the sampling method. In the case of strip sampling, the sample units selected and the strips assessed in the field were equal in shape and area, being 100 m long and either 1 m or 5 m wide. In LIS, sample lines of length 100 m were located randomly inside the sample units selected, which were 1 m wide and 100 m long, while in PRS and TRS the sample units were 20 m×20 m and the relascope points or 20 m sample lines, respectively, were located randomly inside the sample units selected. The strips and lines ran in an east–west direction.

3.4 Time taken for the field inventories

The times taken for the field inventories of CWD using the various methods and designs were needed in papers II–V for comparing sampling efficiencies. The measurement times on the sample plots (points or lines) and the walking times between the plots were estimated or calculated for each sampling method using actual times recorded during the fieldwork. The collection of auxiliary data was assumed to entail no additional cost, and no time consumption or costs for processing the auxiliary data were defined.

For the sampling methods where the plots were located randomly, the average length of the route which had to be walked in the field was defined. The average distance between two plots was assumed to be the square root of the area represented by one plot, and the route length in PLOT_{systematic} was assumed to be the same as in the case of PLOT_{SRS}. The time needed for walking between the plots in each sampling method was calculated by multiplying the average walking distance by the assumed walking speed in a forest of 0.5 h km⁻¹. The total time taken using different methods was obtained as the average of all the simulations with fixed sample sizes.

The times taken to measure CWD on the plots with a fixed area were estimated from the actual measurement times recorded during the fieldwork. The time taken to assess 1 m² was calculated by dividing the total measurement time by the total area measured, and this was transformed to express the measurement time required by two persons. On average, two persons could measure a plot of 400 m² in 3.4 min when considering only one CWD material. Since the measurement time increases with the amount of CWD, another estimate for the measurement time was produced for the secondary sample units in ACS, since the probability of finding CWD is higher in these cases. The measurement time for these sample units was therefore calculated from the field measurement times of the strips which included more CWD than average, and was defined as 10.4 min for a 400 m² plot when considering one CWD material. Furthermore, the revision of trees in strip sampling to determine whether they were located inside the strip or not is a time-consuming process, and there are more trees to be revised with a narrow strip width than with a wider strip in proportion to the area sampled. This was taken into consideration by adding a constant revision time of 30 min km⁻¹ for each strip.

The measurement times for LIS, PRS and TRS could not be calculated from the actual field data, and therefore needed to be estimated. It was assumed that the actual walking and measuring speed in LIS was approximately 1 km h⁻¹, while the measurement time in PRS and TRS depends on the relascope angle (or factor), since with smaller angles trees from further away are included in the sample, and it takes more time to measure trees which are a longer distance away from the sample line or point. The measurement time was taken intuitively to be 50 seconds per tree with a relascope angle of 25 degrees, 45 seconds per tree for an angle of 50 degrees and 40 seconds per tree for an angle of 75 degrees, and the corresponding measurement times were used for the inventories of standing dead trees with relascope factors of 1, 1.5 and 2 (m²ha⁻¹), respectively. In the case of TRS, it was assumed that walking along the line and searching for the trees takes 1 h km⁻¹.

3.5 Producing the probability layers

In papers II–V, auxiliary data values needed to be calculated for each sample unit in the population, since these values were then used either for selecting the sample units by PPS

sampling (papers II–V) or for calculating the estimates using ratio or regression estimators (paper III). ‘Probability layers’ were therefore produced in which the auxiliary data values were calculated for the whole area divided into the sample units of 20 m×20 m (papers II, III, V) or 10 m×10 m, 20 m×20 m, 25 m×25 m and 50 m×50 m (paper IV). Thus, when studying the use of auxiliary information, the sample units were square and are referred to hereafter as grid cells. In addition, the original probability layer in paper V, which consisted of grid cells of size 20 m×20 m, was modified so that sample units of various sizes were produced from the original grid cell network for the purposes of the different sampling methods.

The probability layers were calculated for the area where the sampling methods were simulated in Sonkajärvi, which was distinct from the area where the relationships between CWD volumes and the auxiliary variables were studied (in the modelling data). The sources of auxiliary data and the uses and sources of the modelling data in the various papers are presented in Table 1.

The modelling data were used in papers III and IV to calculate Pearson’s correlations between the auxiliary variables and the observed volumes of different CWD materials. The auxiliary variables found to have the highest absolute correlation values were then used directly to calculate the grid cell values. The results of paper III were also used in paper V, so that the probability layer that was found to be the most efficient in paper III was used in paper V as well. Furthermore, logistic regression models were fitted in papers II and III and used to calculate the grid cell values. In paper II, part of the data from the Sonkajärvi area was used in fitting models for the probability of downed or standing dead wood existing, using ALS metrics as independent variables. In paper III, ALS and CWD inventory data from an independent area in Juuka were used to fit a logistic regression model for the probability of CWD existing. In paper IV, the auxiliary variables were used directly to calculate the grid cell values if only one auxiliary data source was used. Thus, regression models were not fitted when only one data source was used, since it had been found in paper III that if ALS metrics were used as auxiliary variables it was advisable to use these directly to calculate the grid cell values. When two data sources were combined in paper IV, however, linear regression models were constructed for combining the best-correlating ALS metric with the best-correlating variable based on aerial photographs or stand-register

Table 1. Sources of auxiliary data and sources and uses of modelling data in the original papers. SRD = stand-register data, AP = aerial photographs.

Paper	Auxiliary data	Modelling data and use
II	ALS	Part of the data for Sonkajärvi, for fitting the logistic regression models
III	ALS	Data for an independent area in Juuka, for studying the best-correlating auxiliary variables and fitting the logistic regression model
IV	ALS, AP, SRD	Part of the data for Sonkajärvi, for studying the best-correlating auxiliary variables and fitting the linear regression models
V	ALS	The best ALS metric, based on the results in paper III

data. In this case, linear regression models were fitted instead of logistic regression models, for example, since they provided slightly better auxiliary information when two auxiliary data sources were used.

Thus, the grid cell values for the resulting probability layers were the predictions calculated by the model or the values of variables based on ALS, aerial photograph, or stand-register data. Since probability sampling theory requires the selection probabilities for each sample unit to be strictly positive, positive values had to be assigned for those grid cells where no auxiliary data were available or the auxiliary data value was zero (Hájek 1981, Särndal et al. 1992, Schreuder et al. 1993). Different methods for calculating the values for such grid cells were tested in paper IV, while in papers II, III, and V the same selection probability as for the grid cell which had the smallest auxiliary data value or model prediction was assigned to those grid cells where auxiliary data were missing or the value was zero.

3.6 Use of auxiliary information in the design and estimation phases

When auxiliary information was used in the design phase by implementing PPS sampling, auxiliary data values were calculated for each sample unit, $i = 1, \dots, N$, and the probabilities of each unit i being selected in a single draw were determined. The selection probabilities for the sample units, p_i , were calculated by dividing the auxiliary data value x_i for sample unit i by the sum of the auxiliary data values over the whole area of the probability layer, $p_i = x_i / \sum x_i$ (see Figure 1). When auxiliary information was used in the design phase, the sample units were drawn using these selection probabilities (PPS sampling) and with replacement.

When PPS sampling was used in inventories of fixed-sized plots or strip sampling, or in selecting sample units in PRS, TRS or LIS, the selection probabilities for the sample units and the values for the variable of interest observed in the area of each sample unit were used to estimate the population total and mean. The Hansen-Hurwitz estimator (Eqn. 6) was used to calculate an unbiased estimate of the CWD volume (m^3) (Hansen and Hurwitz 1943, Thompson 2002).

$$\hat{\tau}_{HH} = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{p_i}, \quad [6]$$

where y_i is the CWD volume (m^3) for the i th sample unit. n is the number of sample units drawn, and p_i is the probability of selecting the i th unit of the population in a single draw where the sum of p_i , $i = 1, \dots, N$, is one. The estimate for the mean CWD volume (m^3ha^{-1}) was calculated by dividing the estimated total volume by the study area in hectares.

When PPS sampling was used in ACS, an estimate for the mean CWD volume (m^3ha^{-1}) was calculated as (Thompson and Seber 1996)

$$\hat{\mu}_{HT} = \frac{1}{N} \sum_{k=1}^K \frac{y_k^*}{\alpha_k}, \quad [7]$$

where κ is the number of distinct networks intersected by the initial sample, and y_k^* is the sum of CWD volumes (m^3ha^{-1}) for the k th network. α_k is the probability of the initial sample intersecting the network k . The α_k s for all units in the network k are equal. The intersection probabilities were calculated as (Thompson and Seber 1996)

$$\alpha_k = 1 - \left(1 - x_k / \sum_{i=1}^N x_i \right)^n, \quad [8]$$

where n is the number of primary sample units and x_k denotes the sum of the auxiliary data values in the k th network (see Smith et al. 1995, Thompson and Seber 1996).

When auxiliary information was used in the estimation phase, SRS with replacement was first used to select the sample units. After that, the population total and mean of the auxiliary data values were calculated, together with the auxiliary data values in the sample units drawn (see Figure 1). The ratio estimate of the population mean was then calculated as (see Thompson 2002)

$$\hat{\mu}_{ratio} = \frac{\sum_{i=1}^n y_i}{\sum_{i=1}^n x_i} \mu_x = \frac{\bar{y}}{\bar{x}} \mu_x = r \mu_x, \quad [9]$$

where n is the sample size, r is the sample ratio and μ_x is the population mean of the auxiliary data values, calculated as the mean of the auxiliary data values over the whole area. \bar{x} is the sample mean of the auxiliary data values, and \bar{y} is the sample mean of the variable of interest, i.e. the mean CWD volume (m^3ha^{-1}) in the sample units. The regression estimate for the population mean was calculated as

$$\hat{\mu}_{regression} = \bar{y} + b(\mu_x - \bar{x}), \quad [10]$$

where

$$b = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}, \quad [11]$$

where x_i is the auxiliary data value in sample unit i , and y_i is the measured CWD volume (m^3ha^{-1}) in the same area.

3.7 Investigating the probability layers

The skewness of the frequency distributions of the auxiliary data values was analyzed in paper IV, since it has been observed that the efficiency of PPS sampling may depend on this (Schreuder et al. 1987). The R program was used to calculate the skewness for each of the produced probability layers as follows (R Development Core Team 2006):

$$skewness = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2\right)^{3/2}}, \quad [12]$$

where n is the number of grid cells, x_i is the value of grid cell i , and \bar{x} is the mean of the grid cell values over the whole area of the probability layer. The skewness is near to zero for a normal distribution, while positive skewness means that the right tail of the frequency distribution is longer and the data points are skewed to the right. A skewness greater than 0.8 is notable (Bourque and Clark 1992).

3.8 Simulation and comparison of sampling efficiencies

Various sampling methods were simulated in papers II–V, either with or without the use of auxiliary information, on the forest area where every downed and standing dead wood log had been precisely located. When the sample units were drawn and the sample plots (or points or lines) had been located, the CWD data measured for the corresponding plot location in the field were used to calculate estimates for the mean CWD volume in the population as obtained from that sample plot. The simulations were carried out separately for each CWD material studied.

Thousands of samples were simulated for the area with each sampling method and design, on the basis of which estimates were calculated for the population mean, the absolute standard error of the mean (also known as the standard deviation of the mean) and the bias. Proportional values were obtained by dividing the absolute values by the observed mean volume. The proportional standard error of the mean is often referred to as the coefficient of variation (Särndal et al. 1992, Lehtonen and Pahkinen 2004). The simulated sample size was varied and the sampling efficiencies (standard errors of the mean) achieved by the different inventory methods were calculated. The sampling efficiencies for different sampling methods for a given inventory time were compared by first calculating the difference in the standard errors of the means between two sampling methods, and then calculating the relative difference in sampling efficiency.

4 RESULTS

4.1 Models for predicting CWD volumes in natural forests (I)

When constructing the linear regression models for predicting the downed and standing dead wood volumes in natural forests in paper I the smallest RMSEs used for verification of the accuracy of the models were obtained for the models with logarithmic transformations of the dependent variables. The standard deviation of the first return heights was the most significant independent variable in the models. In addition, one intensity metric was added to both of the models as an independent variable, since this was observed to produce notably smaller RMSEs. All the parameters in the models were statistically significant and the signs of the coefficients corresponded to the responses between the dependent and independent variables. The positive parameter estimates for the intensity metric and the variation in the first return heights indicated that when the intensity value or the variation in the first return heights increased, higher downed and standing dead wood volumes were observed.

The absolute and relative RMSEs for downed and standing dead wood volume predictions using ALS-based CWD models were $14.1 \text{ m}^3\text{ha}^{-1}$ (51.6%) and $14.7 \text{ m}^3\text{ha}^{-1}$ (78.8%), respectively. Thus, the downed dead wood volumes were estimated more accurately than were the standing dead wood volumes. The accuracy of the ALS-based CWD models did not improve if the plot-level living tree characteristics measured in the field were added as independent variables. The smallest RMSE obtained for the downed dead wood prediction model which had only living tree characteristics as independent variables was $23.4 \text{ m}^3\text{ha}^{-1}$ (85.7%), whereas that for the ALS-based volume prediction model for living trees was $41.8 \text{ m}^3\text{ha}^{-1}$ (12.7%). The RMSE obtained for total CWD volume calculated as the sum of the ALS-based predictions for downed and standing dead wood volumes was $24.9 \text{ m}^3\text{ha}^{-1}$ (54.2%).

The residuals of the ALS-based CWD models were fairly homogeneous, and no obvious dependences or patterns that might reveal improper specification of the regression models were discovered. The forms of the models for predicting downed and standing dead wood volumes are presented in Figure 3, where the predicted volumes of different CWD materials are drawn as a function of the field observations. The predictions for total CWD volume in Figure 3 were obtained by summing those for downed and standing dead wood volumes.

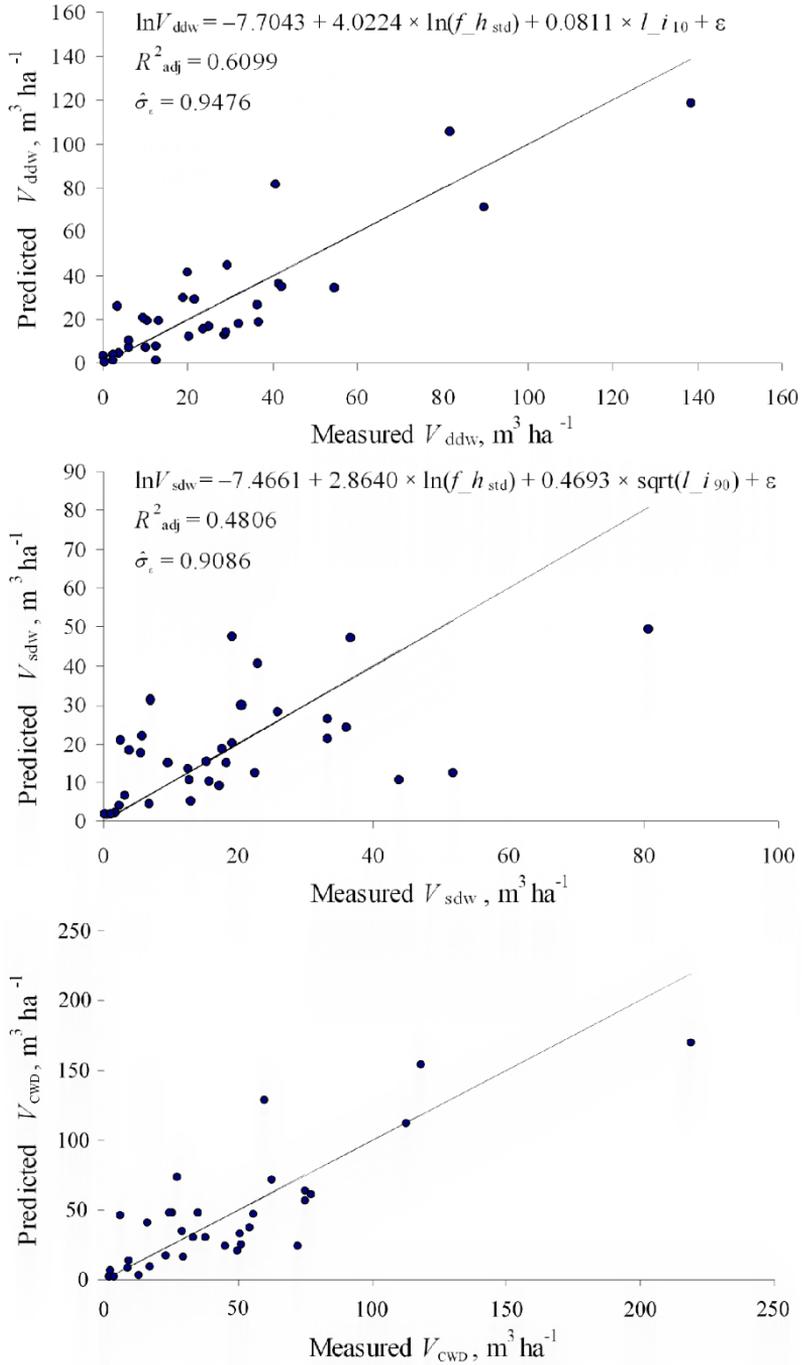


Figure 3. Forms and goodness of fits of the models obtained for the predicted volumes of different CWD materials.

4.2 Sample-based CWD inventory without auxiliary information (II)

When auxiliary information was not used in paper II in the selection of sample units for the field inventory, the sampling methods varied markedly in efficiency. Increasing inventory time improved the sampling efficiency rapidly at first, but more slowly with longer inventory times.

When using ACS in the CWD inventory, the sampling efficiency was highest with large critical values, since with small critical values the area to be surveyed was large and the efficiency of the method did not increase relative to the increased investment of time. The sampling efficiency for strip sampling was highest with narrower strip widths, but the time spent in checking whether trees should be included in the sample reduced the sampling efficiency for inventories with extremely narrow strips less than 5 m in width. The use of different relascope angles (or factors) led to only minimal differences in efficiency, although small angles usually proved to be more efficient in PRS than wider angles, whereas TRS was most efficient when wider angles were used.

Due to autocorrelation of the observations located close to each other in the clusters, $PLOT_{\text{cluster}}$ was the least efficient inventory method. Given a fixed inventory time for assessing downed dead trees, $PLOT_{\text{cluster}}$ produced an average of 8% greater standard errors of the mean than $PLOT_{\text{SRS}}$, while the increases in the standard error of the mean for standing dead trees and total CWD volume were 22% and 28%, respectively. There were no notable differences in the sampling efficiencies for $PLOT_{\text{SRS}}$ and ACS when inventorying different CWD materials, and the sample variances were similar on average in both $PLOT_{\text{SRS}}$ and $PLOT_{\text{systematic}}$, although the true variance in $PLOT_{\text{systematic}}$ was observed to be less consistent. The properties of the data or compilation and the simulation procedure used may have contributed to the observed inconsistency.

The field inventory methods which were specifically designed for inventories of CWD or other rare characteristics were usually observed to be the most efficient. Strip sampling was slightly more efficient than $PLOT_{\text{SRS}}$, and its efficiency in inventories of downed dead trees could be further increased by narrowing the strip width and making observations only on a sample line (LIS). The relascope-based sampling methods TRS and PRS were the most efficient methods for inventories of all CWD materials. When the efficiency comparison was performed using $PLOT_{\text{SRS}}$, the use of TRS_{ddw} and PRS_{ddw} improved the sampling efficiency by 26% and 29%, respectively. The use of TRS_{sdw} and PRS_{sdw} improved the sampling efficiency for the inventory of standing dead wood volumes by 25% and 49%, respectively, while TRS and PRS were 34% and 43% more efficient than $PLOT_{\text{SRS}}$ for surveying total CWD volumes.

Since standing dead trees cannot be assessed using LIS, sampling efficiency was evaluated for methods by which inventories of downed dead trees were performed using LIS at the same time as standing dead trees were assessed from either 1 m wide strips or circular plots, or by TRS_{sdw} or PRS_{sdw} . The most efficient inventory method for total CWD volume among those where LIS was combined with other sampling methods for standing dead trees was PRS_{sdw} where points were measured every 50 m along the sample lines. The methods in which both CWD materials were assessed using TRS or PRS nevertheless had a better sampling efficiency than the combination of LIS with PRS_{sdw} . The proportional standard error of the mean for total CWD volume estimates with different inventory methods is presented as a function of field inventory time in Figure 4.

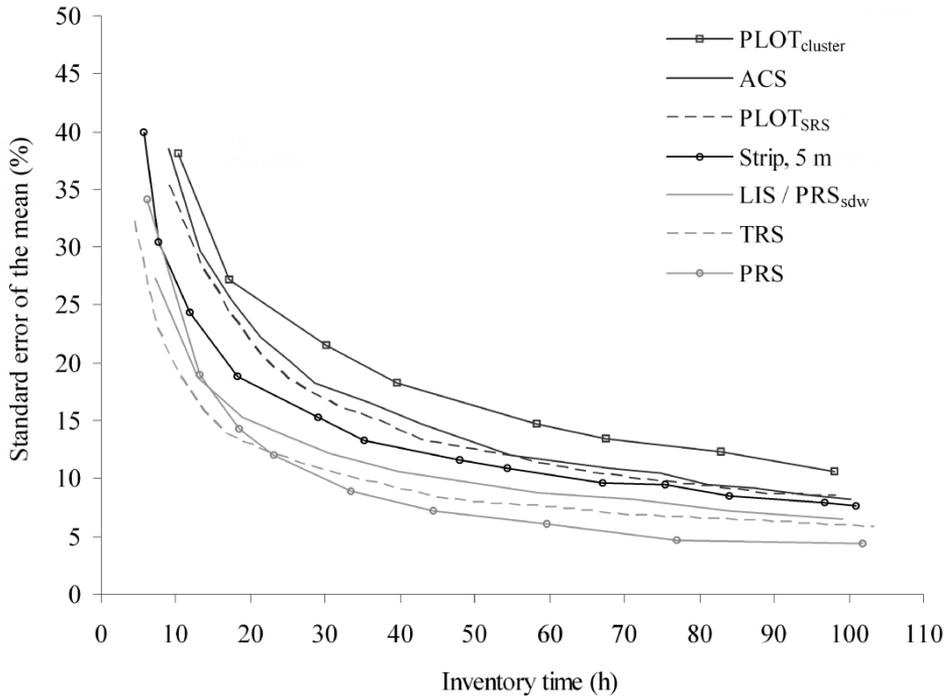


Figure 4. Standard error of the mean (%) for total CWD volume estimates (m^3ha^{-1}) with different sampling methods as a function of inventory time (h).

4.3 Sample-based CWD inventory with the use of auxiliary information

4.3.1 Probability layer values (II–V)

The forms and parameter estimates of the logistic regression models fitted in papers II and III for the different CWD materials are presented in Equations 13–15. The logistic regression models predict the probability, π_i , of sample unit i including dead wood.

$$\pi_{i,ddw} = \frac{\exp(-1.2076 + 0.1249 \times f_{-h_{30i}})}{1 + \exp(-1.2076 + 0.1249 \times f_{-h_{30i}})} \quad [13]$$

$$\pi_{i,sdw} = \frac{\exp(-4.0311 + 1.1525 \times \sqrt{f_{-h_{20i}}} - 0.5433 \times \ln(f_{-p_{0i}}))}{1 + \exp(-4.0311 + 1.1525 \times \sqrt{f_{-h_{20i}}} - 0.5433 \times \ln(f_{-p_{0i}}))} \quad [14]$$

$$\pi_{i,CWD} = \frac{\exp(-3.2607 + 0.3434 \times l_{-h_{90i}})}{1 + \exp(-3.2607 + 0.3434 \times l_{-h_{90i}})} \quad [15]$$

Since the p -values for all the parameter estimates were <0.001 , the independent variables were statistically highly significant. The prefix f or l in Equations 13–15 denotes the laser pulse type: first or last pulse, h_X denotes the height at which the accumulation of laser pulse heights in the vegetation is X percent, and p_X denotes the proportion of laser pulses accumulating at the X percent height. Positive parameter estimates for the height metrics indicate that the higher the accumulated heights in different percentiles are, the greater is the probability of different CWD materials being present. This corresponds to the findings of CWD dynamic studies (Sippola et al. 1998, Siitonen 2001), since the height of the tree stock is positively correlated with CWD volumes. f_{p_0} is same as the inverse of the number of first return canopy pulses, which in turn had a statistically significant positive correlation with standing dead wood volume, so that f_{p_0} was negatively correlated. Since the inclusion of that metric improved the model considerably, it was taken into the logistic regression model for standing dead wood as an independent variable.

Equations 13 and 14 were used in paper II for calculating the auxiliary data values for the grid cells over the whole area of the probability layer. Since only models for downed and standing dead trees were fitted in paper II, the auxiliary data values used for PPS sampling in the inventory of total CWD were obtained by adding the grid cell values for downed and standing dead trees together. In paper III, only total CWD was studied, and Equation 15 was used to calculate the grid cell values.

In addition, in paper III the ALS-derived height, density and deviation metrics which had the highest Pearson's correlation with CWD volume in the independent study data were searched, after which three probability layers were produced by calculating the values of those ALS metrics for each grid cell. The ALS-derived heights in the upper percentiles captured by the first pulse ($f_{h_{60}}$) and the standard deviation of the heights ($f_{h_{std}}$) had the strongest positive correlations with CWD volume (Table 1 in paper III), these being similar in strength in the independent data area in Juuka and the simulation data area in Sonkajärvi: 0.37 and 0.33, respectively, in Juuka and 0.32 and 0.30, respectively, in Sonkajärvi. Thus, if the standard deviation in the heights increased, greater CWD volumes were observed in both areas. The standard deviation of the first return heights was also used to produce the probability layer in paper V, since it had been observed to be efficient in paper III.

In paper IV the Pearson's correlations between the volumes of different CWD materials and auxiliary variables were studied with varying grid cell sizes in the modelling data, whereupon the variables based on ALS, stand-register data and aerial photographs which were observed to be highly correlated with CWD volumes were used to calculate the auxiliary data values for four grid cell sizes in the simulation area. It was observed that the greater the grid cell size was, the higher the observed correlations were.

The living tree volume (m^3ha^{-1}) in the stand-register data usually had the strongest correlation with the observed volumes of different CWD materials, and that variable was therefore used in paper IV to produce the probability layers based on stand-register data. The correlations in the modelling data varied from 0.12 to 0.36 depending on the CWD material and grid cell size. CWD volume is correlated with stand age (Siitonen et al. 2000), and this explains the reason for the positive correlation observed between CWD volumes and the mean living tree volume.

In the modelling data, the height at which the accumulation of first return heights in the ALS data was 50% ($f_{h_{50}}$) had the highest correlations (0.16 to 0.48) with the volumes of almost every CWD material in the different grid cell sizes, and it was therefore this metric that was used in paper IV to produce probability layers based on the ALS data. Since the height of the tree stock is correlated with CWD volumes and the ALS metric $f_{h_{50}}$ is positively correlated with the height of the tree stock, increase in the height of the ALS hits indicates an increase in CWD volume.

It was observed in paper IV that only minor correlations existed between the CWD volumes and textural features of aerial photographs. In the modelling data, the highest correlations involving the percentile-based aerial photograph metrics were negative (-0.12 to -0.36) and the variable which had the strongest correlation with CWD volume varied greatly depending on the CWD material. Since it was observed that the average intensity in the NIR band (avg_{NIR}) was fairly well correlated with CWD volumes in all grid cell sizes and for all CWD materials, that metric was used for all the CWD materials when producing the probability layers based on aerial photographs. Since the correlation was negative, however, two transformations (e.g. inverse) were tested for rendering it positive when producing the probability layers. The negative correlation between avg_{NIR} and CWD volumes stemmed from the low reflectance in spruce-dominated stands, where larger amounts of CWD existed.

4.3.2 Skewness of the frequency distributions (IV)

The skewness of the frequency distributions of the auxiliary data values was studied more closely in paper IV. The frequency distributions of the probability layers based on ALS data were fairly normally distributed and those in the layers based on stand-register data were fairly uniformly distributed, but those in the layers based on aerial photographs were heavily skewed to the right. The frequency distributions of the probability layers in which ALS data were combined with aerial photographs or stand-register data were also somewhat skewed to right. The skewness decreased slightly when the grid cell size was increased. In the case of 50 m grid cell size, the frequency distribution of the values based on aerial photographs differed from those found with smaller grid cell sizes, since the values were nearly normally distributed.

4.3.3 Sampling efficiencies (II–V)

The sampling efficiency for the inventory of the volumes of different CWD materials improved substantially when PPS sampling was used (papers II–V), whereas the use of a ratio or regression estimator was not especially efficient (paper III). It was observed when calculating the sampling efficiencies that the improvements were almost constant for any given inventory time. On average, the use of a ratio estimator improved the sampling efficiency for the inventory of total CWD volume by 5%, and the regression estimator by 6% (paper III). The improvements in the sampling efficiencies for inventories of different CWD materials varied notably when different probability layers and inventory methods were used. Average improvements in sampling efficiencies are presented in Table 2 for different CWD materials and inventory methods when using varying auxiliary data sources in PPS sampling.

It is seen in paper II that the sampling efficiencies in inventories of fixed-sized plots and ACS could be improved by 7–21% and 7–22%, respectively, when estimates calculated with ALS-based logistic regression models fitted using local data were used as auxiliary information in PPS sampling (Table 2). The logistic regression model which was fitted using data from an independent area (paper III) did not improve the sampling efficiency for the inventory of total CWD volume as much as the use of a model fitted using local data (paper II). Furthermore, when only one auxiliary data source was used, the best-correlating ALS metric selected by analyzing the relationships in the data from the independent study area (paper III) or the local data (paper IV) improved the sampling efficiency for the inventory of downed dead wood and total CWD most (Table 2).

Table 2. Improvements in sampling efficiency when using auxiliary information in different inventory methods. The results show the proportional improvement in sampling efficiency when PPS sampling is used instead of SRS for sample unit selection. The term ‘plots’ refers here to an inventory of fixed-sized plots, and the results for that method are presented with a sample unit size of 20 m×20 m.

Paper	Auxiliary information	Downed dead wood					
		Plots	ACS	Strip, 5 m	PRS	TRS	LIS
II	ALS-based logistic model	7%	7%	---	---	---	---
IV	Best ALS metric	12%	---	---	---	---	---
IV	Best variable based on SRD	11%	---	---	---	---	---
IV	Best variable based on AP	4%	---	---	---	---	---
IV	ALS combined with SRD	10%	---	---	---	---	---
IV	ALS combined with AP	12%	---	---	---	---	---
V	Same ALS metric as in paper III	---	---	8%	5%	5%	5%
		Standing dead wood					
		Plots	ACS	Strip, 5 m	PRS	TRS	LIS
II	ALS-based logistic model	21%	22%	---	---	---	---
IV	Best ALS metric	16%	---	---	---	---	---
IV	Best variable based on SRD	15%	---	---	---	---	---
IV	Best variable based on AP	5%	---	---	---	---	---
IV	ALS combined with SRD	16%	---	---	---	---	---
IV	ALS combined with AP	14%	---	---	---	---	---
V	Same ALS metric as in paper III	---	---	17%	10%	15%	---
		Total CWD					
		Plots	ACS	Strip, 5 m	PRS	TRS	LIS
II	ALS-based logistic model	14%	11%	---	---	---	---
III	ALS-based logistic model (indep. area)	7%	4%	---	---	---	---
III	Best ALS metric (indep. area)	17%	12%	---	---	---	---
IV	Best ALS metric	16%	---	---	---	---	---
IV	Best variable based on SRD	13%	---	---	---	---	---
IV	Best variable based on AP	7%	---	---	---	---	---
IV	ALS combined with SRD	18%	---	---	---	---	---
IV	ALS combined with AP	17%	---	---	---	---	---
V	Same ALS metric as in paper III	---	---	17%	5%	10%	---

When a variable based on aerial photographs was used in paper IV, a transformation needed to be performed to render the relationship between CWD volumes and the auxiliary data values positive. The inverse transformation of that variable was slightly more efficient than the other transformation, which kept the relative differences between the auxiliary data

values the same as before the transformation (see paper IV). The sampling efficiencies were similar when either ALS or stand-register data were used in PPS sampling, but when aerial photographs were used the improvements in efficiency were notably smaller (Table 2). When the probability layers were produced by combining the variable based on ALS data with the variable based on aerial photographs or stand-register data, the improvement in sampling efficiency depended on the CWD material and grid cell size. When two auxiliary data sources were combined, the sampling efficiency was not markedly better than when only ALS data were used, and in some cases it was worse (Table 2). Since either stand-register data or ALS metrics were lacking for the areas of over 10% of the grid cells in the simulation data in paper IV, over 10% of the grid cell values in the probability layer made by combining these data sources were equal, and thus the sampling efficiency was not as high as it would have been if auxiliary data had been available for the whole area. In addition, the frequency distributions of the auxiliary data values in the probability layers produced by combining the two data sources were more skewed than the frequency distributions of the ALS or stand-register data separately. These circumstances or other data properties may have led to inefficient samples (paper IV). Furthermore, it was observed in paper IV that the sampling efficiencies were higher if the missing or zero auxiliary data values were replaced with the minimum values rather than using the average of the existing auxiliary data values, for instance.

The use of PPS sampling in PRS_{sdw} and TRS_{sdw} in paper V improved the sampling efficiency for the inventories of standing dead wood volume by 10% and 15%, respectively, but the sampling efficiency for the inventories of downed dead wood volume improved by only 5% if PPS sampling was used in PRS_{ddw} , TRS_{ddw} or LIS (Table 2). When assessing total CWD volume, the use of PPS sampling in PRS and TRS improved the sampling efficiency by 5% and 10%, respectively. Nevertheless, even if the improvements in sampling efficiency were not as high in the relascope samplings, the latter were still the most efficient methods for inventories of different CWD materials (see Figure 5 for total CWD volume). With a given inventory time, the use of PPS sampling with 1 m strips increased the sampling efficiency for the inventories of downed dead wood and total CWD volume by approximately 12% and 11%, respectively, although the efficiency of the inventory of standing dead wood volume improved by only 3%. On the other hand, the improvements in sampling efficiency were different with a strip width of 5 m (Table 2). Thus, strip width and the CWD material concerned had notable effects on the improvement in sampling efficiency, but 5 m strip sampling was consistently more efficient than the use of narrower strips for all CWD materials. In Figure 5, standard errors of the mean for total CWD volume estimates are presented for the different inventory methods as a function of field inventory time using PPS sampling, given that the best-correlating ALS metric from the independent study area was used in the production of the probability layer (papers III and V).

When sampling with equal probabilities was used in inventories of downed and standing dead wood volumes, these were most efficient with grid cell sizes of 20 m and 25 m, while the use of 10 m grid cells was also efficient for total CWD volume. Even though the use of PPS sampling improved the sampling efficiency most with larger grid cell sizes, the smallest grid cells were the most efficient. The standard error of the mean for total CWD volume estimates is presented as a function of field inventory time in Figure 6, using different grid cell sizes and either sampling without auxiliary information or using the most efficient auxiliary data source in PPS sampling (paper IV).

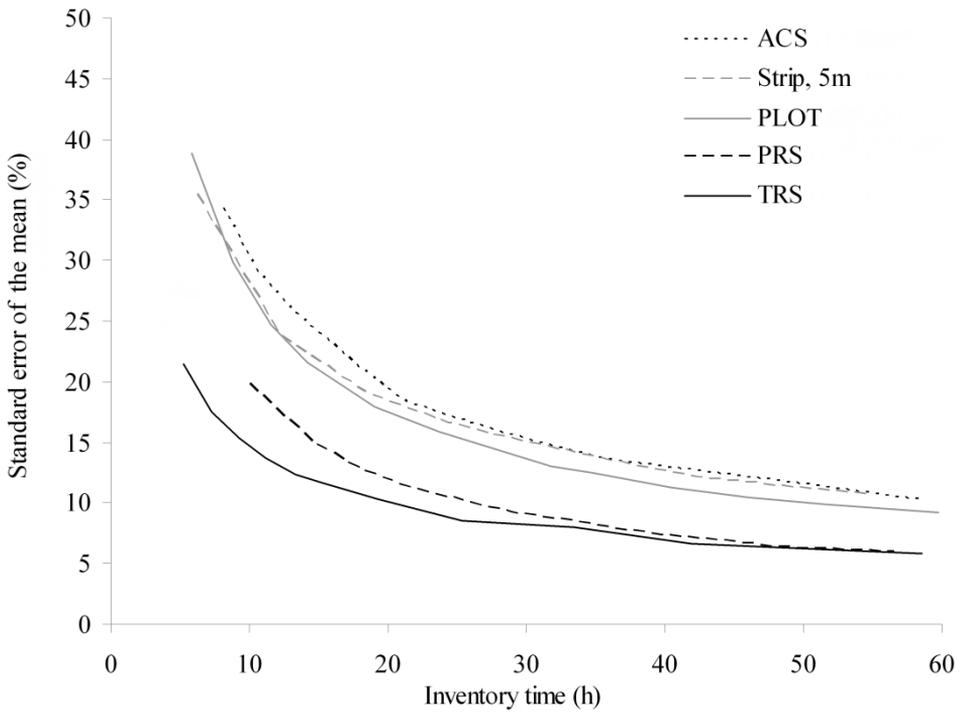


Figure 5. Standard error of the mean (%) as a function of inventory time (h) for CWD volume estimates (m^3ha^{-1}) obtained with different sampling methods using ALS-based auxiliary information in PPS sampling. The term 'plot' refers here to inventories of fixed-sized plots.

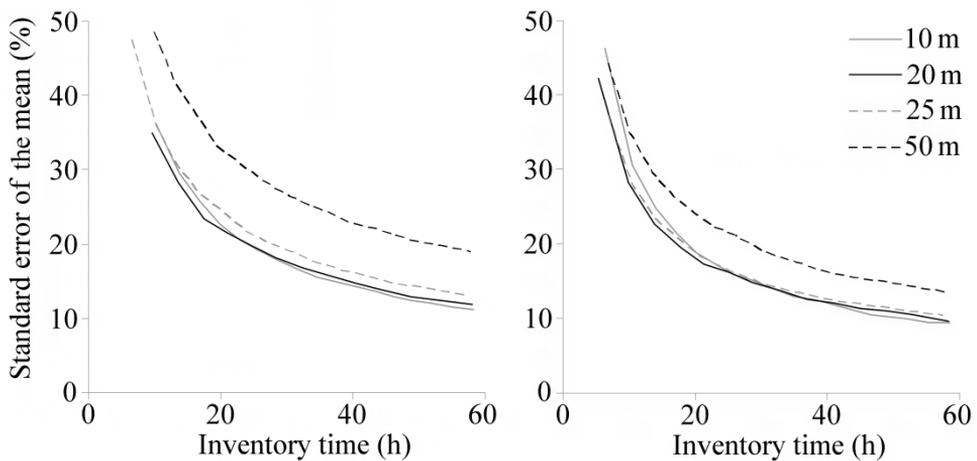


Figure 6. Standard error of the mean (%) for total CWD volume estimates without (left) and with (right) the use of auxiliary information in the design phase of inventories of fixed-sized plots. The standard errors of the means are presented for four grid cell sizes as a function of field inventory time (h).

It was observed in papers III and IV that the efficiency of PPS sampling was not directly proportional to the correlation between the variable of interest and the auxiliary variable. The improvement in sampling efficiency could be well explained by the correlation between the auxiliary data values and CWD volumes, but the skewness of the frequency distribution of the auxiliary data values also had a notable effect on the sampling efficiency. A statistically significant negative correlation existed between the improvement in sampling efficiency and skewness, and the correlation between the auxiliary data values and CWD volumes also had a strong negative relation to skewness. Nonetheless, it was perceived that if the probability layers based on aerial photographs were removed from the analyses, since those were the only layers which were highly skewed with 10–25 m grid cell sizes, the correlations were no longer statistically significant.

5 DISCUSSION

The purpose of this thesis was to study whether ALS data can be used for inventories of CWD volumes. It was observed that ALS data were quite accurate for predicting CWD volumes in natural forests but could be used only as auxiliary information in managed forests, in either the design or the estimation phase of a sample-based field inventory, since the construction of a sufficiently well-functioning model for predicting CWD volumes in managed forests was not successful. The use of aerial photographs and existing stand-register data as auxiliary information was also studied.

5.1 CWD modelling

The prediction of ALS-based living tree volume is notably more accurate than the prediction of downed and standing dead wood volumes. The relative RMSE for plot-level ALS-based estimates of living tree volume obtained here was 12.7%, which is of the same magnitude as the RMSE of 10% observed by Maltamo et al. (2006a) on sample plots of a similar kind. The RMSEs for downed dead wood, standing dead wood and total CWD volumes, however, were 51.6%, 78.8% and 54.2%, respectively.

The amount of CWD is usually considerably smaller than the living tree volume in the same forest (e.g. Siitonen 2001), and when the proportion of dead wood is small, the characteristics of the ALS point data are influenced more by the living trees. Thus, ALS metrics have a potential for representing living tree characteristics better than CWD volumes. This means that it is more difficult to use ALS data to predict CWD volumes than to predict living tree characteristics. In addition, the relative RMSEs for CWD volumes become higher than those for living trees, since even a small absolute RMSE results in a large relative RMSE when the average CWD volume in an area is small.

Metrics derived from the vertical structure of a natural forest were good predictors for downed dead wood volumes, but the estimation of standing dead wood volumes was more challenging. The data used for modelling downed dead wood volumes were not the best possible, however, since there were 18 sample plots which belonged to the permanent network on which only the downed dead trees and logs which had their stumps or large ends inside the plot were measured. The accuracy of the downed dead wood volume

prediction model might have been slightly better if only the downed dead wood pieces lying inside the plot boundaries had been measured on all the plots, since the ALS metrics used as independent variables were calculated for the canopy points inside the plot area.

Kim et al. (2009) used intensity metrics derived from ALS data of over 6 pulses m^{-2} to estimate the above-ground biomass of standing dead trees in conifer-dominated forests in the USA, and obtained a RMSE of 63.2% for the plot-level standing dead wood biomass, i.e. their estimates for standing dead wood biomass were slightly more accurate than those for standing dead wood volume presented in paper I of this thesis. Even though the geographical area and data differ considerably, the two sets of results can be regarded as being of the same magnitude.

Using aerial photographs, Uuttera and Hyppänen (1998) observed an average error of 50–108% for the estimate of standing dead wood volumes. The use of aerial photographs for inventories of CWD has usually been based on visual or manual interpretation, however (e.g. Büttler and Schlaepfer 2004, Holopainen et al. 2006), which may be time-consuming and prone to subjective errors, and therefore more automated inventory methods should be considered. Pasher and King (2009) have observed recently that aerial photographs and various direct mapping methods are highly accurate for the assessment of the number of dead branches and snags, but the standard error for the predicted plot-level downed dead wood volumes was still 62.1%. It should be noted in connection with the use of aerial photographs that the spectral variation within and between the images limits the usability of photographs acquired with different instruments or under different weather conditions, for example (see Holopainen and Wang 1998, Packalén 2009). Problems related to changing illumination conditions do not occur when using ALS data, and the latter are therefore regarded as a promising data source for future forest inventories, including inventories of CWD.

5.2 Field inventories of CWD

Sample-based field inventories of CWD in managed forests were most efficient when special methods developed for CWD or other rare forest characteristics were used. Relascope-based inventory methods in particular were observed to be efficient for both downed and standing dead trees. Similar results have been reported elsewhere, in that Ståhl and Lämås (1998), for instance, perceived that strip sampling and TRS were the most efficient methods for assessing downed dead wood volumes in different kinds of forests, while Brisette et al. (2003) and Jordan et al. (2004) in the North America have observed PRS to be a highly efficient inventory method. The variable of interest (e.g. volume, length or number of CWD pieces) and the forest conditions, for instance, have nevertheless been observed to have a notable effect on the preferred sampling method (Jordan et al. 2004, Woldendorp et al. 2004). In addition, several problems have occurred in the use of relascope sampling for CWD inventories (e.g. Ståhl and Lämås 1998, Ringvall and Ståhl 1999b). If the visibility is poor, it may be difficult to observe the dead trees and the ends of logs from further away. Ringvall and Ståhl (1999a and 1999b) noted when studying the effect of the surveyor on estimates for downed dead wood that TRS may be prone to subjective errors and large differences between surveyors whereas LIS estimates are less sensitive to surveyor effects. Thus, even though relascope-based methods for assessing CWD have been observed to be highly efficient in various areas and under different forest conditions, no single inventory method exists which is the most efficient and generally

recommended method for all forest types. Nevertheless, it is suggested that those inventory methods should be used which are especially designed for rare forest characteristics.

The sampling efficiency of all the field inventory methods for CWD could be further increased if PPS sampling was used when selecting the sample units, and in this sense the use of low-cost auxiliary information can reduce the inventory costs and increase the accuracy of the estimates considerably whenever CWD is to be assessed. It should be noted that when downed dead trees and logs were assessed in Sonkajärvi and Juuka (papers II–V), only those trees which had their stump or large end inside the strip or plot area were measured, which provides unbiased estimates of the CWD in the area concerned. Especially with small sample unit sizes, however, this may have reduced the correlation between the auxiliary data values and downed dead wood volumes. Thus, the correlations and the improvements in sampling efficiencies might have been higher if the downed dead wood volumes were calculated exactly within the sample unit boundaries, as this is the area for which the auxiliary data values were calculated.

The use of ALS data as auxiliary information has been studied only recently. Corona and Fattorini (2008) observed an approximately 2/3 smaller confidence interval for the estimate of total living tree volume when ALS data were used for calculating the estimates by means of a ratio estimator. In this thesis, the sampling efficiency for the CWD inventory did not improve markedly when ALS data were used in the estimation phase. Hawbaker et al. (2009) observed that the use of ALS data in the design phase for pre-stratifying the area to be studied was useful, since the prediction errors of the models constructed using random sample data were up to 68% larger than in the case where the modelling data were collected using stratified sampling. Although it was suggested quite a long time ago that auxiliary information could be used more in assessing CWD (see Ståhl et al. 2001), only few reports have been published on the use of auxiliary information in CWD assessments. Until now, GTS has been the only substantially studied field inventory method in which auxiliary information has been used for assessing rare characteristics such as CWD (Ståhl 1997, 1998, Ståhl et al. 2000, Ringvall et al. 2007). It was assumed in the present work that the use of auxiliary data does not incur extra costs, and that such data sets are available free of charge for use in inventories of CWD. If this assumption does not apply, more thorough research into the data acquisition, processing and field inventory costs of different inventory methods will be needed in order to obtain a more profound analysis of the sampling efficiencies of different inventory methods using auxiliary information.

The times taken to measure CWD in the field using different inventory methods occupy a key role in papers II–V. The sampling efficiencies for different methods were calculated with varying inventory times, and their sampling efficiencies were compared by calculating the differences in the standard errors of the means given the same inventory times (see Ståhl 1997, Ståhl and Lämås 1998). Therefore, if the time consumption in some inventory methods differ considerably from the estimated times, the relative efficiencies of the various inventory methods would differ from those established here. Field inventory data for 100 m wide strips were used to calculate the inventory times for the sample simulations of plots with fixed area, but the times taken to assess CWD using LIS, PRS and TRS had to be estimated, since no field inventory data on time consumption were available for these methods. When PPS sampling was compared with equal probabilities sampling in the case of fixed-sized plots, strip sampling, ACS and LIS, the measurement time was defined based on the number of sample units measured. Thus, no additional time consumption was defined with respect to the amount of CWD. It should be taken into account, however, that since the target in PPS sampling is to locate the sample units in areas where more CWD

exists, it will take slightly longer on average to measure such plots than to measure plots selected by SRS. If the time consumption of all the inventory methods were measured in the field, the differences in sampling efficiency would not result from the various manners of defining the measurement times. Relascope sampling were observed to be the most efficient with fixed inventory times, and the same approach was also observed to be the most efficient in cases where the time required for making relascope measurements was doubled. Thus, the higher sampling efficiency achieved with relascope sampling does not arise only from fast measurement of relascope sample points or lines, but it may also be due to the concentration of sampling on the largest trees, which form most of the CWD volume.

In paper IV, the best-correlating ALS metric was combined with the best-correlating variable based on aerial photographs or stand-register data. It is possible, however, that more accurate auxiliary information could be achieved if the ALS metric and other auxiliary variable used in the model are selected from among all the possible auxiliary variables and not by combining the best-correlating variables from two different data sources. In particular, if the best-correlating variables in two data sources are highly correlated, their combination will not always provide a better fit than the use of only one data source. In addition, it was observed in paper I, where ALS metrics were used for modelling downed dead wood volumes, that the accuracy of the model could not be increased if living tree characteristics were added to the model as independent variables. This may be due to high correlation between ALS metrics and the characteristics of the growing stock.

The use of PPS sampling used in a CWD inventory can increase sampling efficiency considerably, but if the frequency distribution of the auxiliary data values is highly skewed and the correlation between the variable of interest and the auxiliary variable is weak, PPS sampling should be avoided, since unequal probability sampling may then lead to highly inefficient procedures (see Schreuder et al. 1987). When the improvements in sampling efficiencies, the correlations between the variable of interest and the auxiliary data values, and the skewness were studied, it was observed that the use of ALS-based auxiliary information was most profitable. The risk of highly inefficient samples can be regarded as minimal in the case of ALS-based auxiliary information, since the correlations were usually higher than in the case of other data sources and skewness did not occur. The same also applies to stand-register data, but problems exist if the latter are not available for large parts of the study area concerned, since minor improvement in sampling efficiency may then be achieved. In addition, the quality of the existing stand-register data may vary greatly between areas. The data may be up-to-date, or as much as several decades old, whereupon growth models will have to be used to update the data to the current state. The effects of thinnings and other forest management operations should nevertheless be taken into account when updating stand-register data.

5.3 Future research

Auxiliary information was used in the design phase here by implementing PPS sampling with different inventory methods for CWD. When auxiliary information was used in the estimation phase, a ratio or regression estimator was used for calculating the CWD estimates. There exist many other manners in which auxiliary information could be utilized, however, and therefore there still exist a vast number of possible topics for future research into alternative means of making a CWD inventory more efficient. One interesting subject

which could be studied in the future is the use of stratified sampling to find out whether ALS-based stratification is more efficient than PPS sampling in the case of a CWD inventory. When stratified sampling is used in the design phase, the area concerned is pre-stratified using ALS data, for example, and the strata are then regarded as separate populations in each of which the sampling is performed independently (see Lehtonen and Pahkinen 2004). If no data for stratification are available before the field inventory, such data can be used afterwards, for post-stratification. The sampling efficiency can be increased considerably if within-stratum variation is small in either pre-stratification or post-stratification. Kozak and Zieliński (2007) observed that correlation and variability in the variable of interest have an effect on whether stratification is more efficient than sampling with unequal probabilities. The efficiency of PPS sampling with respect to stratified sampling depends, for example, on the number of strata, the stratification method, the sampling strategy and the sample unit size. This is another matter that would require thorough research.

Since CWD is seldom the main target of a forest inventory, dead trees are usually assessed in parallel with living trees. If PPS sampling is used for the inventory of living trees, it could also improve the sampling efficiency for CWD if the variables which correlate with the living tree characteristics were also to correlate with CWD volumes. In forest inventories, sampling is often concentrated on large trees, as in the case of relascope sampling, since large trees form most of the total volume, which is often the variable of interest. The auxiliary variables which correlate with the size of living trees are therefore often used as auxiliary information in inventories of living trees, and the same auxiliary information could also be used for CWD inventory since the size of living trees has been observed to be correlated with CWD (Sippola et al. 1998, Siitonen 2001).

The same situation may also be valid if the forest area is stratified for an inventory of living trees but the same stratification is used for CWD as well. The companies which perform large-scale forest inventories in Finland usually collect the field data for modelling the variables of interest using remote sensing metrics as independent variables. In general, the areas for field data collection are selected subjectively, or else remote sensing material such as ALS data are used to stratify the area. The sample plots in stratified sampling could also be used to obtain estimates for CWD.

In cases where the sampling and inventory methods for living trees are not suitable for CWD assessments, PPS sampling in connection with the CWD inventory could be restricted to the close vicinity of the plots selected for measuring living trees. Especially in state forests, wood production is not the only forest use, and ecological aspects are considered as well. In some areas, biodiversity indicators may be the most important variables of interest, and the inventory of living trees may be carried out along with an inventory of other variables.

In CWD inventories over large areas, it may be more sensible to design the sample plot locations so that the time taken to transfer between plots is not excessive. The use of PPS sampling in the manner in which it was performed in the present work would not be efficient in large areas, however, because the sample plots may be very scattered. Therefore clusters similar to those used in the NFI could be considered for locating the plots, and their size could be fixed so that the field inventory in the area of one cluster takes one working day. Auxiliary information could then be gathered from nearby areas where NFI plots or clusters are located, and PPS sampling for measuring CWD could be performed in those areas. The efficiency of PPS sampling when restricted in this way remains to be examined in the future. When PPS sampling is used in large areas, it could be beneficial to employ

geographical maps, such as masks to distinguish water areas from land areas. Undesirable areas could then be removed from the analyses and the field inventory would not be targeted at them. Spatial information on the existence of CWD could be produced by means of ALS data and field inventory plots in the manner similar to that in which spatial information on growing stock volumes is produced based on NFI plots and satellite images (see Luque et al. 2004, Tomppo 2006), where field inventory and remote sensing data for NFI plots are used for reference purposes when estimating the variables of interest for the target areas by the non-parametric k-nearest neighbour method (see Tomppo and Halme 2004). CWD volumes could also be estimated, using the constructed regression models, for instance, and the CWD volume estimates could then be used to provide spatial information on the existence of CWD or as auxiliary information when selecting field inventory areas.

The accuracy of ALS-based CWD volume estimates as a function of CWD volumes cannot be evaluated on the basis of the present results, and thus it is not possible to say how reliable the estimates for CWD that can be acquired using ALS data are in forests of different kinds and with varying amounts of CWD. Furthermore, since forests can vary considerably in their structure and management history, further research would be needed to find out the accuracy of ALS-based estimates for CWD volumes in different situations. The total CWD volume in the natural forest data from Koli was about $46.0 \text{ m}^3\text{ha}^{-1}$, and the estimation of CWD volumes using ALS data was successful in that case. In the data for the managed forests in Sonkajärvi and Juuka, however, the CWD volumes were only $2.7 \text{ m}^3\text{ha}^{-1}$ and $6.3 \text{ m}^3\text{ha}^{-1}$, respectively, and then the accuracy of the CWD volume estimates was poor, and therefore in that case it was studied how ALS data could be used only as auxiliary information. In addition, experiences from trials in Norwegian forests have proved that the estimation of CWD volumes was not particularly successful when the CWD volume was about $10 \text{ m}^3\text{ha}^{-1}$. Thus, to get reliable CWD volume estimates using ALS data the CWD volume should probably be well over $10 \text{ m}^3\text{ha}^{-1}$. Nonetheless, the accuracy requirements and the information needs differ considerably depending on the purpose of the inventory, and for some purposes poorer estimates are adequate. In addition, wall-to-wall information and a map representing the locations of CWD-rich areas may be needed in some cases, whereas in others an estimate of the mean CWD volume in an area may be sufficient. Sometimes even a map with poor estimation accuracy may be better than a good estimate for the mean CWD volume, and therefore it ultimately depends on the use as to whether spatial estimates for the total inventory area are desirable or whether a sample-based inventory will be satisfactory.

The forest succession and forest management operations have notable effects on the forest structure and on the formation of CWD, for example, which contributes to the distribution and number of species in the area (Kouki 2007). Since the spatial and temporal continuity of CWD is important for many species (Hanski and Hammond 1995, Esseen et al. 1997, Hottola and Siitonen 2008), it is important to monitor changes in the forest ecosystem over time. The rapid development of ALS technology and the large amount of available remote sensing data has made it possible to monitor changes in forests at fairly low costs. The CWD volume prediction models constructed in paper I can be used for estimating CWD volumes in natural forests at different times, enabling changes in amounts of CWD to be detected. The laser scanning system and the flying parameters used in the inventory should nevertheless be the same from one inventory to another, since if they differ considerably the same ALS-based models cannot be used for estimating CWD volumes, or else the models will not provide reliable estimates. It is also possible to detect changes in the amounts of CWD by studying the values of single ALS metrics. An increase

in the standard deviation of heights, for instance, may indicate an increase in the amount of CWD. In managed forests, however, the same effect may also be due to thinnings. In addition, since changes in the ALS-derived height metrics may also indicate forest growth (see Næsset and Gobakken 2005), more effort should be devoted in future to studying how changes in the amounts of CWD can be detected from forest growth and forest management operations. Estimation of the amounts of CWD in managed forests at different times requires a field inventory, and unbiased CWD data can be acquired cost-efficiently using the most efficient field inventory methods for CWD together with auxiliary information in the design phase of the inventory.

Many saproxylics require a certain amount of CWD to survive. For them the existence of CWD is significant only if the amount is large enough. Since habitat requirements differ considerably between species, however, no specific target level for CWD can be defined for the conservation of saproxylics (e.g. Ranius and Jonsson 2007). In addition, a certain decay stage or tree species is important for the survival of some species, but it may be impossible to detect these by means of ALS data. Estimates for the species of living trees can be used to assess the species distribution of dead trees in the area, but estimation of the decay stage is more problematical. Therefore, when ALS data is used the major focus is on estimating the amount of CWD.

Since notable differences occur in the requirements of different species, and the natural states or characteristics of conservation areas and managed forests vary considerably, forests which are managed on different principles should be considered equally, as ecologically valuable habitats may occur anywhere (Kouki 2007). If 'hot spot areas' where the amount of CWD is very high could be found in managed forests, it would be interesting to target a field inventory at such areas. ALS-based auxiliary information could be used to search for potential places where hot spots might occur, and if hot spots are found on the basis of a field inventory, these could be of benefit when designing forest management operations, planning conservation areas and entering into private conservation contracts. It has been observed that only minimal economic losses can occur in boreal forests if the conservation of ecological values is considered in the managed forests by delaying thinnings (Tikkanen et al. 2007). As Ranius and Jonsson (2007) state, it is impossible to preserve all species, but it is realistic to try to preserve the majority of species in managed forests if biodiversity aspects are taken into account in forest management operations and decision-making. The use of ALS data can notably improve the cost-efficiency of future CWD assessments.

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